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Special Issue Reprint

Safety Management and Occupational Health in Construction

Edited by
Krishna Kisi and Kishor Shrestha

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Safety Management and Occupational Health in Construction

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Guest Editors

Krishna Kisi
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Contents

About the Editors . . . . . **vii**

Chung Chyi Chou, Mu Fan Tsai, Chi An Hsu, Ching Sen Chuang, Wei Ta Chang and Chia Chou Tsai
Bridging the Cognitive–Execution Gap in MEP Engineering: A Mixed-Methods Study from Taiwan
Reprinted from: *Buildings* **2026**, *16*, 2060, https://doi.org/10.3390/buildings16112060 . . . . . **1**

Mohammed Y. Wahan, Chunyan Yuan and Hafiz Zahoor
Exploring the Factors Influencing Construction Workers' Safety Behavior: An Artificial Intelligence-Based Model Approach
Reprinted from: *Buildings* **2026**, *16*, 1965, https://doi.org/10.3390/buildings16101965 . . . . . **21**

Mohamed Mohamed and Benard Vetbuje
Using Safety Accountability to Enhance Construction Safety Performance: The Mediating Roles of Safety Monitoring and Safety Learning Under Inclusive Leadership
Reprinted from: *Buildings* **2026**, *16*, 1244, https://doi.org/10.3390/buildings16061244 . . . . . **49**

Jose Javier Guevara-Torres, Jhon Alexander Quiñones-Preciado, Alexander Paz, Héctor E. Jaramillo Suarez, José Jaime García and Lessby Gómez-Salazar
A Musculoskeletal Simulation Study to Evaluate the Influence of Postural and Anthropometric Variability on Intervertebral Loads During Manual Lifting in Construction
Reprinted from: *Buildings* **2026**, *16*, 1156, https://doi.org/10.3390/buildings16061156 . . . . . **75**

Krishna Kisi and Omar S. López
Ergonomic Risk and Musculoskeletal Disorders in Construction: Assessing Job-Related Determinants in the U.S. Workforce
Reprinted from: *Buildings* **2026**, *16*, 286, https://doi.org/10.3390/buildings16020286 . . . . . **91**

Mohammed Alamoudi
Hierarchical Modeling of Safety Factors in the Construction Industry Using Interpretive Structural Modeling (ISM) and Decision-Making Trial and Evaluation Laboratory (DEMATEL)
Reprinted from: *Buildings* **2026**, *16*, 155, https://doi.org/10.3390/buildings16010155 . . . . . **105**

Qingzhen Yao and Lue Lan
Transnational Construction Project Risk Factors and Their Impact Pathways
Reprinted from: *Buildings* **2025**, *15*, 4526, https://doi.org/10.3390/buildings15244526 . . . . . **128**

Darío Collado-Mariscal, Juan Pedro Cortés-Pérez, Mario Núñez-Fernández and Alfonso Cortés-Pérez
LOINSH Information Structure for the Assessment of Occupational Risks in the Execution of Roads Based on the LOIN Standard
Reprinted from: *Buildings* **2025**, *15*, 4452, https://doi.org/10.3390/buildings15244452 . . . . . **149**

Hyeon-Ji Jeong and Jeong-Hun Won
Proposed Safety Control Structure Model for Building Demolition Projects Based on STAMP Model in South Korea
Reprinted from: *Buildings* **2025**, *15*, 3680, https://doi.org/10.3390/buildings15203680 . . . . . **188**

Mohamed Ali, Kolawole Iyiola, Ahmad Alzubi and Hasan Yousef Aljuhmani
Using Safety-Specific Transformational Leadership to Improve Safety Behavior Among Construction Workers: Exploring the Role of Knowledge Sharing and Psychological Safety
Reprinted from: *Buildings* **2025**, *15*, 3340, https://doi.org/10.3390/buildings15183340 . . . . . **207**

Sujan Acharya, Krishna Kisi, Sabrin Raj Gautam, Tarek Mahmud and Rujan Kayastha
A High-Performance Hybrid Transformer–LSTM–XGBoost Model for sEMG-Based Fatigue Detection in Simulated Roofing Postures
Reprinted from: *Buildings* **2025**, *15*, 3005, https://doi.org/10.3390/buildings15173005 . . . . . **231**

Hai Chien Pham, Si Van-Tien Tran and Ung-Kyun Lee
Prioritizing Critical Factors Affecting Occupational Safety in High-Rise Construction: A Hybrid EFA-AHP Approach
Reprinted from: *Buildings* **2025**, *15*, 2677, https://doi.org/10.3390/ buildings15152677 . . . . . **261**

Ndaleni Phinias Rantsatsi
Exploring Factors Impeding the Implementation of Health and Safety Control Measures in the South African Construction Industry
Reprinted from: *Buildings* **2025**, *15*, 2439, https://doi.org/10.3390/buildings15142439 . . . . . **276**

Ali Katooziani, Idris Jeelani and Masoud Gheisari
GPT Applications for Construction Safety: A Use Case Analysis
Reprinted from: *Buildings* **2025**, *15*, 2410, https://doi.org/10.3390/buildings15142410 . . . . . **294**

About the Editors

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Krishna Kisi is an Associate Professor in the Department of Engineering Technology at Texas State University, San Marcos, USA. Dr. Kisi holds a Ph.D. in Engineering from the University of Nebraska–Lincoln, an M.S. in Construction Management from the University of Nevada, Las Vegas, and a B.S. in Civil Engineering from Tribhuvan University, Nepal. Dr. Kisi's research is highly prolific, documented in over 62 peer-reviewed publications. He contributes significantly to both teaching and research in the field. A licensed Professional Engineer (P.E.) in Texas, Dr. Kisi focuses on creating safer and more efficient construction environments. He is a recognized expert in areas including occupational safety, human performance, ergonomics, construction labor productivity, and dispute resolution. Dr. Kisi is at the forefront of integrating cutting-edge technologies such as AI, AR/VR for workforce safety game development, and sensors including IMU, foot pressure, sEMG, and fNIRS to predict and mitigate safety and injury risks among workers. His excellence in academia has been recognized with awards, including the Associated School of Construction Regional Teaching Award, the Board of Regents Research Award, and the LBJ Institute Faculty Research Fellowship. Dr. Kisi has demonstrated exceptional success in securing competitive funding as a Project Director from the U.S. Department of Labor, addressing critical safety topics such as Fall Prevention, Temperature Extremes, Ergonomics, and Workplace Safety related to Infectious Diseases in Construction and general industries. He has also received funding as a PI on AR/VR game development, safety prediction/prevention, and musculoskeletal health issues among construction workers.

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Article

Bridging the Cognitive–Execution Gap in MEP Engineering: A Mixed-Methods Study from Taiwan

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Abstract

This study examined how mechanical, electrical, and plumbing (MEP) practitioners understand and apply quality and safety management in construction projects in Taiwan. It focused on the gap between what practitioners know about best practices and what they can carry out on site, defined here as the "Cognitive–Execution Gap." A mixed-methods design was used, combining a questionnaire survey of 130 MEP practitioners with semi-structured interviews with six senior experts. Practitioners with MEP-related academic backgrounds scored significantly higher in professional knowledge and practice than those from unrelated fields, with mean differences of 0.87 and 0.78 points on a 5-point scale, respectively (both $p < 0.001$). In contrast, awareness of management optimization strategies was high and similar across all demographic groups. Interview findings suggest that schedule pressure, the lower organizational status of MEP compared with civil engineering, and persistent talent shortages prevent practitioners from applying the practices that they recognize as necessary. The results provide evidence consistent with a Cognitive–Execution Gap and suggest that bridging it requires organization-level reforms, including prospectively evaluated BIM-based coordination, clearer standard operating procedures and performance indicators, and structured mentorship programs to strengthen professional capacity in MEP engineering.

Keywords: mechanical electrical and plumbing (MEP); construction management; cognitive–execution gap; building safety; quality control; organizational culture; building information modeling (BIM)

1. Introduction

Mechanical, electrical, and plumbing (MEP) systems are central to building operation because they govern energy use, indoor comfort, and life safety. As buildings become larger and more complex, MEP installations account for a substantial share of total construction costs and often occupy a comparable portion of the project critical path [1]. However, MEP works are often planned and managed less systematically than structural and architectural works. Coordination between MEP systems and civil or structural elements is frequently postponed or treated as secondary to other project priorities [2,3]. This practice leads

to spatial clashes, rework, and delays, and it has been linked to substantial cost growth, with direct rework costs averaging around 5% of the total construction costs in prior studies [4]. Hidden defects in plumbing, electrical, and HVAC systems may remain unnoticed during construction and only emerge during operation, causing safety incidents, higher maintenance costs, and reputational damage to developers and contractors. Recent studies indicate that MEP works contribute disproportionately to construction accidents, often in congested spaces with multiple trades and inadequate hazard awareness [1,5].

In recent years, digital tools, particularly Building Information Modeling (BIM), have been promoted as a means of addressing coordination and safety deficiencies. BIM facilitates clash detection and design verification before physical work begins [6]. Despite this, the uptake of BIM in MEP-specific applications remains uneven. Research has documented multiple barriers to BIM adoption, including insufficient skilled personnel, a lack of BIM awareness among field-level staff, interoperability problems across software platforms, and the absence of contractual mandates or government-enforced standards [7,8]. These barriers are especially pronounced for smaller MEP subcontractors, who often lack the resources to train staff or purchase compatible tools. Studies of behavior-based safety programs further show that new safety initiatives do not automatically lead to better outcomes when human and organizational issues are not addressed [9]. This body of evidence suggests that the main constraint on MEP construction quality and safety is no longer the availability of technology but rather the way that projects are organized and managed.

Construction safety researchers have increasingly recognized the importance of the organizational context in shaping individual behavior. Safety climate—defined as shared perceptions of the priority given to safety by management—has been shown to be a strong predictor of worker safety behavior in Taiwan and internationally [10,11]. Prior studies have also documented that schedule pressure is one of the most consistent drivers of unsafe behavior and degraded safety performance, with workers bypassing standard procedures when deadlines are tight [12,13]. However, few studies have examined whether high levels of knowledge and awareness are themselves sufficient to produce safe and high-quality field behavior, or whether structural and organizational barriers can block translation from awareness to execution. This gap motivates the central construct of the present study.

We therefore propose the concept of a "Cognitive–Execution Gap" in the MEP sector, defined as a mismatch between practitioners' understanding of quality, safety, and management principles and their ability to apply these principles consistently in the field. In this framework, construction personnel may score highly on assessments of awareness and attitudes yet still struggle to implement the same practices on site. The key research questions are as follows:

1. Do MEP practitioners in Taiwan demonstrate systematically higher management optimization awareness scores than professional knowledge and practice scores? Does this pattern differ by demographic group?
2. What organizational and structural mechanisms prevent practitioners from converting their awareness into consistent field execution?

Previous research on construction has often examined technical skills, safety climate, or technology adoption separately. Prior studies have documented differences in technical ability by education level and have shown that work and schedule pressure are important drivers of unsafe behavior. A smaller but growing body of literature has examined the knowing–doing gap in organizational settings—the observation that the understanding of good practice does not automatically translate into consistent behavior—but this concept has rarely been applied to MEP-specific contexts in Asia. Fewer studies have measured whether high levels of technical and managerial knowledge are translated into reliable implementation in the field, or how organizational hierarchies may prevent this

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translation. The present study addresses this gap by evaluating professional awareness in three dimensions—professional knowledge, professional practice, and management optimization awareness—and linking these measures to demographic factors and organizational conditions in the Taiwan MEP sector, thereby contributing an empirically grounded framework applicable to other regional contexts where MEP skills gaps and civil–MEP hierarchical tensions exist.

2. Literature Review

Table 1 presents a structured synthesis of the key literature informing this study, illustrating the research gaps that the present work addresses.

Table 1. Summary of key prior studies and their focus and the contributions of the present study.

Study	Focus	Key Finding	Gap Addressed by Present Study
Korman et al. (2003) [2]	MEP coordination knowledge	MEP coordination requires specialized cross-disciplinary knowledge	Does not measure practitioner awareness–execution discrepancy
Choudhry & Fang (2008) [5]	Unsafe behavior, construction	Schedule pressure and supervision deficiency are key drivers	Does not examine knowledge–execution mismatch dimensionally
Zhang & Fang (2013) [14]	Cognitive analysis, safety harness use	Workers know correct behavior but normalize non-compliance	Does not quantify gap across three professional dimensions
Guo et al. (2018) [9]	Behavior-based safety, system dynamics	New safety initiatives fail when organizational issues are unaddressed	Does not quantify the awareness–execution discrepancy
Liu et al. (2024) [15]	Managers' safety cognition → worker behavior	Safety awareness and capability mediate cognition–behavior link	Does not examine MEP-specific organizational hierarchy effects
Fang et al. (2006) [10]	Safety climate, Hong Kong construction	Organizational factors shape safety outcomes	Does not address execution gap under schedule pressure
Mohamed (2002) [11]	Safety climate, construction sites	Management commitment predicts safety climate	Does not examine MEP talent and structural dominance issues
Chen et al. (2021) [16]	Safety climate and worker behavior, Taiwan	Strong safety climate–behavior relationship on Taiwan construction sites	Does not examine the MEP sector specifically
Akram et al. (2021) [8]	BIM implementation challenges	Lack of skilled staff and awareness are primary barriers	Does not link barriers to the practitioner-level cognitive gap
He et al. (2020) [12]	Schedule pressure and safety behavior	Supervisor pressure negatively impacts safety compliance	Does not examine MEP management awareness dimensions
Present study	MEP professional awareness, 3 dimensions, Taiwan	Cognitive Execution Gap supported/evidence consistent	First study quantifying 3-dimension awareness–execution gap in the Taiwan MEP sector

2.1. MEP Construction Challenges and Safety

MEP systems form the backbone of building operation, yet their management within construction projects is systematically disadvantaged. In project hierarchies, civil and structural engineering work typically takes precedence over MEP installation in scheduling and spatial planning. This "civil-first" culture forces MEP teams to adapt to residual spaces and condensed timelines, increasing the risk of concealed defects and construction accidents. MEP-related accidents disproportionately occur in congested multi-trade environments where hazard recognition is inadequate and spatial planning is completed without adequate MEP input. The rework costs attributable to poor MEP coordination have been estimated

at approximately 5% of the total construction costs, representing a substantial and largely preventable economic loss.

2.2. The Knowing–Doing Gap in Organizational Settings

The notion that knowledge does not automatically translate into action has been documented extensively in organizational research. Pfeffer and Sutton (2000) [17] identified the "knowing–doing gap" as a pervasive organizational problem in which firms fail to execute what they know because of inertia, fear, measurement dysfunction, and competing priorities. In construction safety contexts, Zhang and Fang (2013) demonstrated a similar cognitive behavioral disconnect where workers knew the correct safety behavior but normalized non-compliance due to peer norms and supervisory indifference under schedule pressure [14]. Liu et al. (2024) showed that managers' safety cognition affects workers' safety behavior through the mediating roles of safety awareness and capability but that organizational context strongly conditions this relationship [15,18]. He et al. (2020) further demonstrated that supervisor-induced time pressure directly undermines safety compliance, even when workers are fully aware of the required procedures [12]. The present study extends this conceptual framework to MEP professional practice, operationalizing the knowing–doing gap as a three-dimensional measurable construct.

2.3. BIM Adoption and Barriers

BIM has been widely promoted as a tool for clash detection, coordination, and quality management in construction. Studies have shown that BIM can substantially reduce rework costs and improve cross-disciplinary coordination when its use is institutionally enforced and supported [19]. However, adoption barriers remain significant, particularly for MEP subcontractors. These barriers include a lack of BIM-skilled staff, high software and training costs, interoperability issues between platforms, and the absence of contractual or regulatory requirements mandating use [20–22]. Critically, awareness of BIM's benefits does not automatically translate into systematic BIM use in practice—a pattern directly consistent with the Cognitive–Execution Gap framework proposed in this study.

2.4. Professional Development and Talent Gaps in MEP

The MEP construction sector faces a well-documented talent shortage globally and in Asia. Over half of construction workers in many regions lack formal trade training, and the aging of experienced workforces threatens knowledge transfer [23,24]. In Taiwan's MEP sector, non-relevant academic backgrounds are the norm among field practitioners, as demonstrated by the present study sample (with 62% being from unrelated fields). Prior research has shown that workers with less domain-specific formal training demonstrate lower safety knowledge and practice scores, but the magnitude and specific dimensions of this gap in MEP have not been quantified. Structured mentorship programs and industry–academia partnerships have been proposed as remedies, though their systematic implementation remains limited.

3. Materials and Methods

This study used a mixed-methods design to investigate the Cognitive–Execution Gap in MEP engineering. A mixed-methods approach was selected because the research questions required both the breadth of quantitative measurement across a heterogeneous sample and the depth of contextual explanation that only qualitative inquiry can provide. This follows established frameworks for mixed-methods research in construction management [25–27], where the sequential explanatory design has been increasingly recommended for investigating socio-technical phenomena that combine measurable outcomes with organizational and behavioral context [28]. A quantitative questionnaire survey was conducted

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to measure professional awareness across different demographic groups, followed by qualitative interviews to explain and deepen the survey findings. Figure 1 presents the overall research methodology.

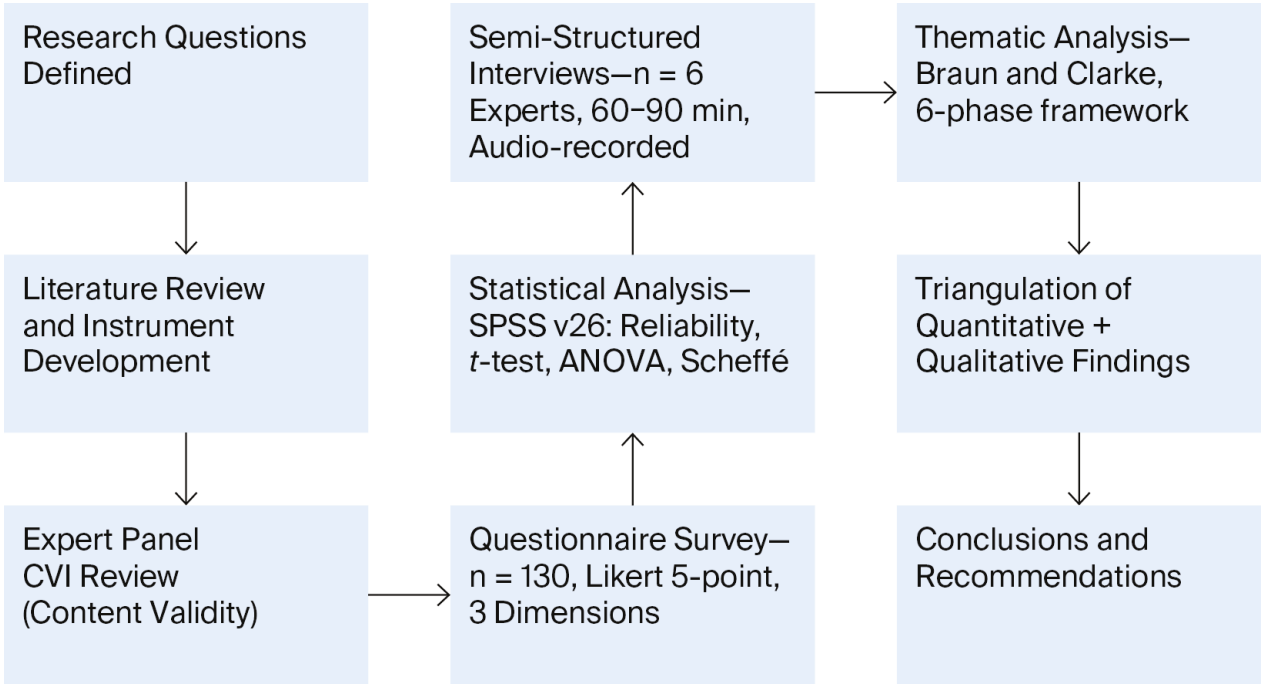

Figure 1. Flowchart of research methodology.

3.1. Quantitative Phase: Survey Instrument

In the quantitative phase, this study used a structured questionnaire with items rated on a 5-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree), a format widely defended in survey-based construction-management research for balancing measurement precision and respondent cognitive load [29]. The draft instrument was developed by the research team based on a review of relevant literature and standards in MEP engineering, fire safety, and occupational health. It was then reviewed by a panel of academic and industry experts in fire protection, structural engineering, and occupational safety. Content validity was assessed using the Content Validity Index (CVI), computed at both the item level (I-CVI) and the scale level (S-CVI) following the procedures established by Lynn [30] and refined by Polit and Beck [31] and Polit, Beck, and Owen [32]; this procedure has recently been applied in construction-management questionnaire research [33]. Items with an I-CVI of 0.80 or above were retained, which is the threshold typically recommended for expert panels of three to five raters [32]; the overall scale was required to meet S-CVI/Ave $\geq$ 0.88 [31,32]. This process ensured that the instrument measured what it was theoretically designed to measure, beyond the confirmation of internal consistency provided by reliability analysis (see Section 4.1). The final questionnaire comprised 24 items across three dimensions:

1. Professional knowledge (7 items): This dimension assessed the understanding of basic engineering principles, relevant regulations and codes, design calculation logic, and common schematic symbols across major MEP systems.
2. Professional practice (8 items): This dimension measured self-reported ability to perform field tasks such as participating in coordination meetings, resolving on-site clashes, modifying CAD/BIM drawings, and supervising testing procedures.

3. Management optimization awareness (9 items): This dimension captured perceptions of the need for systematic management strategies, including BIM-based simulation, regular cross-departmental meetings, clear change-order responsibility, and early risk prevention.

The full questionnaire is provided in Appendix A.

3.2. Sample and Data Collection

The target population was practicing MEP-related personnel in Taiwan, including staff from large construction firms, specialized MEP subcontractors, and supervisory bodies. A non-probability convenience sampling approach was used, relying on professional networks and online distribution channels to reach respondents. This approach is widely adopted in exploratory construction-management questionnaire research where a complete sampling frame is not available [34]; while it limits statistical generalization, homogeneous convenience samples have been shown to support valid internal inferences when generalization claims are appropriately bounded [35], and the limitation is explicitly addressed in Section 6. A total of 130 valid questionnaires were collected. Table 2 presents the participants' demographic profile.

Table 2. Participants' demographic profile (n = 130).

Variable	Category	*n*	%
Gender	Male	118	90.8
	Female	12	9.2
Years of Experience	<3 years	32	25.4
	3–6 years	17	13.1
	>6 years	81	61.5
Job Level	Assistant/Junior Engineer	29	22.3
	Director/Vice Director	42	32.3
	Senior Manager or Above	59	45.4
Education Level	High school/Vocational	19	15.4
	University/College	88	67.7
	Graduate Degree	23	16.9
Academic Major	MEP-Relevant	50	38.5
	Unrelated	80	61.5

3.3. Qualitative Phase: Semi-Structured Interviews

To interpret the survey results and explore underlying mechanisms, semi-structured interviews were conducted with six senior industry experts. Purposeful sampling was used to recruit Vice Presidents, Engineering Directors, and General Managers from major construction and MEP firms. The decision to recruit six high-information participants is consistent with the "information power" principle of Malterud, Siersma, and Guassora [36], which holds that a narrow study aim, high sample specificity, and strong theoretical anchoring substantially reduce the number of interviews required to generate analytically rich data. Earlier empirical work likewise demonstrates that the principal elements of meta-themes typically emerge within the first six interviews of a homogeneous expert sample [37], and a building-engineering-specific saturation analysis reaches the same conclusion for highly experienced respondents [38]. Table 3 presents the experts' profiles.

Table 3. Profiles of interviewed expert participants.

Expert	Role	Seniority
Expert 01	Vice President	>30 years
Expert 02	Construction Assistant Director	>40 years
Expert 03	Engineering Assistant Director	>40 years
Expert 04	Vice Engineering Manager	>30 years
Expert 05	President	>40 years
Expert 06	Vice President	>40 years

All interviews were conducted individually (one-on-one), in person at the participants' offices, with audio recording and subsequent verbatim transcription, following informed consent procedures. Each interview lasted for 60–90 min and was guided by a semi-structured protocol covering the following topics: (1) differences between corporate quality policies and site practice; (2) the impact of talent shortages on MEP operations; (3) relations between civil and MEP engineering units; (4) recommended strategies for improving management; and (5) barriers to the adoption of digital tools such as BIM.

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki and the relevant regulations in Taiwan. Participation was voluntary, and all data were collected anonymously or de-identified.

3.4. Quantitative Data Analysis

Quantitative data were analyzed using SPSS version 26. Descriptive statistics were used to summarize central tendencies and variability for all items and dimensions. Internal consistency was evaluated using Cronbach's alpha coefficients, with values interpreted against the conventional thresholds established by Nunnally and Bernstein [39] and clarified by Tavakol and Dennick [40], in which alpha > 0.90 indicates excellent internal consistency. Before conducting inferential tests, the data distribution was examined for each dimension. Following the guidance of Ghasemi and Zahediasl [41] and Norman [42], we did not rely on formal normality tests for inferential decision-making: at $N = 130$ the sampling distribution of the mean approximates normality by the Central Limit Theorem, and parametric tests have repeatedly been shown to be robust to mild departures from normality and to the ordinal nature of multi-item Likert composites [42]. Independent-samples *t*-tests were conducted to examine differences between binary groups (gender and academic major relevance). One-way ANOVAs were conducted to test differences across multiple-category variables (years of experience, job level, and education level). Scheffé post hoc tests [43] were applied when the ANOVA results were statistically significant ($p < 0.05$) to identify specific group differences; Scheffé was selected because it is the most conservative pairwise comparison procedure and is robust to unequal sample sizes, which is the situation in the present study. Exact *p*-values are reported throughout.

3.5. Qualitative Data Analysis

Interview data were analyzed using the six-phase thematic analysis framework proposed by Braun and Clarke [44], applied here in the "reflexive" orientation later articulated by the same authors [45] to acknowledge the active role of the analyst in theme generation. This involved (1) familiarization with the data through repeated reading of transcripts; (2) generating initial codes by labeling segments of data that captured meaningful features; (3) collating codes into potential themes; (4) reviewing and refining the themes against the coded data and the full dataset; (5) defining and naming the themes with clear descriptions; and (6) producing the final analysis with representative quotes. Two members of the research team coded the data independently and then compared codes; disagreements were

resolved through reflective discussion until consensus was reached, in line with current guidance on transparent coding practices in qualitative research [46]. Consistent with the reflexive thematic analysis tradition [45], we did not compute a statistical inter-coder reliability coefficient; the dual-coding procedure was used to enhance analytic credibility and trustworthiness rather than to claim coding objectivity.

4. Results

4.1. Reliability Analysis

The questionnaire demonstrated high internal consistency across all three dimensions (Table 4). Cronbach's alpha values were 0.944 for professional knowledge, 0.952 for professional practice, and 0.925 for management optimization awareness. The overall 24-item scale yielded an alpha of 0.943, classified as excellent against the Nunnally and Bernstein [39] and Tavakol and Dennick [40] thresholds. The high internal consistency confirms that the items within each dimension measure a coherent underlying construct. Content validity was ensured at the instrument development stage through expert panel review and CVI scoring following Lynn [30] and Polit et al. [31,32] (overall S-CVI/Ave = 0.95; all retained items achieved I-CVI $\geq$ 0.80), providing independent evidence that each dimension covers its intended conceptual domain beyond what Cronbach's alpha alone indicates. Table 4 presents the results of the reliability analysis.

Table 4. Reliability analysis (Cronbach's alpha).

Dimension	Number of Items	Cronbach's Alpha	Interpretation
Professional Knowledge	7	0.944	Excellent
Professional Practice	8	0.952	Excellent
Management Optimization Awareness	9	0.925	Excellent
Total Scale	24	0.943	Excellent

4.2. Descriptive Statistics of the Dimensions

Descriptive results revealed a clear and consistent pattern across all 130 respondents: management optimization awareness scores were uniformly high, while professional knowledge and professional practice scores were substantially lower and more variable. For management optimization awareness, the item "MEP should conduct detailed interface coordination before construction to reduce future changes and conflicts" had the highest mean in the entire questionnaire (M = 4.59, SD = 0.62), and the item "Regular cross-departmental coordination meetings are very important for problem prevention" scored M = 4.58 (SD = 0.69). By contrast, in the professional knowledge dimension, the item on explaining design basis and load calculations had a mean of only 2.82 (SD = 1.11), illustrating substantial gaps in specific technical competencies. This divergence between high awareness scores and lower, more dispersed knowledge and practice scores constitutes the primary quantitative signature of the Cognitive–Execution Gap.

4.3. Gender Differences

Independent-samples *t*-tests revealed statistically significant differences between male and female practitioners at the overall dimension level (Table 5). Male practitioners scored significantly higher than female practitioners in professional knowledge (male: M = 3.35, SD = 0.89; female: M = 2.54, SD = 1.05; t = -2.982, $p = 0.003$) and management optimization awareness (male: M = 4.49, SD = 0.57; female: M = 4.09, SD = 0.52; t = -2.319, $p = 0.022$). The difference in professional practice did not reach statistical significance (male: M = 3.59, SD = 0.91; female: M = 2.81, SD = 1.24; t = -2.117, $p = 0.055$).

Table 5. Independent-samples *t*-test results by gender.

Dimension	Gender	*n*	Mean	SD	t-Value	*p*-Value
Professional Knowledge	Male	118	3.35	0.89	−2.982	0.003 *
	Female	12	2.54	1.05		
Professional Practice	Male	118	3.59	0.91	−2.117	0.055
	Female	12	2.81	1.24		
Management Optimization Awareness	Male	118	4.49	0.57	−2.319	0.022 *
	Female	12	4.09	0.52		

Note: * indicates statistical significance at $p < 0.05$.

The reasons underlying these gender differences cannot be determined from the present data. A plausible structural explanation is that male practitioners are more frequently assigned to on-site technical and supervisory roles, while female practitioners are concentrated in administrative roles, as has been suggested in the construction workforce literature, but this interpretation remains a hypothesis that requires dedicated investigation with role-specific data. Future research should collect job function data alongside gender to test this explanation directly.

4.4. The "Relevance" Gap: Impact of Academic Background

Academic major relevance was strongly associated with differences in professional awareness (Table 6). Practitioners with MEP-related degrees scored higher than those with unrelated degrees in both professional knowledge (means 3.81 vs. 2.94, $p < 0.001$) and professional practice (means 4.00 vs. 3.22, $p < 0.001$). Management optimization awareness scores were virtually identical between the two groups (relevant: M = 4.47, SD = 0.65; unrelated: M = 4.44, SD = 0.53; t = −0.276, $p = 0.783$).

Table 6. Independent-samples *t*-test by academic major relevance.

Dimension	Academic Background	*n*	Mean	SD	t-Value	*p*-Value
Professional Knowledge	Relevant Major	50	3.81	0.79	−5.792	<0.0001 *
	Unrelated Major	80	2.94	0.86		
Professional Practice	Relevant Major	50	4.00	0.79	−4.867	<0.0001 *
	Unrelated Major	80	3.22	0.94		
Management Optimization	Relevant Major	50	4.47	0.65	−0.276	0.783
	Unrelated Major	80	4.44	0.53		

Note: * indicates statistical significance at $p < 0.05$.

Item-level analysis showed that the relevant major group reported a better understanding of the basic principles of the main MEP pipelines, higher familiarity with testing and inspection standards, and greater ability to use CAD/BIM tools for spatial coordination. Management optimization awareness scores, however, were similar between the two groups (4.47 vs. 4.44, $p = 0.783$), indicating that they held comparable views on the importance of management strategies. The convergence of both groups on management optimization awareness—despite large divergences in knowledge and practice—is the central empirical finding supporting the Cognitive–Execution Gap framework. Figure 2 presents this pattern visually.

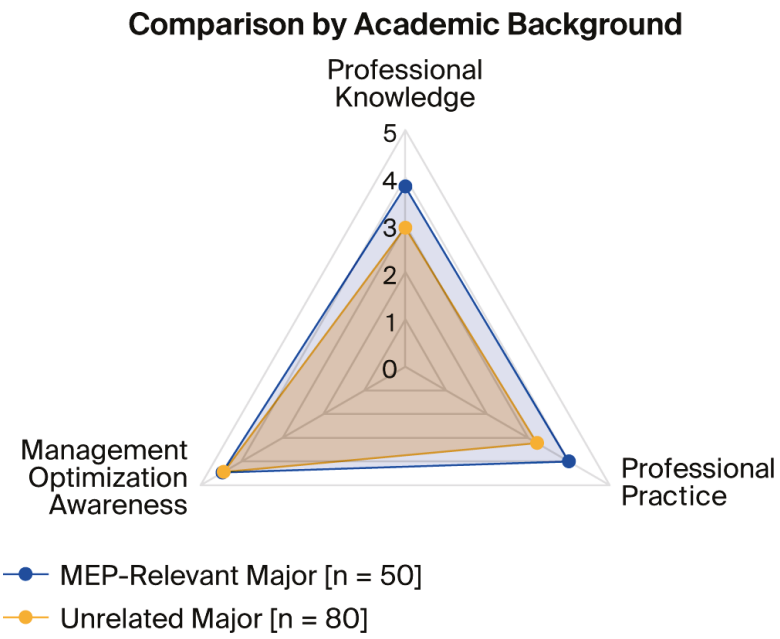

Figure 2. Radar chart: mean dimension scores by academic major relevance.

4.5. The Impact of Years of Experience

One-way ANOVAs showed no statistically significant differences in overall professional knowledge (F = 0.596, p = 0.552), professional practice (F = 2.069, p = 0.131), or management optimization awareness (F = 2.751, p = 0.068) scores by years of experience. Because dimension-level tests were not significant, no dimension-level post hoc comparisons were conducted; item-level ANOVAs were nevertheless examined to identify whether specific competencies might still differ by seniority, and Scheffé post hoc tests were applied only to those items where the item-level ANOVA reached statistical significance ($p < 0.05$). On this basis, practitioners with more than 6 years of experience scored significantly higher than those with fewer than 3 years on the item assessing familiarity with building technical regulations and fire protection laws (p = 0.026), indicating that regulatory knowledge accrues meaningfully with field experience, even when overall dimension scores do not differ significantly across seniority groups.

4.6. The Impact of Job Level

Job level showed clearer and more consistent differences than years of experience (Table 7). Assistant and Junior Engineers had significantly lower mean scores in professional practice than Directors/Vice Directors and Senior Managers (3.03 vs. 3.67 and 3.65; F = 5.164, p = 0.0068). They also scored significantly lower in management optimization awareness than higher-level staff (4.16 vs. 4.49 and 4.58; F = 5.346, p = 0.006). Professional knowledge showed no significant overall difference by job level (F = 1.440, p = 0.241).

Post hoc Scheffé tests indicated that Senior Managers scored significantly higher than Junior Engineers on items assessing the ability to lead cross-departmental coordination meetings, propose specific technical solutions to on-site problems, train and mentor junior staff, and recognize the operational importance of BIM and clear change-order responsibilities. These findings suggest that professional practice competency accumulates meaningfully with career progression and organizational authority, whereas management optimization awareness—already elevated among junior staff—increases more modestly with seniority. This pattern further supports the Cognitive–Execution Gap interpretation: junior practitioners are aware of what good management practice requires but have not yet developed the capability or authority to execute it.

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Table 7. Results by job level.

Dimension	Job Level	*n*	Mean	SD	F-Value	*p*-Value
Professional Knowledge	Assistant/Junior Engineer	29	3.03	0.91	1.440	0.241
	Director/Vice Director	42	3.30	0.81		
	Senior Manager or Above	59	3.39	1.01		
Professional Practice	Assistant/Junior Engineer	29	3.03	0.99	5.164	0.0068 *
	Director/Vice Director	42	3.67	0.82		
	Senior Manager or Above	59	3.65	0.99		
Management Optimization	Assistant/Junior Engineer	29	4.16	0.69	5.346	0.006 *
	Director/Vice Director	42	4.49	0.54		
	Senior Manager or Above	59	4.58	0.5		

Note: * indicates statistical significance at $p < 0.05$.

4.7. Impact of Education Level

One-way ANOVAs showed no statistically significant differences across levels of overall educational attainment (high school/vocational, university/college, graduate degree) in any of the three dimensions (professional knowledge: F = 0.071, $p = 0.932$; professional practice: F = 0.212, $p = 0.810$; management optimization awareness: F = 0.298, $p = 0.743$). These findings indicate that the relevance of one's academic major to MEP work is substantially more important than the level of the degree for developing professional competence in the field. Upgrading educational credentials without ensuring domain relevance is therefore unlikely to close the Cognitive–Execution Gap.

4.8. Qualitative Findings: Unearthing the Execution Gap

Thematic analysis of the six expert interviews, conducted following Braun and Clarke's six-phase framework, identified three main themes explaining why uniformly high management optimization awareness does not reliably translate into consistent field execution. Figure 3 presents this pattern visually. Fifteen coded interview units (labeled 1-1V to 3-5V) were distributed across the three themes, as summarized in Table 8.

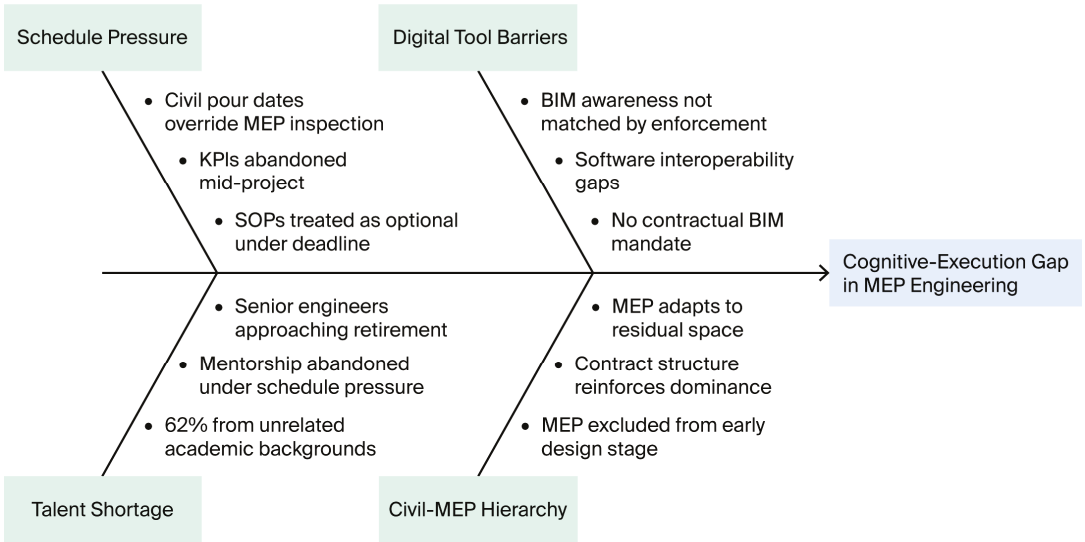

Figure 3. Ishikawa cause-and-effect diagram of the Cognitive–Execution Gap in MEP engineering, derived from thematic analysis of expert interviews. Schedule Pressure and Digital Tool Barriers map to Theme 1; Civil–MEP Hierarchy to Theme 2; Talent Shortage to Theme 3 (Table 8).

Table 8. Overview of qualitative themes and coded interview units.

Theme	Description	Code	Unit Description	Supporting Experts
1	Gap between quality ideals and execution under schedule pressure	1-1V	Schedule pressure overrides SOP compliance	Experts 01–06
		1-2V	KPIs abandoned mid-project under client pressure	
		1-3V	Quality commitments aspirational, not operational	
		1-4V	Improvised solutions replace systematic inspection	
		1-5V	Lack of institutionalized quality control mechanisms	
2	Marginalization of MEP under civil engineering dominance	2-1V	MEP excluded from early design decisions	
		2-2V	Civil team controls schedule and spatial layout	
		2-3V	MEP adapts to residual space, increasing hidden defect risk	
		2-4V	Hierarchy embedded in contract structure	
		2-5V	MEP last consulted, first blamed for site failures	
3	Talent fault line and succession challenges	3-1V	New hires cannot independently read full MEP schematics	
		3-2V	Senior engineers do work themselves instead of mentoring	
		3-3V	Vocational education system collapse cuts talent supply	
		3-4V	Cross-disciplinary MEP integration skills not taught in any curriculum	
		3-5V	Structured mentorship and industry-academia programs absent	

Note: All three themes were supported by all six experts (Experts 01–06).

Theme 1: The Gap Between Ideals and Execution Under Schedule Pressure

Practitioners universally recognized the importance of SOPs, KPIs, and systematic inspection procedures in principle. However, experts consistently described a pattern in which these standards are suspended when project schedules tighten. Corporate quality commitments function as aspirational ideals rather than operational constraints, and on-site engineers resort to improvised solutions when deadlines cannot be moved. This theme is consistent with prior research documenting the adverse effect of schedule pressure on adherence to safety procedures.

> "*Everyone at the management level can recite the quality procedures and safety checkpoints. But on site, when the civil team has locked in the pour date and the MEP inspection is not yet complete, the engineer must make a choice. The schedule almost always wins. The SOP becomes a reference document, not a binding rule.*" [Expert 02, Construction Assistant Director, >40 years' experience]

> "*We set KPIs at the beginning of every project. By the third month, nobody is looking at them anymore. The pressure from the client and the general contractor overrides everything we planned. Quality becomes something you deal with after the fact.*" [Expert 05, President, >40 years' experience]

Theme 2: The Marginalization of MEP Under Civil Engineering Dominance

Civil and structural units typically control the project schedule and spatial layout, leaving MEP teams with limited influence on early design decisions. As a result, MEP installations must adapt to constrained spaces, increasing the risk of hidden defects—such as problematic re-routing and penetrations—that may be difficult to detect until the operational phase. One senior expert reflected the following:

> *"The civil team decides the slab penetrations, the pipe routing zones, the ceiling clearances—all of it. By the time MEP gets involved, it is a 2D drawing being adapted into*

3D reality on site. We spend most of our coordination time solving problems that should have been caught at the design stage, but we were not at the table when those decisions were made." [Expert 03, Engineering Assistant Director, >40 years' experience]

"MEP has always been the last discipline to be consulted and the first to be blamed when something goes wrong on site. This is not a technical problem. It is an organizational culture problem. The hierarchy is built into the contract structure." [Expert 06, Vice President, >40 years' experience]

Theme 3: The Talent Fault Line and Succession Challenges

Experts consistently mentioned the difficulty of recruiting and retaining personnel with formal MEP training. Many workers enter the sector from unrelated academic backgrounds and lack the theoretical foundation needed to independently interpret complex drawings, anticipate system interactions, or apply regulatory requirements. Senior engineers approaching retirement represent a critical reservoir of tacit knowledge at risk of being lost:

"The new generation coming in—most of them cannot read a full MEP schematic without guidance. They learn by watching, which worked when there was time for mentoring. Now everyone is under schedule pressure, so the senior engineer does it himself instead of teaching. The knowledge stays with one person and disappears when he retires." [Expert 01, Vice President, >30 years' experience]

"We need structured mentorship programs, not just informal on-the-job exposure. Industry and academia need to build this together—the university provides the theoretical foundation; the company provides the site experience. Right now, neither side is doing it systematically. BIM training, SOP literacy, safety regulation knowledge—none of this is being passed on in a structured way." [Expert 04, Vice Engineering Manager, >30 years' experience]

5. Discussion

5.1. The Cognitive–Execution Paradox

The findings provide evidence consistent with the existence of a Cognitive–Execution Gap in MEP engineering. The respondents reported high awareness of management optimization principles—including early coordination, standard procedures, and the use of BIM—with mean scores near the upper end of the scale (4.44–4.59). At the same time, lower and more variable scores in knowledge and practice, together with evidence from expert interviews, showed that many practitioners cannot consistently implement these practices in the field.

This pattern aligns directly with the knowing–doing gap documented in organizational research, where the understanding of good practice does not automatically translate into consistent behavior. Pfeffer and Sutton (1999) [17] argued that organizations fail to execute what they know because of organizational inertia, fear, measurement dysfunction, and internal competition—factors that are structurally analogous to the schedule pressure, civil–MEP hierarchy, and talent shortages identified in the present study. In the construction safety literature, Zhang and Fang (2013) [14] demonstrated a similar cognitive–behavioral disconnect among Chinese scaffolders: workers knew the correct safety behavior but normalized non-compliance due to peer norms and supervisory indifference. The present findings extend this pattern to MEP management competence in Taiwan, showing that it not only operates at the individual cognitive level but is also structurally reproduced by organizational hierarchies and resource constraints.

Compared with Liu et al. (2024) [15], who found that managers' safety cognition influences workers' safety behavior through awareness and capability as mediators, the

present study suggests that, even when awareness is high—as it is uniformly across all demographic groups in the Management Optimization dimension—the capability component (captured here as professional practice) remains the binding constraint. This implies that future interventions should prioritize capability-building over awareness-raising, as awareness has already approached a ceiling.

Chen et al. (2021) [16] found a strong positive relationship between safety climate and worker safety behavior on Taiwanese construction sites, consistent with the present finding that organizational and structural factors—rather than individual knowledge deficits—are the primary barriers to execution. Together, these studies support a model in which individual awareness is a necessary but not sufficient condition for safe and high-quality field performance, and organizational climate, hierarchy, and resource adequacy are the moderating variables that determine whether awareness translates into execution.

5.2. Civil Dominance and Structural Inequality

This study also highlights the role of organizational hierarchies in creating risk. Experts described a "civil-first, MEP support" culture in which civil engineering decisions often take precedence, and MEP teams have limited power to enforce spatial or sequencing requirements. This imbalance pushes MEP work into a reactive position, where installations are adapted to remaining space rather than planned integrally, increasing the likelihood of hidden defects and long-term performance problems. This structural dynamic has been noted in broader construction coordination research, which documents that MEP clash detection and spatial coordination are most effective when MEP input is incorporated at the early design stage rather than during construction. Addressing this issue requires elevating MEP input in early design and planning and giving MEP teams stronger formal authority in coordination processes.

5.3. The Consequences of the Talent Fault Line

The quantitative result that practitioners from non-relevant academic majors score substantially lower in knowledge and practice (mean difference = 0.87 in professional knowledge and 0.78 in professional practice) provides a clear metric of the sector's talent challenge. With more than 60% of the surveyed workforce trained in unrelated fields, many practitioners lack the theoretical base needed to independently identify risks and evaluate design choices. This finding is consistent with that in the broader construction workforce literature, which has documented that over half of construction workers in many regions lack formal trade training, and that structured apprenticeship and mentorship programs represent the most effective response. Experts noted that the industry's reliance on on-the-job learning is strained by schedule pressure and the impending retirement of senior engineers, which limits opportunities for systematic knowledge transfer. Without targeted strategies for recruitment, training, and succession, this talent fault line is likely to deepen.

5.4. Strategic Imperatives for Institutional Restructuring

Bridging the Cognitive–Execution Gap likely requires organization-level reforms beyond individual training. The data indicate that further gains from awareness training alone appear limited, given the already high awareness scores. Instead, the industry must deploy system-level mechanisms that help sustain good practice, even under schedule pressure.

First, the integration of BIM into contractually enforced coordination protocols represents a promising but as-yet untested institutional reform. The data indicate high awareness of BIM's potential and consistent barriers to its application but do not directly measure whether contractual enforcement improves outcomes. BIM serves as a neutral, data-driven platform that forces cross-disciplinary spatial coordination before physical construction

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begins. By identifying clashes virtually, BIM has the potential to neutralize traditional authority asymmetries between civil and MEP teams. This relationship should be treated as a hypothesis for future research. Organizations piloting such mandates should monitor quality indicators, safety incident rates, and rework costs systematically to generate the evidence base needed to evaluate this hypothesis.

Second, organizations should systematically replace their reliance on individual, ad hoc experience with formalized Standard Operating Procedures (SOPs) and Key Performance Indicators (KPIs). Quality control mechanisms should be institutionalized and tied directly to project performance reviews, ensuring that they cannot be bypassed when schedule pressures mount. This recommendation is supported by evidence that rigid procedural frameworks reduce the discretionary space within which schedule pressure operates to undermine safety and quality compliance.

Third, to address the talent fault line, firms should invest in structured mentorship and apprenticeship programs that systematically pair incoming personnel from non-MEP backgrounds with experienced engineers. Given that over 60% of the current surveyed workforce holds degrees from unrelated fields, tacit knowledge transfer must be prioritized and financially incentivized by corporate leadership before senior cohorts retire. Structured mentorship ensures that critical theoretical and practical knowledge is systematically transmitted to junior staff rather than lost through attrition.

6. Conclusions

This mixed-methods study examined how mechanical, electrical, and plumbing (MEP) practitioners in Taiwan understand and implement quality and safety management principles in construction projects. Survey results showed that awareness of management optimization strategies such as early interface coordination, standardized procedures, and the use of BIM was consistently high across all demographic groups (overall range: M = 4.44–4.59, SD = 0.50–0.69), confirming that high awareness is not confined to any particular experience level, educational background, or gender. In contrast, technical knowledge and practical execution varied more widely, particularly by academic major relevance and job level, with practitioners from MEP-related disciplines and those in senior positions reporting higher competence.

Qualitative evidence from senior experts indicated that tight schedules, the organizational dominance of civil engineering over MEP, and shortages of formally trained MEP personnel often prevent practitioners from applying the management practices that they recognize as important. Together, these findings support the proposed concept of a Cognitive–Execution Gap, whereby knowledge of best practice exists but is not reliably translated into field behavior because of structural and organizational constraints.

The findings suggest that, to narrow this gap, construction organizations should complement awareness-raising initiatives with reforms at both project and corporate levels. Priorities include (1) piloting and systematically evaluating BIM-based multidisciplinary coordination as a mandatory contractual component of design and pre-construction processes; (2) institutionalizing clear standard operating procedures and quality-related performance indicators that cannot be bypassed under schedule pressure; and (3) developing structured mentorship and training systems to support staff from non-MEP educational backgrounds, with particular urgency given the approaching retirement of the experienced cohort that currently carries critical tacit knowledge.

7. Limitations

Several limitations of this study should be acknowledged. First, a convenience sampling approach was used, which may limit the representativeness of the findings for the

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broader Taiwan MEP population. Second, the qualitative component involved only six expert interviewees; while purposeful sampling ensured substantial industry experience (all with 30+ years), this number cannot represent the full range of site-level challenges and should be treated as illustrative rather than exhaustive. Third, the study relied on self-reported survey data, which introduces the possibility of social desirability bias, particularly for items assessing field practice. Fourth, the sample was drawn exclusively from Taiwan, and while the Cognitive–Execution Gap framework has theoretical generalizability, its specific dimensions and magnitudes may differ in other national construction cultures with different regulatory environments, industry structures, and workforce compositions. Fifth, the cross-sectional design does not permit causal inference; longitudinal or quasi-experimental data are needed to establish whether targeted interventions reduce the gap over time. Finally, the small female sample size (n = 12) limits the statistical power of the gender-based t-tests, and future research should seek a more balanced gender demographic to confirm these specific comparative findings.

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Institutional Review Board Statement: The study involves minimal risk, includes only non-vulnerable adult professionals, uses anonymous survey data and de-identified interview data, and focuses on educational/professional assessment of knowledge and management awareness in the MEP sector. These characteristics meet the statutory exemption criteria.

Informed Consent Statement: For the quantitative phase, participation in the anonymous questionnaire was voluntary, and completion of the survey implied informed consent. For the qualitative phase, informed consent was obtained from all interviewed experts before the interviews; all interview data are de-identified and reported only using anonymized codes (Expert 01–Expert 06). A separate standardized written consent form template was not used.

Data Availability Statement: Data are available upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BIM	Building Information Modeling
HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
KPI	Key Performance Indicator
MEP	Mechanical, Electrical, and Plumbing
SOP	Standard Operating Procedure
CVI	Content Validity Index

Appendix A. Questionnaire on the Cognitive–Execution Gap in MEP Engineering

Instructions to respondents

Please indicate how strongly you agree or disagree with each statement based on your current knowledge and usual practice.

Scale:

1 = Strongly disagree
2 = Disagree
3 = Neither agree nor disagree
4 = Agree
5 = Strongly agree

Dimension	Code	Item
Professional Knowledge	K1	I understand the basic operating principles of the main MEP systems (electrical, plumbing, HVAC) used in typical building projects.
	K2	I am familiar with the key national and local regulations governing electrical safety and fire protection in buildings.
	K3	I can correctly interpret common schematic symbols used in MEP drawings (e.g., valves, ducts, cable trays, fire equipment).
	K4	I understand the basic logic behind MEP design load calculations (e.g., current, flow rate, pressure, capacity).
	K5	I am familiar with the main testing and inspection standards that apply to MEP installations before handover.
	K6	I can explain how MEP systems interact with civil and structural elements (e.g., slab penetrations, beam clearances, ceiling space).
	K7	I understand the typical causes of hidden defects in MEP systems and their potential impact on building safety and performance.
Professional Practice	P1	I can independently read and interpret detailed MEP construction drawings without relying on others' explanations.
	P2	I am able to participate effectively in on-site coordination meetings and communicate MEP requirements to other disciplines.
	P3	I can identify potential clashes between MEP systems and structural/architectural elements before installation begins.
	P4	I am able to propose feasible technical solutions when MEP clashes or conflicts are discovered on site.
	P5	I can use CAD or BIM software (or work closely with staff who do) to adjust routing and layouts based on site conditions.
	P6	I am familiar with the standard procedures for on-site testing and commissioning of major MEP systems.
	P7	I can supervise subcontractors or junior staff to ensure that MEP installation quality meets design and regulatory requirements.
	P8	When unexpected problems occur on site, I can systematically record causes, corrective actions, and lessons learned for future projects.

Dimension	Code	Item
Management Optimization Awareness	M1	Detailed interface coordination between civil, architectural, and MEP teams should be completed before construction starts to reduce future changes and conflicts.
	M2	Regular cross-departmental coordination meetings are very important for preventing quality and safety problems.
	M3	Using BIM or similar digital tools to perform clash detection before construction can significantly reduce rework and hidden defects.
	M4	Clear Standard Operating Procedures (SOPs) for MEP installation should be documented and followed on every project.
	M5	Key Performance Indicators (KPIs) for MEP quality and safety should be monitored throughout the project, not only at the final inspection stage.
	M6	Responsibilities for design changes and change orders should be clearly defined so that problems can be traced and resolved efficiently.
	M7	Senior engineers and managers should allocate time for structured mentoring and training of junior MEP staff.
	M8	Early identification and prevention of quality and safety risks in MEP works are more effective than relying only on final inspections.
	M9	Contractual or regulatory requirements that mandate BIM-based coordination and quality management would help improve MEP project outcomes.

Note: All items are rated on a 5-point Likert scale from 1 (Strongly disagree) to 5 (Strongly agree).

References

1. Hong Kong Polytechnic University. *Electrical and Mechanical Safety in Construction*; Construction Industry Council: Hong Kong, China, 2013.
2. Korman, T.M.; Fischer, M.A.; Tatum, C.B. Knowledge and reasoning for MEP coordination. *J. Constr. Eng. Manag.* **2003**, *129*, 627–634. [CrossRef]
3. Hwang, B.G.; Thomas, S.R.; Haas, C.T.; Caldas, C.H. Measuring the impact of rework on construction cost performance. *J. Constr. Eng. Manag.* **2009**, *135*, 187–198. [CrossRef]
4. Love, P.E.; Edwards, D.J. Determinants of rework in building construction projects. *Eng. Constr. Archit. Manag.* **2004**, *11*, 259–274. [CrossRef]
5. Choudhry, R.M.; Fang, D. Why operatives engage in unsafe work behavior: Investigating factors on construction sites. *Saf. Sci.* **2008**, *46*, 566–584. [CrossRef]
6. Boan, T.; Jiajun, L.; Bosché, F. Autonomous Mixed Reality Framework for Real-Time Construction Inspection. *J. Inf. Technol. Constr. (ITcon)* **2025**, *30*, 852–874. [CrossRef]
7. Alshibani, A.; Aldossary, M.S.; Hassanain, M.A.; Hamida, H.; Aldabbagh, H.; Ouis, D. Investigation of the driving power of the barriers affecting BIM adoption in construction management through ISM. *Results Eng.* **2024**, *24*, 102987. [CrossRef]
8. Akram, R.; Thaheem, M.J.; Khan, S.; Nasir, A.R.; Maqsoom, A. Exploring the role of BIM in construction safety in developing countries: Toward automated hazard analysis. *Sustainability* **2022**, *14*, 12905. [CrossRef]
9. Guo, B.H.; Goh, Y.M.; Wong, K.L.X. A system dynamics view of a behavior-based safety program in the construction industry. *Saf. Sci.* **2018**, *104*, 202–215. [CrossRef]
10. Fang, D.; Chen, Y.; Wong, L. Safety climate in construction industry: A case study in Hong Kong. *J. Constr. Eng. Manag.* **2006**, *132*, 573–584. [CrossRef]
11. Mohamed, S. Safety climate in construction site environments. *J. Constr. Eng. Manag.* **2002**, *128*, 375–384. [CrossRef]

12. He, C.; McCabe, B.; Jia, G.; Sun, J. Effects of safety climate and safety behavior on safety outcomes between supervisors and construction workers. *J. Constr. Eng. Manag.* **2020**, *146*, 04019092. [CrossRef]
13. Lee, J.S.; Ham, Y. Paradox of time pressure: Cognitive and task performance during time-sensitive and challenging teleoperation. *J. Constr. Eng. Manag.* **2025**, *151*, 04024186. [CrossRef]
14. Zhang, M.; Fang, D. A cognitive analysis of why Chinese scaffolders do not use safety harnesses in construction. *Constr. Manag. Econ.* **2013**, *31*, 207–222. [CrossRef]
15. Liu, K.; Luo, X.; Feng, J.; Li, H.; Liu, B.; Jian, Y. Research on the impact of managers' safety perception on construction workers' safety behaviors. *Buildings* **2024**, *14*, 3467. [CrossRef]
16. Chen, W.T.; Merrett, H.C.; Huang, Y.H.; Bria, T.A.; Lin, Y.H. Exploring the relationship between safety climate and worker safety behavior on building construction sites in Taiwan. *Sustainability* **2021**, *13*, 3326. [CrossRef]
17. Pfeffer, J.; Sutton, R.I. *The Knowing-Doing Gap: How Smart Companies Turn Knowledge into Action*; Harvard Business Press: Brighton, MA, USA, 1999.
18. Fang, D.; Wu, H. Development of a Safety Culture Interaction (SCI) model for construction projects. *Saf. Sci.* **2013**, *57*, 138–149. [CrossRef]
19. Koseoglu, O.; Nurtan-Gunes, E.T. Mobile BIM implementation and lean interaction on construction site: A case study of a complex airport project. *Eng. Constr. Archit. Manag.* **2018**, *25*, 1298–1321. [CrossRef]
20. Hall, A.T.; Durdyev, S.; Koc, K.; Ekmekcioglu, O.; Tupenaite, L. Multi-criteria analysis of barriers to building information modeling (BIM) adoption for SMEs in New Zealand construction industry. *Eng. Constr. Archit. Manag.* **2023**, *30*, 3798–3816. [CrossRef]
21. Babatunde, S.O.; Ekundayo, D.; Adekunle, A.O.; Bello, W. Comparative analysis of drivers to BIM adoption among AEC firms in developing countries: A case of Nigeria. *J. Eng. Des. Technol.* **2020**, *18*, 1425–1447. [CrossRef]
22. Olanrewaju, O.I.; Chileshe, N.; Babarinde, S.A.; Sandanayake, M. Investigating the barriers to building information modeling (BIM) implementation within the Nigerian construction industry. *Eng. Constr. Archit. Manag.* **2020**, *27*, 2931–2958. [CrossRef]
23. Barbosa, F.; Woetzel, J.; Mischke, J.; Ribeirinho, M.J.; Sridhar, M.; Parsons, M.; Bertram, N.; Brown, S. *Reinventing Construction Through a Productivity Revolution*; McKinsey Global Institute: Washington, DC, USA, 2017; 27(1). Available online: https://www.mckinsey.com/capabilities/operations/our-insights/reinventing-construction-through-a-productivity-revolution (accessed on 10 February 2026).
24. Aidoo, I.; Ansah, N.B.; Bondinuba, F.K.; Allotey, E.S. Ghanaian construction workers' health and safety knowledge and compliance. *Afr. J. Appl. Res.* **2024**, *10*, 161–177. [CrossRef]
25. Creswell, J.W.; Plano Clark, V.L. *Designing and Conducting Mixed Methods Research*, 3rd ed.; SAGE Publications: Thousand Oaks, CA, USA, 2018.
26. Fellows, R.; Liu, A. *Research Methods for Construction*, 5th ed.; Wiley-Blackwell: Hoboken, NJ, USA, 2021.
27. Abowitz, D.A.; Toole, T.M. Mixed method research: Fundamental issues of design, validity, and reliability in construction research. *J. Constr. Eng. Manag.* **2010**, *136*, 108–116. [CrossRef]
28. Gogo, S.; Musonda, I. The use of the exploratory sequential approach in mixed-method research: A case of contextual top leadership interventions in construction H&S. *Int. J. Environ. Res. Public Health* **2022**, *19*, 7276. [CrossRef]
29. Joshi, A.; Kale, S.; Chandel, S.; Pal, D.K. Likert scale: Explored and explained. *Br. J. Appl. Sci. Technol.* **2015**, *7*, 396–403. [CrossRef]
30. Lynn, M.R. Determination and quantification of content validity. *Nurs. Res.* **1986**, *35*, 382–386. [CrossRef] [PubMed]
31. Polit, D.F.; Beck, C.T. The content validity index: Are you sure you know what's being reported? Critique and recommendations. *Res. Nurs. Health* **2006**, *29*, 489–497. [CrossRef]
32. Polit, D.F.; Beck, C.T.; Owen, S.V. Is the CVI an acceptable indicator of content validity? Appraisal and recommendations. *Res. Nurs. Health* **2007**, *30*, 459–467. [CrossRef]
33. Alazaiza, N.; Ramli, M.Z.; Al Maskari, T.; Mohamad, D. Value Management Implementation as Determinants of Overall Project Success: An Empirical PLS-SEM Study of Building Projects in Oman. *Buildings* **2026**, *16*, 818. [CrossRef]
34. Etikan, I.; Musa, S.A.; Alkassim, R.S. Comparison of convenience sampling and purposive sampling. *Am. J. Theor. Appl. Stat.* **2015**, *5*, 1–4. [CrossRef]
35. Jager, J.; Putnick, D.L.; Bornstein, M.H. More than just convenient: The scientific merits of homogeneous convenience samples. *Monogr. Soc. Res. Child. Dev.* **2017**, *82*, 13–30. [CrossRef] [PubMed]
36. Malterud, K.; Siersma, V.D.; Guassora, A.D. Sample size in qualitative interview studies: Guided by information power. *Qual. Health Res.* **2016**, *26*, 1753–1760. [CrossRef] [PubMed]
37. Guest, G.; Bunce, A.; Johnson, L. How many interviews are enough? An experiment with data saturation and variability. *Field Methods* **2006**, *18*, 59–82. [CrossRef]
38. Galvin, R. How many interviews are enough? Do qualitative interviews in building energy consumption research produce reliable knowledge? *J. Build. Eng.* **2015**, *1*, 2–12. [CrossRef]
39. Nunnally, J.C.; Bernstein, I.H. *Psychometric Theory*, 3rd ed.; McGraw-Hill: New York, NY, USA, 1994.
40. Tavakol, M.; Dennick, R. Making sense of Cronbach's alpha. *Int. J. Med. Educ.* **2011**, *2*, 53–55. [CrossRef]

41. Ghasemi, A.; Zahediasl, S. Normality tests for statistical analysis: A guide for non-statisticians. *Int. J. Endocrinol. Metab.* **2012**, *10*, 486–489. [CrossRef]
42. Norman, G. Likert scales, levels of measurement and the "laws" of statistics. *Adv. Health Sci. Educ.* **2010**, *15*, 625–632. [CrossRef]
43. Scheffé, H. A method for judging all contrasts in the analysis of variance. *Biometrika* **1953**, *40*, 87–110. [CrossRef]
44. Braun, V.; Clarke, V. Using thematic analysis in psychology. *Qual. Res. Psychol.* **2006**, *3*, 77–101. [CrossRef]
45. Braun, V.; Clarke, V. One size fits all? What counts as quality practice in (reflexive) thematic analysis? *Qual. Res. Psychol.* **2021**, *18*, 328–352. [CrossRef]
46. O'Connor, C.; Joffe, H. Intercoder reliability in qualitative research: Debates and practical guidelines. *Int. J. Qual. Methods* **2020**, *19*, 1609406919899220. [CrossRef]

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Exploring the Factors Influencing Construction Workers' Safety Behavior: An Artificial Intelligence-Based Model Approach

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Abstract

A substantial proportion of construction accidents is associated with unsafe worker behavior. Identifying their underlying mechanism is vital for designing effective interventions. As prior studies could not capture complex nonlinear interactions among organizational and individual factors, this study leverages machine learning (ML) techniques, which can capture complex relationships by handling large datasets, and can identify patterns in worker behavior. The study proposes an explainable ML model to interpret key determinants of safe behavior. The data were collected from 425 construction workers in Saudi Arabia. Multiple ensemble and benchmark ML algorithms—including random forest (RF), categorical boosting, decision jungle, light gradient boosting machine, support vector machine, and adaptive boosting—were implemented and compared. The results indicate that the RF model achieved the best predictive performance, outperforming several competing models. To enhance the model's interpretability, explainable artificial intelligence (XAI) techniques were applied to reveal the interaction of key predictors influencing workers' behaviors. The results demonstrate that safety communication, risk perception, and supportive work environment are the most influential determinants shaping safety behavior. As a key novelty, this study introduces an ML-based approach for predicting construction workers' safety behavior and applies XAI techniques to systematically interpret the key determinants of safety behavior. The results also provide valuable insights for safety managers and offer data-driven guidance to enhance the effectiveness of safety interventions.

Keywords: construction safety behavior; explainable machine learning (XML); explainable artificial intelligence (XAI); random forest; model-agnostic methods

1. Introduction

Construction is still one of the most hazardous industries globally [1,2]. Despite considerable advancement in safety regulations, workforce training, and technological innovations, injuries and fatalities continue to persist at an alarmingly high rate [3]. Human factors and unsafe behavioral patterns are widely recognized as primary contributors to workplace accidents, in addition to equipment failures and hazardous environmental conditions. This underscores the urgent need to develop a deeper understanding of safety behaviors of construction workers, and to actively promote safer work practices. Such insights are crucial for improving safety performance and achieving sustainable on-site safety outcomes [4].

Conventional safety management practices, relying on inspections, audits, compliance checks and behavioral training, have yielded significant improvements; however, these

strategies are mostly reactive and cannot foresee unsafe acts before they happen. Furthermore, the feature of subjective judgments in many behavioral models lacks precision and adaptability, required by complex and dynamic jobs [2,5,6]. Consequently, safety professionals find it difficult to pinpoint root causes of unsafe behavior for implementing timely interventions [7,8].

Workers' behavior on construction sites is shaped by multiple interconnected factors, including individual attitude, safety knowledge, risk perception, peer influence, management commitment, work pressure, and physical conditions. Moreover, traditional statistical analysis faces difficulties in solving the tricky, non-linear relationships or detecting subtle patterns within large datasets [9,10]. This deficiency necessitates exploring advanced analytical methods that can accurately analyze the data. Such advance approaches emphasize treating the data as a core asset to drive insights for decision-making.

Previous studies on unsafe behavior in the construction industry have mainly relied on statistical and probabilistic modeling approaches, particularly Structural Equation Modeling (SEM) [11–14] and Bayesian Networks [15]. SEM, a theory-driven method, explains the relationships among latent constructs using linear regression techniques [16]. For example, Mei et al. [17] integrated Social Exchange Theory (SET) and the Theory of Planned Behavior (TPB) within an SEM framework to analyze workers' willingness to share safety knowledge, while Deng et al. [11] applied SEM to investigate the influence of group cognitive characteristics on unsafe behavior. In contrast, Bayesian Network models describe probabilistic dependencies among variables and can identify key safety-related factors under nonlinear conditions; thus, limitations of SEM are addressed partially [15,18].

However, both SEM and Bayesian Networks are designed for testing predefined hypotheses and conducting relational inference. These methods typically depend on strong assumptions about data structure such as linearity in SEM, because of which these methods often struggle to capture complex nonlinear relationships and result in poor predictive performance. To overcome these constraints, several studies have introduced causal inference and simulation-based approaches. For instance, Zhang et al. [19] employed causal inference techniques to examine the effects of management interventions on safety behavior, while Shin et al. [20] used system dynamics modeling to represent the psychological processes underlying safety attitudes and behaviors.

Safety behavior on construction sites is shaped by complex interactions among organizational and individual factors that are unlikely to be purely linear. For example, the relationship between safety training and safety behavior may exhibit diminishing returns (saturation effect), where additional training yields marginal improvements after a certain threshold. Similarly, the combined effect of work pressure and risk perception may be multiplicative rather than additive, as high pressure amplifies the behavioral impact of perceived risks. These nonlinear patterns cannot be captured by traditional linear models like SEM, providing theoretical justification for applying machine learning (ML) approaches. Therefore, this study adopts a complementary approach, leveraging ML for predictive modeling and data-driven pattern discovery, with the aim of generating insights into safety behavior that can supplement theory-building approaches.

In parallel, an increasing number of studies have applied ML methods to address the shortcomings of traditional analytical approaches. Among these, artificial neural networks (ANNs) have been widely applied to analyze safety-related behavior. Ayhan et al. [21] combined latent class clustering with ANN models to identify key factors influencing accident occurrence. Deng et al. [22] developed an ML-based artificial cognitive system to predict unsafe worker behavior. However, despite these methodological advancements, the application of advanced ML algorithms, particularly random forest (RF), in research related to construction workers' safety behavior (WSB) remains relatively scarce.

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A few of the studies have integrated ML with explainable artificial intelligence (XAI) to improve model interpretability [23,24]. It enables the quantification of each feature's contribution to model prediction, providing clear insight into the model's decision logic. This combined framework enhances the transparency, strengthens the reliability of prediction outcomes, and increases the practical applicability of ML models, particularly in domains where interpretability of decision processes is critical.

While previous studies have identified various factors influencing safety behavior, this study addresses the inability of traditional safety models to capture the complex, nonlinear interactions between organizational and individual factors that affect construction WSB. The study attempts to bridge this by making the following contributions: (1) It applies advanced ML models to predict construction WSB, (2) it integrates XAI techniques to enhance the interpretability of these models, and (3) it identifies key factors influencing WSB in the construction industry.

Within this context, the study employs a random forest–explainable artificial intelligence (RF–XAI) framework to predict and interpret WSB in the construction industry. The proposed approach uniquely combines an advanced interpretable ML model with a joint examination of organizational-level and individual-level factors in the Saudi construction industry. By analyzing the influence of both organizational and individual dimensions on safety performance, the integrated RF–XAI method aims to achieve high predictive accuracy while maintaining clear interpretability of the drivers of unsafe behavior. To further demonstrate its effectiveness, the proposed approach is quantitatively compared with several state-of-the-art models reported in the literature. The comparative results show that the proposed model has achieved superior performance across multiple evaluation metrics. The study provides a robust empirical basis and evidence-based guidance for identifying critical risk factors and designing targeted safety interventions. It also offers actionable insights for implementing effective safety management strategies in high-risk construction environments. The study advances the construction safety research by integrating predictive ML with model-agnostic interpretability techniques, enabling a deeper understanding of the complex mechanisms underlying safe behavior.

2. Literature Review

2.1. Factors Affecting WSB on Construction Sites

Workers' unsafe behavior and poor site conditions can cause injuries and death. Therefore, identification of the factors resulting in worker unsafe behavior is imperative to formulate targeted safety interventions for improving safety culture on construction sites [25–27]. Safety behavior is the consequence of a complex interaction between a number of activities that employees engage in to prevent accidents and lower the likelihood of their occurrence. Broadly, these factors can be classified into organizational, individual, psychological, social, environmental, and situational factors [25–27].

The organizational factors refer to safety culture, management's commitment to creating a safe worksite, and the existence of written safety rules and procedures [28]. Likewise, individual factors pertain to human attributes such as demographic data, safety awareness, and perception of danger. Similarly, psychological and social factors include the impact of peers, societal expectations, individual attitudes and ideas towards safety compliance [29]. Lastly, environmental and situational factors refer to physical conditions of the jobsite and contextual characteristics such as time pressure and workload [30].

The factors influencing WSB, as illustrated in Figure 1, play a significant role in shaping workers' safety-related behaviors. These factors have also been organized into organizational and individual factors. Organizational factors comprised management safety commitment (MSC), safety communication (SC), safety training (ST), safety rules and

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procedures (SRP), and supportive environment (SE) [28]. These factors reflect the safety climate and management system within the construction firm. Individual factors include risk perception (RP), safety attitude (SAT), work pressure (WP), social support (SS), and workers' safety involvement (WSI) [29,30]. These factors represent the personal characteristics, perceptions, and social interactions of workers. Both groups directly influence WSB, and their interactions jointly shape safety outcomes.

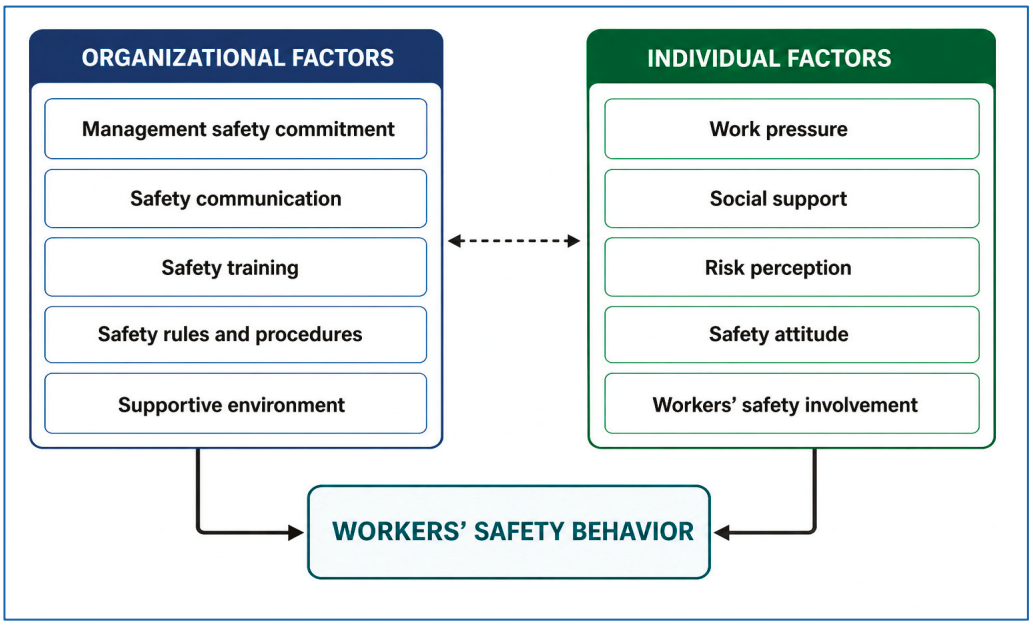

Figure 1. Factors affecting WSB.

MSC has a pivotal role in ensuring workers' safe behavior at construction sites. It can be obtained by fostering the perception among managers that managerial support underpins a shared responsibility for safety [31]. Moreover, the communication system strengthens the safety vigilance and safety compliance, thereby solidifying WSB [32]. Supervisors also play a critical role in converting safety plans into actionable instructions, and effectively communicate them to employees to ensure proper implementation [33]. Furthermore, safe conduct is observed to be higher in workers who undergo detailed safety training, since training increases their aptitude to respond actively to workplace risks [34]. The standard of safety training serves as a visible indication of an organization's investment in worker safety, which can significantly improve their workers' safety-related attitudes [33]. Similarly, well-developed and constantly enforced safety regulations and procedures that define safe working practices are fundamental to fostering a positive safety climate [7]. Moreover, employees' participation in decision-making enhances the sense of ownership and accountability of workers, thereby strengthening their engagement in safe work behavior [33,35]. Active involvement of employees in safety-related processes cultivates a collaborative safety climate that significantly reduces the likelihood of workplace incidents [36]. Compliance with safety procedures is not solely a function of formal rules but is also shaped by individual's intrinsic willingness to adhere to established guidelines. Moreover, strong social support within the workplace reinforces mutual commitment, collective efficacy, and a shared sense of pride in maintaining high safety standards [33]. The past studies indicate that workers who benefit from helpful relationships with both supervisors and coworkers are more likely to report hazards and act safely, because social support considers safety a group responsibility [36]. Prior research has also highlighted similar elements, such as risk perception and safety attitudes, often referred to as "safety climate", as significant predictors of WSB in the construction industry [37].

Despite the contributions of previous studies in exploring WSB, they typically relied on linear statistical methods like SEM and Bayesian Networks, which are not well suited to capturing the complex, non-linear interactions between safety factors. Additionally, these models lack interpretability, thus limiting their practical application in real-world construction sites. Hence, it is vital to develop a comprehensive understanding of the determinants that influence safety outcomes, and to investigate how relevant variables interact with and collectively shape WSB. The complex interrelationship among these variables also needs to be explored to generate deeper insights into behavioral risk patterns. Adopting such a holistic perspective can potentially improve the effectiveness of safety protocols and practices, and contribute to a reduction in workplace accidents and injuries.

2.2. Machine Learning

ML, a subset of artificial intelligence (AI), focuses on creating algorithms and statistical approaches that allow machines to understand connections in the data and continuously improve their performance. Rather than being manually coded, the systems enhance their capabilities by analyzing the data, enabling them to make predictions. Supervised learning, a common ML approach, maps input features to output using labeled datasets [38,39]. Well-known supervised ML methods include ANN, RF, support vector machine (SVM), Logistic Regression, Decision Tree, and K-Nearest Neighbors [40].

ML approaches are increasingly being used to predict safety-related results in the construction industry. One study employed stochastic gradient tree boosting and RF models to forecast damage details such as kind of energy, type of injury, and affected body part [41]. In another study, a predictive model for preventing construction accidents was developed using Decision Tree, Logistic Regression, RF, and adaptive boosting (AdaBoost) [42]. Likewise, a few past studies developed an ANN model to predict and analyze worker behavior based on safety climate features for building construction sites, thus helping the clients and contractors to efficiently manage site safety [43,44]. Yuan et al. [45] also developed an ANN model to examine WSB, emphasizing the critical role of organizational and human factors—such as work stress and leadership—in shaping safety outcomes.

Recently, ML-based safety studies have gained popularity; however, they have reported certain limitations. They could not precisely capture complex and nonlinear relationships between various safety factors. Additionally, the developed models suffered from interpretability issues, thereby reducing their practical applicability in real-world safety management contexts. These ML models often struggled with overfitting because of small or imbalanced datasets. It is worth noting that selecting appropriate models for predicting safety behavior is quite challenging due to complexity and variability of the underlying data. Consequently, safety professionals are still struggling to make fully informed and optimal decisions to improve WSB [43–45].

2.3. Explainable Artificial Intelligence

XAI is a collection of techniques intended to improve the comprehensibility, transparency, and usability of AI model outputs for human users [46]. Explainability is important in safety-critical fields such as finance, engineering, and healthcare, where adherence to regulatory standards is required. As ML models, particularly ensemble and deep learning models, are more complex, the demand for transparent and interpretable predictions continues to grow [47]. The most challenging aspect of advanced ML models is their interpretability, even though their superior prediction ability over linear models is noteworthy [47].

To address this tradeoff between interpretability and accuracy, several methods have been proposed, including permutation importance (PI) [48], Partial dependence plots

(PDPs) [49], Local Interpretable Model-agnostic Explanations (LIME) [24], and SHapley Additive exPlanations (SHAP) [50]. Notably, SHAP supports both local and global interpretation, and its widespread use across scientific disciplines underscores its effectiveness and success [38,40,41,51]. While maintaining interpretability, model-agnostic techniques enable the data inference using more advanced ML models than linear ones. XAI bridges the gap between black-box predictions and human interpretability, enabling stakeholders to trust and effectively utilize AI technologies. Despite providing valuable interpretability, XAI models are not without limitations. The methods used by XAI, such as SHAP and LIME, can be computationally expensive, particularly when dealing with large datasets. Additionally, the tradeoff between model accuracy and interpretability often complicates their application, especially in domains like construction safety, where both predictive performance and transparency are crucial [50,51].

3. Materials and Methods

3.1. Data Collection

The research framework of the study is shown in Figure 2. The data were collected using a large-scale questionnaire survey administered to construction workers. A random sample of 600 respondents was targeted from multiple construction sites across Saudi Arabia. Projects of different sizes and geographical locations were included based on the criterion that the primary activity at each site should be related to building construction, and each site should have employed over 30 workers. To ensure robust and representative data collection, stratified random sampling was used. This approach strengthened the reliability of the results by minimizing sampling bias and improving the generalizability of findings to the broader construction workforce.

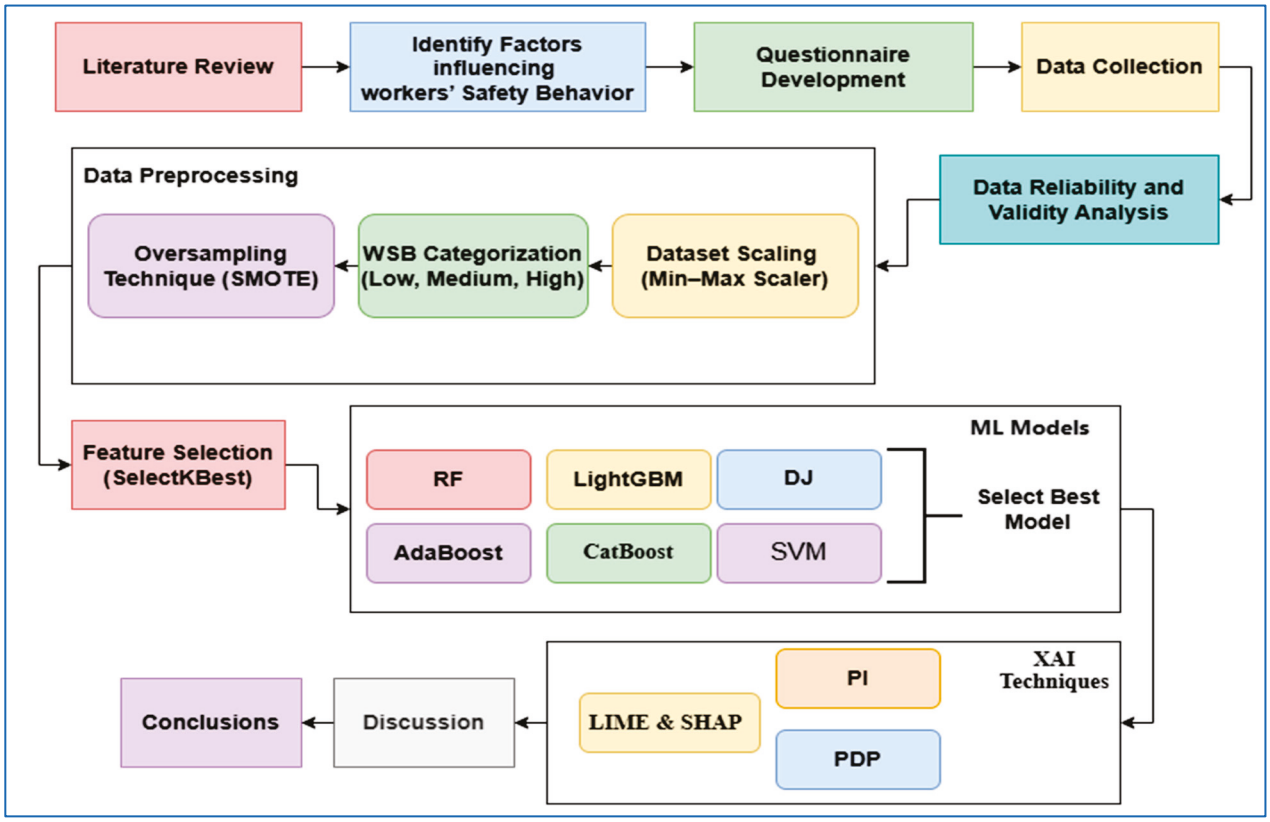

Figure 2. Research framework of the study.

The questionnaire was modified from established safety behavior scales developed by past safety studies. Measurement scales related to MSC, WSI, and WSB were adapted from Mohamed [52] and Newaz et al. [53]. The safety communication scale was adapted from Cigularov et al. [54]. Safety training was measured using the scale developed by Man et al. [55], while the "safety rules and procedures" scale was adapted from Pilanawithana [56]. Work pressure was assessed using the scale developed by Chen et al. [57]. The social support scale was adapted from Guo et al. [58], and the supportive environment scale was based on Mohamed [52]. Finally, the scales for measuring risk perception and safety attitude were adapted from Mohamed [52] and Gyekye and Salminen [59]. These scales were carefully selected to ensure their relevance to the context of construction safety, with necessary adjustments made to better suit the challenges and safety practices observed in the selected region.

Six items were used to assess MSC, five items each for safety training and safety communication, four each for social support and "safety rules and procedures", seven for WSI, three for work pressure, six each for supportive environment and WSB, five for risk perception, and four for safety attitude. A five-point Likert scale (1 to 5) was used to evaluate every item, with verbal anchors ranging from "strongly disagree" to "strongly agree" [14,27].

A total of 475 workers completed the questionnaire. After removing 50 responses with missing data or an inconsistent pattern, 425 valid responses were retained for final analysis, yielding an effective response rate of 70.8%. The data were collected through site visits, face-to-face interviews, and Google Forms. The response integrity was ensured by restricting each participant to a single submission. All the respondents were male; 8.9% of respondents were aged between 18 and 25 years, 47.8% between 26 and 35 years, 32.7% between 36 and 45 years, 7.8% between 46 and 55 years, and 2.8% were over 55 years age. The sample predominantly consisted of experienced construction workers; 75% of them had over 5 years of industry experience.

3.2. Reliability and Validity Test

3.2.1. Reliability Test

A reliability test was conducted to evaluate the internal consistency of the safety climate mechanism and safety behavior factors [60]. A Cronbach's alpha (α) coefficient of 0.7 or above denotes approved reliability [61,62]. All the factors had an α value above 0.7: 0.861 for work pressure, 0.864 for safety training, 0.881 for safety communication, 0.845 for safety rules and procedures, 0.867 for WSI, 0.795 for social support, 0.889 for supportive environment, 0.872 for risk perception, 0.879 for safety attitude, and 0.886 for WSB.

To assess common method bias (CMB), Harman's single-factor test was conducted. The first factor accounted for 12.919% of the total variance, which is substantially below the 50% threshold typically indicative of significant CMB [14,61], suggesting that CMB is unlikely to have inflated the observed relationships.

3.2.2. Convergent Validity Test

This analysis assesses the precision with which a measurement tool represents the variable it is intended to measure. Table 1 summarizes the results of convergent validity, which was evaluated by examining the values of standardized factor loading (SFL) and average variance extracted (AVE). All SFL values ranged from 0.527 to 0.87, exceeding the recommended threshold of 0.5 [14,27,62], except for Item 7 "I usually avoid being involved in accident investigations" in the WSI construct, and Item 3 "There is adequate support to meet work deadlines" in the work pressure construct. Similarly, except for WSI and work pressure, all variables met the recommended AVE value of 0.5 [61,63,64]. Furthermore,

composite reliability (CR) values for all variables ranged from 0.798 to 0.891, exceeding the acceptable threshold of 0.6 [27,63].

Table 1. Mean, SD, SFL, CR, VIF and AVE values.

Item	Description	Mean	SD	SFL	VIF	AVE	CR
	Management Safety Commitment (MSC) [52,53]						
MSC1	Management works to raise safety standards on a constant basis.	4.131	1.007	0.808	1.046	0.517	0.864
MSC2	Management is strict about working safely—even when work falls behind schedule.	4.096	0.920	0.77			
MSC3	Management quickly corrects any safety hazard—even if it is costly.	4.129	0.946	0.541			
MSC4	Management gives workers a lot of information about safety concerns.	4.164	0.976	0.708			
MSC5	Management considers safety when setting production speed and schedules.	4.171	0.934	0.745			
MSC6	Management use all relevant information to enhance existing safety regulations.	4.141	1.025	0.712			
	Safety Communication (SC) [54]						
SC1	I feel comfortable discussing safety issues with management.	4.077	0.898	0.746	1.167	0.602	0.883
SC2	I feel that my management openly accepts ideas for improving safety.	4.110	0.857	0.749			
SC3	I feel that management encourages open communication about safety.	4.343	0.755	0.803			
SC4	I discuss safety issues with my management.	4.249	0.809	0.777			
SC5	I always discuss safety-related problems with my management.	4.263	0.774	0.801			
	Safety Training (ST) [55]						
ST1	Your company frequently gives comprehensive training to the employees on workplace health and safety issues.	4.082	0.887	0.758	1.195	0.562	0.865
ST2	New recruits are trained adequately to learn safety rules and procedures.	4.120	0.845	0.763			
ST3	Safety issues are frequently given high priority in training programs.	4.350	0.747	0.755			
ST4	Management frequently encourages the workers to attend safety training programs.	4.261	0.798	0.764			
ST5	The safety training given to employees is adequate to enable workers to assess hazards in the workplace.	4.192	0.835	0.706			
	Safety Rules and Procedures (SRP) [56]						
SRP1	Current safety rules and procedures are made available to prevent and protect us from accidents.	4.150	0.885	0.574	1.158	0.596	0.853
SRP2	Current safety rules and procedures meet my needs as a source of information on safety and risk control.	4.256	0.814	0.871			
SRP3	All safety rules and procedures are practical, realistic and appropriate.	4.155	0.835	0.804			
SRP4	Safety rules and procedures are stringent in relation to the safety risk.	4.218	0.807	0.807			

Table 1. *Cont.*

Item	Description	Mean	SD	SFL	VIF	AVE	CR
	Workers' Safety Involvement (WSI) [52,53]						
WSI1	I play an active role in identifying site hazards.	4.287	0.836	0.766	1.078	0.555	0.882
WSI2	I always aim to achieve high levels of safety performance.	4.242	0.780	0.718			
WSI3	If asked, I participate in safety planning according to our safety policy.	4.392	0.702	0.688			
WSI4	I have the responsibility to reflect on safety practice.	4.317	0.798	0.712			
WSI5	If asked, I contribute to job safety analysis.	4.298	0.793	0.824			
WSI6	I report accidents, incidents, and potentially hazardous situations.	4.308	0.825	0.752			
	Work Pressure (WP) [57]						
WP1	There are enough workers to carry out the required work (R).	1.894	0.893	0.859	1.328	0.664	0.798
WP2	There is sufficient "thinking time" to enable workers to plan and carry out work.	1.865	0.851	0.769			
	Social Support (SS) [58]						
SS1	When my supervisor and coworkers see me working at risk, they caution me.	4.197	0.820	0.705	1.083	0.568	0.840
SS2	My supervisor carries out ongoing safety instruction at the workplace.	4.181	0.862	0.844			
SS3	My supervisor diligently reviews the safety behaviors of the employees.	4.164	0.816	0.793			
SS4	My supervisor frequently moves around inspecting the workplace.	4.235	0.777	0.797			
	Supportive Environment (SE) [52]						
SE1	We all endeavor to ensure that individuals are not working by themselves under risky or hazardous conditions.	4.435	0.611	0.713	1.314	0.578	0.891
SE2	We all ensure that the workload is reasonably balanced among ourselves.	4.378	0.651	0.718			
SE3	We all always offer help when needed to perform the job safely.	4.383	0.659	0.818			
SE4	We all maintain good working relationships.	4.381	0.641	0.769			
SE5	We all often remind each other of how to work safely.	4.376	0.640	0.841			
SE6	We all believe it is our business to maintain a safe workplace environment.	4.416	0.664	0.686			
	Risk Perception (RP) [50,52,59]						
RP1	I frequently worry about cuts, bumps, stabs, etc. when working.	4.360	0.676	0.696	1.327	0.582	0.874
RP2	I frequently worry about safety incidents such as electrical device blows, shock-related falls, mechanical injuries, etc.	4.305	0.700	0.736			
RP3	I am always concerned that heat, dust, or toxic fumes at work will harm my health.	4.414	0.642	0.800			
RP4	I believe my job is extremely dangerous.	4.407	0.623	0.720			
RP5	I am able to recognize the sources of concealed hazards in my workplace.	4.367	0.652	0.851			
	Safety Attitude (SAT) [50,52,59]						
SAT1	I know the importance of safety in the construction industry.	4.254	0.783	0.722	1.153	0.649	0.880
SAT2	When I detect a safety hazard, I stop working first.	4.263	0.807	0.87			
SAT3	SI always pay attention to safety issues in production operations.	4.157	0.836	0.80			
SAT4	I work with special care when I am not sure if it is safe.	4.237	0.799	0.823			

Table 1. *Cont.*

Item	Description	Mean	SD	SFL	VIF	AVE	CR
	Workers' Safety Behavior (WSB) [52,53]						
WSB1	I use the correct safety procedures for carrying out my job.	4.425	0.621	0.731			
WSB2	When I do my job, I make sure to maintain the highest level of safety.	4.390	0.685	0.688			
WSB3	I use all the necessary safety equipment to do my job.	4.327	0.729	0.807	-	0.571	0.888
WSB4	I promote the safety program within the organization.	4.312	0.748	0.752			
WSB5	I make an extra effort to improve workplace safety.	4.388	0.642	0.81			
WSB6	I voluntarily conduct initiatives that serve to improve workplace safety.	4.355	0.732	0.738			

After removing Item 7 from WSI, the AVE value for this factor improved to 0.554, and the removal of Item 3 from work pressure led to an increase in its AVE value to 0.664, reflecting improved construct validity and overall model quality.

3.2.3. Discriminant Validity Test

A discriminant validity test was conducted to assess whether the measurement model captured conceptually distinct constructs. It was determined using the criterion developed by Fornell–Larcker [63], which stipulates that the square root of AVE for each latent construct has to be greater than its association with other components. Table 2 shows the square roots of AVE values in parentheses across the sides on the diagonal, and the inter-construct correlation coefficients below the diagonal. The results show that the square root of AVE for all constructs is greater than the equivalent inter-construct correlation. For instance, the square root of AVE for WSB is 0.755, which is higher than all of its absolute correlation values with other constructs (ranging from 0.018 to 0.410), denoting adequate discriminant validity [63].

Table 2. Discriminant validity test results.

	WSB	SC	ST	SRP	WSI	SE	SAT	WP	SS	RP	MSC
WSB	(0.755)										
SC	0.236	(0.776)									
ST	0.065	−0.110	(0.750)								
SRP	0.070	−0.057	0.011	(0.772)							
WSI	0.039	0.054	0.052	−0.062	(0.745)						
SE	0.410	0.361	0.007	0.274	0.039	(0.760)					
SAT	0.105	−0.057	0.338	0.138	0.123	0.074	(0.805)				
WP	−0.050	−0.138	0.220	−0.262	0.048	−0.267	0.061	(0.815)			
SS	0.061	−0.009	0.030	0.150	0.220	0.132	0.156	0.048	(0.786)		
RP	0.146	0.101	0.124	0.124	0.120	0.321	−0.023	−0.446	0.042	(0.763)	
MSC	−0.018	−0.007	−0.056	0.057	0.120	0.026	−0.037	−0.080	0.042	0.187	(0.719)

3.3. Data Preprocessing and Feature Selection

To enable a systematic analysis of interaction effects between organizational and individual factors, the normalized mean scores of the six WSB items (WSB1–WSB6) were categorized into three levels using threshold values derived from the observed minimum and maximum scores: low (0–0.33), medium (0.33–0.67), and high (0.67–1.00) [65]. Hence, the prediction of WSB was formulated as a three-class classification problem, facilitating the identification of key determinants that distinguish workers across different levels of safety performance levels.

To ensure an unbiased evaluation of the multiclass classification framework (low, medium, and high behavior), stratified sampling was employed for all train–test splits [66,67] using train_test_split (test_size = 0.2, random_state = 42, stratify = y). This approach preserves the proportional representation of each class in both the training and test sets, thereby mitigating potential evaluation bias. As shown in Table 3, the results confirm that stratified sampling successfully preserved the class distributions in both the training and test sets, confirming an unbiased evaluation of model performance.

Table 3. Class distribution and chi-square test for train–test split.

Class	Training Set (n = 340)	Test Set (n = 85)	Expected (Training)	Expected (Test)	Chi-Square
Low	17 (5.0%)	4 (4.7%)	16.8	4.2	$\chi^2 = 0.0288$,
Medium	145 (42.6%)	37 (43.5%)	145.6	36.4	df = 2,
High	178 (52.4%)	44 (51.8%)	177.6	44.4	$p = 0.9857$

Due to class imbalance in the original dataset, the Synthetic Minority Oversampling Technique (SMOTE) was applied to balance the dataset [68]. This approach reduced the class bias and improved classification stability. To limit overfitting from oversampling, it was applied only to the training set, while performance was evaluated on an independent test set. Ensemble learning and feature selection further reduced the noise sensitivity, whereas stable evaluation metrics indicated that the overfitting was effectively controlled [66].

The analysis of variance (ANOVA) F-test was employed to select the most relevant predictors for classification using the f_classif function in the scikit-learn package in Python 3.10 [69]. This method evaluates and ranks input features according to their statistical association with a categorical target variable using the F-statistic, which compares the difference "between groups" to the difference "within groups". Features with higher F-values depict a stronger ability to differentiate between the defined classes [70].

A Variance Inflation Factor (VIF) analysis was conducted on the eight construct-level mean scores, yielding values ranging from 1.05 for MSC to 1.33 for WP (see Table 1). All values were well below the conservative threshold of 2.5 as well as the commonly accepted threshold of 5.0 [14,27], indicating the absence of multicollinearity and reliability of the ANOVA F-statistic-based feature rankings.

SelectKBest, as a filter method, works independently of any particular classifier, resulting in a great choice for preprocessing in highly dimensional environments. SelectKBest has been found to work efficiently in various domains. Cheng [71] emphasized its role in reducing dimensionality across well-established ML datasets. For feature selection, SelectKBest has been found to increase both model interpretability and generalization. The top k features, ranked by the F-statistic, were selected to improve training efficiency and minimize the risk of overfitting during model development [72]. Equations (1)–(3) explain how ANOVA-F values are calculated.

$$variance_{between_{groups}} = \frac{\sum_{i=1}^{j} j_i \left(K_i - \overline{K}\right)^2}{(S-1)} \quad (1)$$

$$variance_{within_{groups}} = \frac{\sum_{i=1}^{s} \sum_{p=1}^{j_i} \left[K_{ip} - \overline{K}_i \right]^2}{(N-S)} \quad (2)$$

$$F_{value} = \frac{variance_{between_{groups}}}{variance_{within_{groups}}} \quad (3)$$

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where:

N represents the total sample size.

S denotes the number of groups.

j_i represents the number of observations in the j-th group.

$\overline{K}_i$ denotes the sample mean of the i-th group.

$\overline{K}$ denotes the overall mean across all groups.

3.4. ML Models

The study formulates the prediction of safety behavior of construction workers as a multiclass classification problem with three categories: low, medium, and high. Ensemble ML models were employed to enhance predictive accuracy and to reduce generalization error. To improve interpretability, the influence of individual factors on safety behavior was analyzed using Shapley values, providing insights into feature contributions and interactions. To ensure unbiased evaluation, five-fold cross-validation was applied exclusively to the training set for hyperparameter tuning and model selection [73]. The test set was kept completely isolated and was used for final evaluation only, ensuring no data leakage. The dataset was initially split into 80/20 training and test sets using stratified sampling to preserve the class proportions. After performing cross-validation on the training set, the final model was trained on the entire training set and evaluated on the test set, thus ensuring that the test set was not involved in any part of the model selection process, providing a fair and unbiased assessment of the model's performance. Moreover, hyperparameter tuning was performed using grid search with five-fold cross-validation prior to applying the ML techniques. The optimal hyperparameters for each model were determined separately and are presented in Table 4.

Table 4. Hyperparameters used in the present study.

Type of Model	Parameters
Random forest	n_estimators=100, criterion="gini", max_depth=20, min_samples_split=5, min_samples_leaf=2, max_features="sqrt", bootstrap=True, random_state=42
Adaptive boosting	n_estimators=200, algorithm="SAMME", learning_rate=1.0
Light gradient boosting machine	boosting_type='gbdt', learning_rate=0.1, max_depth=15, n_estimators=100, num_leaves=50
Categorical boosting	iterations=100, depth=6, learning_rate=0.1, l2_leaf_reg=3, silent=True
Decision jungle	criterion="entropy", max_depth=20, min_samples_split=2, min_samples_leaf=2
Support vector machine	C=5.0, kernel="rbf", gamma="scale"

The reported performance metrics correspond exclusively to the test-set evaluation and not to the cross-validation results. Cross-validation was used only for model selection and hyperparameter tuning was performed for training, while the test set was used solely for final evaluation after model selection and training.

The efficacy of various ensemble ML models was evaluated based on their ability to predict safety behavior reliably. Model performance was assessed using five complementary metrics. Four metrics—accuracy, precision, recall, and F1-score—evaluated the classification performance at a fixed decision threshold, while the area under the receiver operating characteristic curve (ROC–AUC) assessed the model's discriminative capability across all possible thresholds, rendering it less sensitive to class imbalance. Collectively, these metrics provide a comprehensive evaluation of classification performance [74]. These metrics are further explained in succeeding paragraphs.

The accuracy is the ratio of accurately predicting the occurrences to all instances in the dataset. It is a straightforward metric that provides a general sense of the model's frequency of truth [74]. It can be calculated using Equation (4) [75].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}. \quad (4)$$

where:

TP refers to true positive cases.

FP represents false positive cases.

TN refers to true negative cases.

FN denotes false negative cases.

The precision is the proportion of accurately predicted positive observations among all expected positive cases. It calculates the fraction of cases that are projected to be positive and turn out to be so [74]. It can be computed using Equation (5).

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

The recall is the proportion of accurately anticipated positive observations among all class observations. It can be calculated using Equation (6) and reflects the proportion of true positive cases captured by the model. Recall is especially critical in situations of failing to identify a positive occurrence, because a false negative can have serious implications.

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

The F1-score, derived as the combined mean of precision and recall, is a useful indicator for analyzing model performance. It offers a single metric that weighs the tradeoff between false positives and false negatives [76]. The F1-score can be calculated using Equation (7).

$$F1score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (7)$$

The ROC-AUC is a key indicator of the performance of classification models. It reflects the tradeoff between accuracy and sensitivity, and examines the model's capacity to differentiate between diverse classes [77]. The area under the curve (AUC) can be calculated using Equations (8) and (9).

$$AUC = \int_0^1 TPR\ (FPR) dFPR \quad (8)$$

$$FPR = \frac{FP}{FP + TN} \quad (9)$$

where:

TPR stands for true positive rate, which is also referred to as recall.

FPR stands for false positive rate.

Subsequent subsections present a succinct summary of the ML methods implemented in this study.

3.4.1. Random Forest

RF is a widely used supervised learning approach that employs several decision trees to enhance predictive accuracy while mitigating overfitting. Key hyperparameters significantly affect the performance of RF, including the number of trees in the groups,

the minimum size of the terminal node, and the number of features considered at each split [38,39]. Furthermore, RF provides a robust mechanism for determining feature importance, enabling the evaluation and quantification of safety-related characteristics and their influence on behavior. As illustrated in Figure 3, the RF algorithm begins by applying bootstrap resampling to the training data to generate multiple subsets for individual decision trees. Each tree is constructed by randomly selecting a subset of features at each split and expanding until a predefined stopping criterion is satisfied. The trees generate predictions independently, and then the final output for regression tasks is obtained by averaging the predictions of all trees. This ensemble strategy enhances model robustness, captures complex nonlinear relationships, and reduces the risk of overfitting [66].

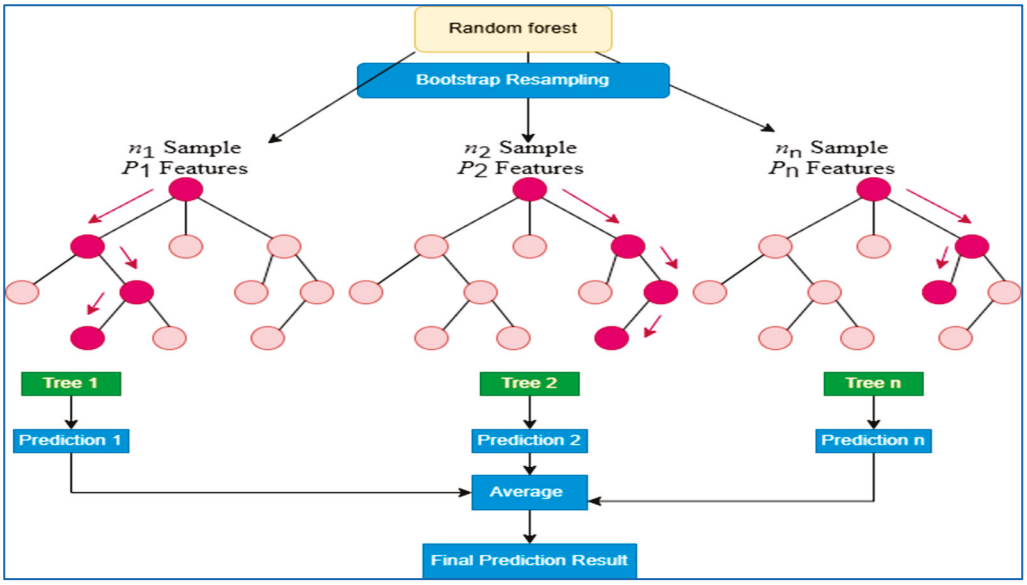

Figure 3. Random forest algorithm (adapted from [78]).

3.4.2. Adaptive Boosting

Adaptive boosting (AdaBoost) is a fundamental boosting algorithm that builds an ensemble of decision trees through an iterative and adaptive process [42]. In each iteration, it updates the weights of training instances, assigning greater emphasis to those previously misclassified, so as to improve overall model performance. Unlike standard decision tree models, AdaBoost typically uses shallow decision trees, often just a single decision node with two terminal leaves, rather than fully grown trees. This simple structure enables the algorithm to focus on improving accuracy by correcting errors from one iteration to the next [42].

3.4.3. Light Gradient Boosting Machine

Light gradient boosting machine (LightGBM) is a decision tree-based algorithm that uses a unique leaf-wise growth strategy [79]. In this method, trees grow vertically by splitting the leaf that provides the greatest reduction in information loss, while other leaves stay at their current depth. This method leads to a more effective gradient optimization than the level-wise tree growth of typical methods. LightGBM is fast when training has high prediction accuracy and uses less memory, making it effective for large-scale ML tasks [79].

3.4.4. Categorical Boosting

Categorical boosting (CatBoost) is a gradient boosting algorithm that has been created to deal effectively with categorical features within decision trees and ensembles [79]. It utilizes one-hot encoding and other advanced methods of processing categorical data

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without requiring extensive preprocessing. It utilizes a minimal variance sampling method to split the nodes and to reduce the number of instances needed for boosting at each iteration [79]. Consequently, this technique enhances the computational cost as well as model performance.

3.4.5. Decision Jungle

Decision jungle (DJ) advances upon the standard decision trees and forests by being able to reduce exponential tree growth, which results in high memory requirements and computation complexity [80]. Typically, RF only allows for a single route from the root to a leaf node, whereas DJ allows for multiple paths via directed acyclic graphs. This results in more compact and flexible models [80].

3.4.6. Support Vector Machine

SVM classification sorts data points based on input features with the use of a linear or nonlinear hyperplane, or a group of such hyperplanes, in the feature space [81]. The optimal hyperplane is chosen by minimizing classification errors and maximizing the distance between different data classes.

3.5. XAI Techniques

In ML, explanations are classified into three types: global vs local, model-agnostic vs model-specific, and fundamental versus post hoc. Among these, model-agnostic techniques are particularly valuable, as they provide interpretable explanations without requiring access to the internal structure of complex ML models [82]. Consequently, such techniques can be applied across a wide range of algorithms to gain significant benefit.

In this study, XAI techniques—namely LIME, SHAP, PI, and PDPs—were applied explicitly to the final trained RF model. This model was selected following hyperparameter optimization and model selection, using five-fold cross-validation on the training set (80% of the data). The trained model was subsequently used to generate explanations for the independent test set (20% holdout), which was completely kept separate during both training and hyperparameter tuning processes. This approach ensures that the generated explanations reflect the model's performance on out-of-sample data. No aggregation of explanations across cross-validation folds was performed. The following subsections describe each technique in detail.

3.5.1. Permutation Importance

PI measures a feature's impact by shuffling its values and observing the change in model error; larger increases indicate greater importance [48]. The PI of feature j can be calculated using Equation (10).

$$PI_j \approx \frac{1}{N}\sum_{n=1}^{N} L(f(x_i, y_i)) - L(f(X^j_{perm}, y_i)) \quad (10)$$

where:

$L(\cdot)$ is the loss function, such as cross-entropy for classification or mean squared error for regression.

n is the total number of samples.

$X^{(j)}_{\text{perm},i}$ represents the i-th sample with the j-th feature randomly permuted.

3.5.2. Partial Dependence Plots

PDPs visually shows how specific features affect model predictions, revealing relationships that may be linear, monotonic or complex [49]. They are simple to compute using

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Equation (11), and accurately reflect a feature's average effect when not strongly correlated with others. However, PDPs are intrinsically limited to examining one or two features at a time, while neglecting the joint distribution of input variables. Furthermore, reliance on averaging can mask opposing effects across distinct data subsets, thereby leading to misleading interpretations of the true impact. The partial dependence function $\boldsymbol{pd}(\boldsymbol{x_i})$ is estimated as the marginal effect of the feature value $\boldsymbol{x_i}$ on the model response by averaging all observations in the dataset [49]. Consequently, for each value of $\mathbf{x_i}$, this approach requires a complete pass over the dataset.

$$\boldsymbol{Pd}(\boldsymbol{x_i}) \approx \frac{1}{\boldsymbol{N}}\sum_{\boldsymbol{n}=1}^{\boldsymbol{N}} \boldsymbol{f}\left(\boldsymbol{x_i}, \boldsymbol{x_c^{(n)}}\right) \tag{11}$$

where:

$\boldsymbol{N}$ denotes the total number of samples in the dataset.

$\boldsymbol{x_c^{(n)}}$ represents the values of the complementary feature set $\boldsymbol{X_C}$ for the $\boldsymbol{n}$-th observation.

3.5.3. Local Interpretable Model-Agnostic Explanations and SHapley Additive exPlanations

LIME and SHAP are widely used to improve ML model interpretability. LIME explains individual predictions by perturbing a data point's features and fitting a simple local surrogate model, but it is limited to local explanations and ignores feature interactions [24]. In contrast, SHAP provides both local and global explanations by fairly attributing each feature's contribution to predictions based on cooperative game theory, making it a robust method for feature attribution in XAI [23,24]. Shapley values are estimated by considering all possible feature subsets $\boldsymbol{S} \subseteq \boldsymbol{X}$, where $\boldsymbol{X}$ denotes the set of all input features. Each feature is assigned a contribution value that reflects its impact on the model's prediction when the feature is included. Specifically, this effect is computed by comparing the predictions of two models: one trained on the feature subset $\boldsymbol{S}\cup$, denoted as $\boldsymbol{f_{S\cup}}$, and another trained on the subset $\boldsymbol{S}$, denoted as $\boldsymbol{f_S}$. The marginal contribution of feature $\boldsymbol{i}$ is then quantified as the difference between the predictions of these two models, $\boldsymbol{f_{S\cup} - f_S}$, averaged over all possible subsets $\boldsymbol{S}$, using Equation (12).

$$v_i = \sum_{S \subseteq X} \frac{|S|!(|X| - |S| - 1)!}{|X|!} \left[f_{S\cup\{i\}}(S \cup \{i\}) - f_S(X_S)\right] \tag{12}$$

4. Results

4.1. ML Model Results

The classification performance of ML models was evaluated using a five-fold cross-validation process [65], based on accuracy, precision, recall, F1-score, and AUC, as presented in Figure 4 and Table 5. To assess the impact of SMOTE on model performance, a sensitivity analysis was conducted by comparing models trained on SMOTE-balanced data with those trained on the original imbalanced dataset (without SMOTE). The results indicate that SMOTE substantially improved classification performance across all models. Notably, the RF model exhibited the largest gains, with accuracy improving by 12.0% (from 0.7882 to 0.9086), F1-score by 13.2%, and AUC by 23.9% (from 0.7419 to 0.9815). These improvements are particularly significant for the minority low-behavior class, which is critically underrepresented in the original data. As the test set remained unchanged, the observed improvements can be confidently attributed to the mitigation of class imbalance via SMOTE, rather than to data leakage.

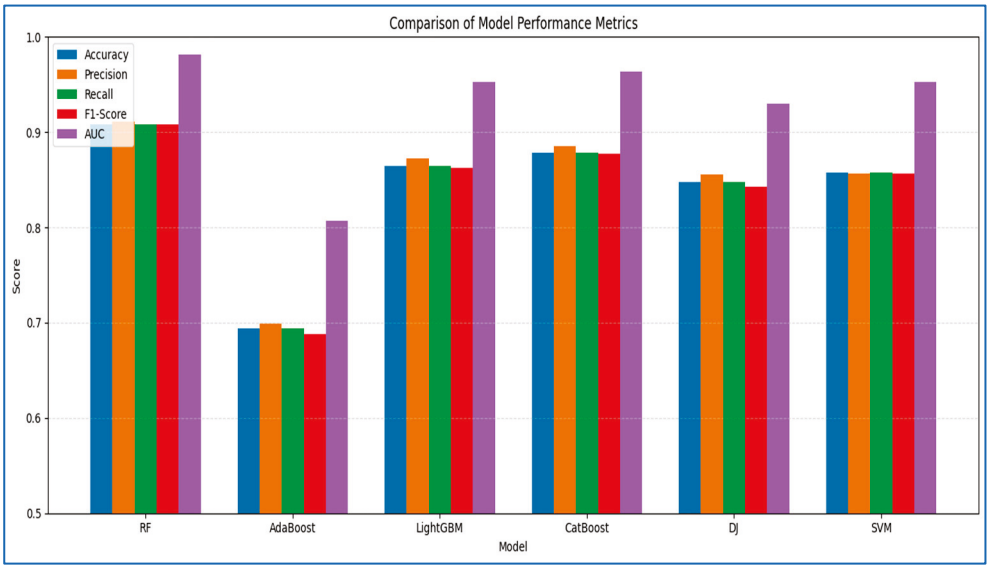

Figure 4. Comparison of model performance metrics.

Table 5. Performance of models for prediction of multiclass WSB.

Model	Imbalanced Data					Balanced Data				
	Accuracy	**Precision**	**Recall**	**F1-Score**	**AUC**	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC**
RF	0.7882	0.7765	0.7882	0.7752	0.7419	0.9086	0.9110	0.9086	0.9079	0.9815
AdaBoost	0.5647	0.5620	0.5647	0.5630	0.5799	0.6940	0.6988	0.6940	0.6883	0.8073
LightGBM	0.7765	0.7723	0.7765	0.7675	0.7169	0.8644	0.8728	0.8644	0.8622	0.9532
CatBoost	0.7647	0.6821	0.7647	0.7054	0.7299	0.8782	0.8855	0.8782	0.8772	0.9634
DJ	0.7765	0.7625	0.7765	0.7669	0.6815	0.8477	0.8552	0.8477	0.8423	0.9298
SVM	0.7765	0.6029	0.7765	0.6788	0.6791	0.8579	0.8569	0.8579	0.8565	0.9531

The results also indicate that the RF model outperformed the other five models, as RF achieved the highest accuracy (90.86%), followed by CatBoost (87.82%), LightGBM (86.44%), SVM (85.79%), DJ (84.77%), and AdaBoost (69.40%). As accuracy alone may be misleading in multiclass classification, additional performance metrics were considered. RF obtained the highest precision (91.10%), recall (90.86%), and F1-score (90.79%), slightly outperforming CatBoost. Moreover, RF achieved the highest AUC (98.15%), confirming its overall superior classification performance.

The confusion matrix in Figure 5 (balanced) illustrates the RF model's performance in classifying workers into three safety behavior categories: low, medium, and high. The model demonstrates strong accuracy, correctly identifying 65 low-behavior workers, 61 medium-behavior workers, and 53 high-behavior workers. Notably, all low-behavior workers are correctly classified, with no misclassifications from this category. Misclassifications occur primarily between adjacent categories: 5 medium-behavior workers are predicted as high, and 12 high-behavior workers are predicted as medium. Additionally, one high-behavior worker is predicted as low. The model performs particularly well for the low-behavior category, achieving perfect classification, and also captures the majority of high-behavior workers correctly. Overall, the confusion matrix provides a comprehensive view of the model's predictions, highlighting its ability to distinguish low-risk workers while offering insights for further refinement between medium and high categories.

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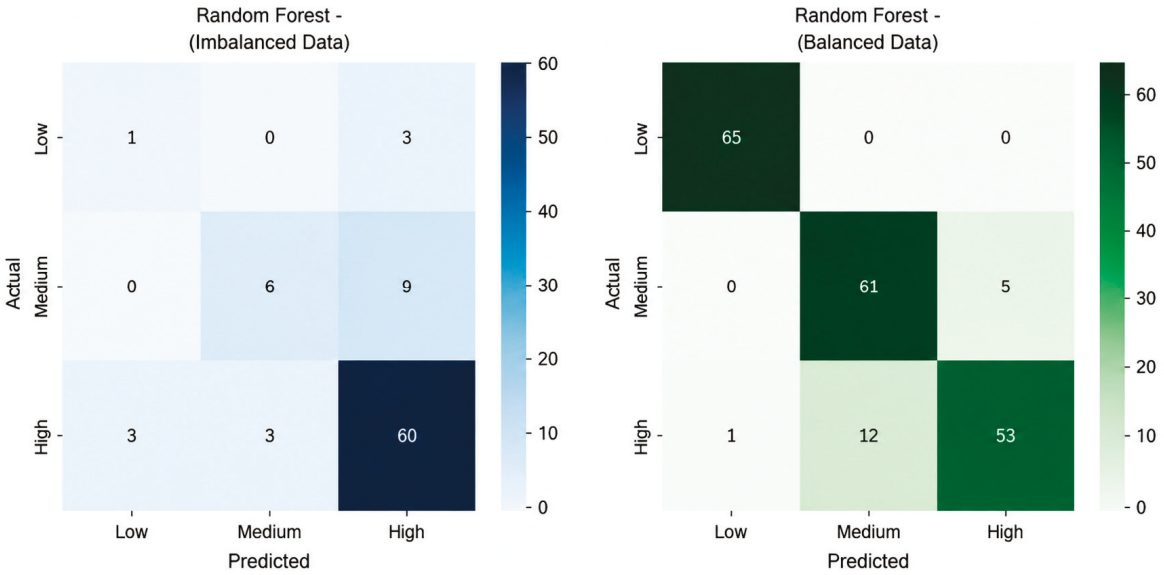


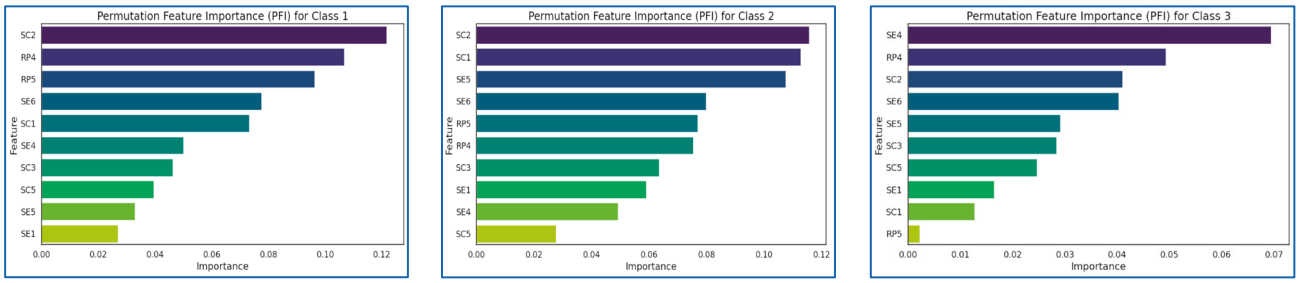
Figure 5. Confusion matrix for the RF model.

4.2. XAI Results

Explaining and interpreting ML outcomes constitutes a critical final stage in the ML lifecycle [83]. In this study, XAI was applied to identify the key determinants affecting WSB and to elucidate the relationships between input features and the target variable. All XAI results (LIME, SHAP, PI, PDP) in this section were obtained from the final RF model—selected after hyperparameter tuning via five-fold cross-validation on the training set—and evaluated on a separate 20% test holdout. The test set was never used in training or tuning, so the explanations reliably reflect model behavior on unseen data. No aggregation of explanations across cross-validation folds was performed.

4.2.1. PI Results

The PI plot in Figure 6 shows that "safety communication (SC2)" was most influential feature of the model's evaluation of WSB of low and medium behavior, while "supportive environment (SE4)" was the most influential factor affecting high behavior.



(**a**) Low behavior (**b**) Medium behavior (**c**) High behavior

Figure 6. Permutation importance plots.

4.2.2. PDP Results

The PDPs show how the most important features affect the predicted probabilities for the "low", "medium" and "high" classes of behavior. According to PI scores, for "low behavior", the SC2 value increased slightly then decreased, whereas RP4 and RP5 decreased as their values increased (Figure 7a). For "medium behavior", SC1 and SC2 showed maximum values around 0.75, while the SE5 value decreased as its value increased (Figure 7b). For "high behavior", SE4 was mostly stable, while RP4 and SC2 increased,

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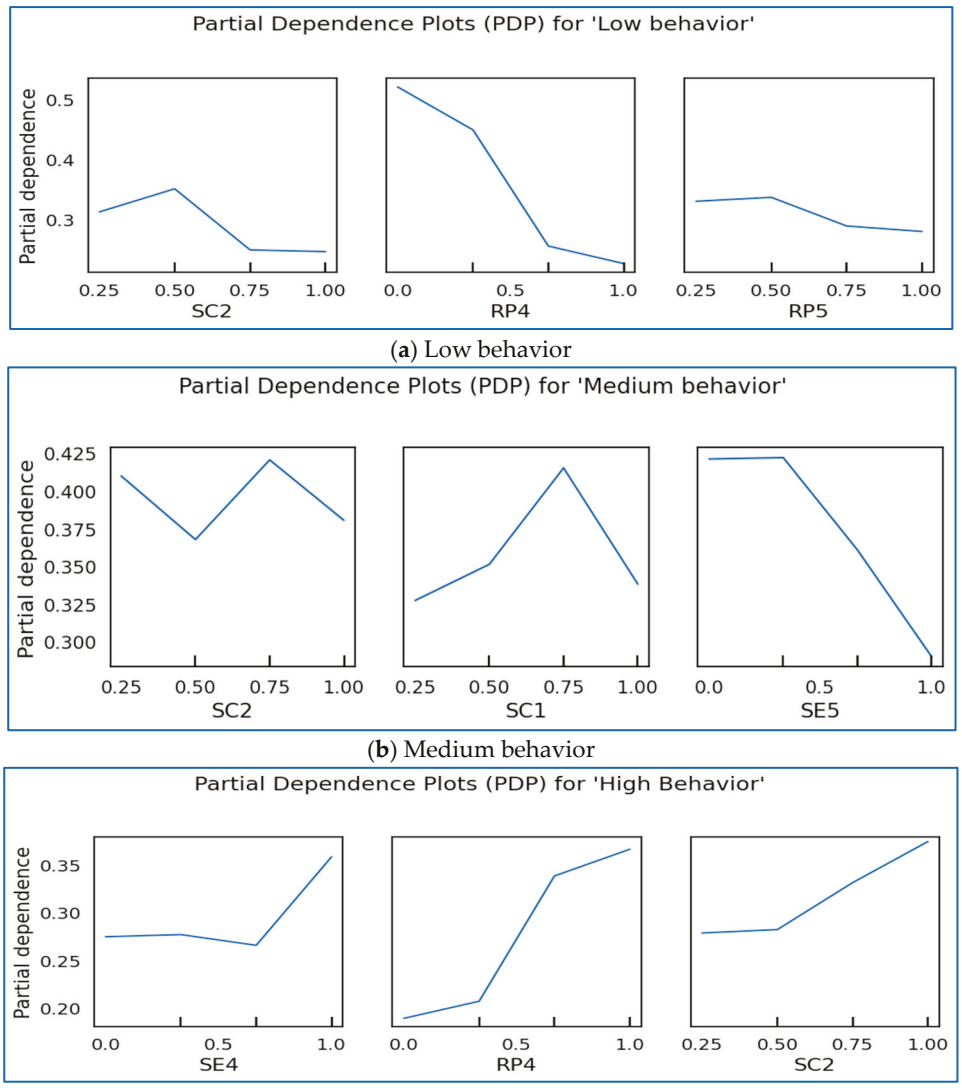
indicating a positive relationship with the predicted probability (Figure 7c). These plots help illustrate how changes in the features affect the model's predictions for each behavior class.



(**a**) Low behavior

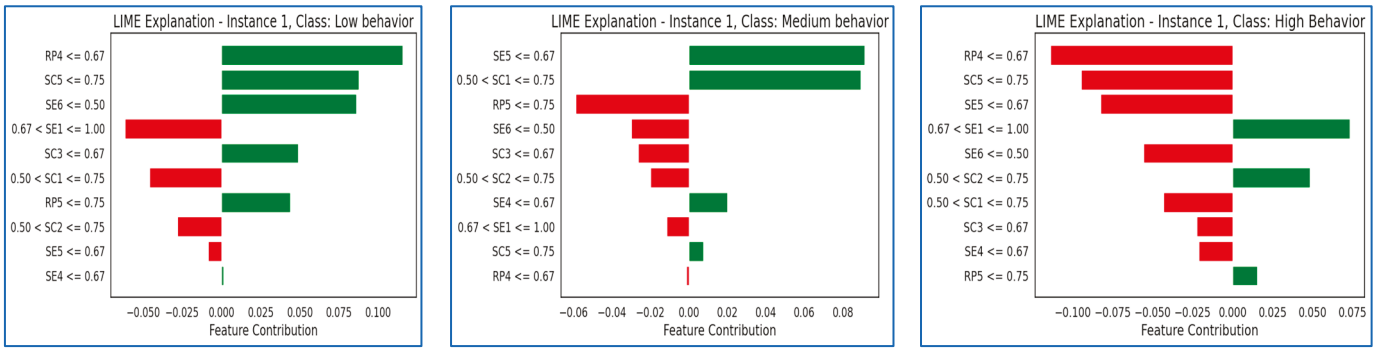
(**b**) Medium behavior

(**c**) High behavior

Figure 7. Partial dependence plots.

4.2.3. Results of Local Interpretable Model-Agnostic Explanations (LIME)

The LIME explanation for test instance 1 (Figure 8) illustrates the contributions of the most influential feature, driving the ML model's classification across low, medium, and high behavior classes. Each plot highlights features that support or oppose the prediction through positive and negative contributions, respectively. For the low behavior class, lower values of RP4, SC5, and SE6 strongly supported the prediction, whereas higher values of SE1 and SC1 inhibited it. The high behavior class was mainly supported by higher values of SE1 and SC2, while lower values of RP4, SC5, and SE5 reduced its likelihood. The medium behavior class was primarily influenced by SE5 and SC1 within specific ranges, with RP5 and SE6 contributing negatively. These results demonstrate class-dependent feature interactions and provide insight into the model's instance-level decision-making.

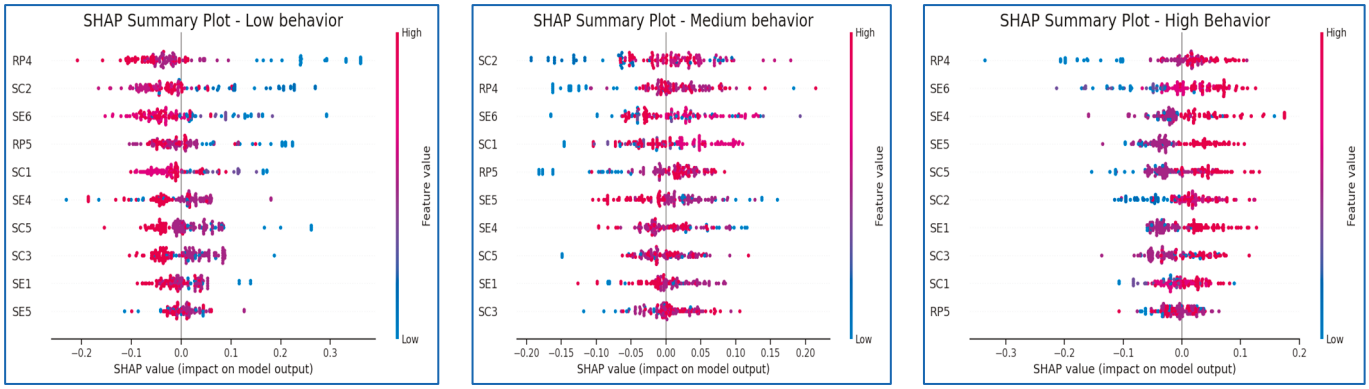


(**a**) Low behavior (**b**) Medium behavior (**c**) High behavior

Figure 8. LIME explanations.

4.2.4. Results of SHapley Additive exPlanations (SHAP)

The SHAP summary plots further reveal how feature effects varied across behavior levels (Figure 9). For low behavior, RP4 and SC2 were the most influential features, with lower values leading to lower prediction scores. In the medium behavior class, SC2 and RP4 remained dominant, indicating a shift in feature influence. For high behavior, RP4 and SE6 showed the strongest positive impact on model output. Other features, including SC1, RP5, SE4, SE5, SC5, SE1, and SC3, exhibited moderate and class-dependent effects. Overall, these findings identify RP4, SC2, and SE6 as the key determinants of the model's predictions.



(**a**) Low behavior (**b**) Medium behavior (**c**) High behavior

Figure 9. SHAP summary plots.

4.3. Comparison with Existing State-of-the-Art Models

Table 6 presents a quantitative comparison between the proposed models and several state-of-the-art approaches for safety behavior prediction reported in the literature. To ensure a fair and objective comparison, the data were requested from the respective authors, as they were not publicly available. The comparison was conducted using four standard performance metrics—accuracy, precision, recall, and F1-score—thereby enabling a comprehensive evaluation of model effectiveness. All models, including the proposed model and the benchmark models, were evaluated on the same dataset to ensure a fair and meaningful comparison. This strategy eliminates potential bias that might arise from using heterogeneous datasets and enhances the reliability of the comparative results.

For the RF classifier, the proposed model significantly outperformed the work of Tang et al. [65]. The accuracy increased from 0.87 to 0.9227, while recall improved markedly from 0.73 to 0.9227, indicating a significantly enhanced ability to correctly identify safety behavior and reduce the number of false negatives. The higher F1-score (0.9225 vs. 0.79)

further demonstrates a superior balance between precision and recall, underscoring the robustness of the proposed approach.

Table 6. Quantitative comparison of proposed models with state-of-the-art models.

Type of Model	Study Reference	Accuracy	Precision	Recall	F1-Score
RF	Tang et al. [65]	0.87	0.90	0.73	0.79
RF	This study	0.9227	0.9272	0.9227	0.9225
CatBoost	Tang et al. [65]	0.90	0.92	0.79	0.84
CatBoost	This study	0.9008	0.9100	0.9031	0.9035
SVM	Yuan et al. [45]	0.68	0.66	0.680	0.660
SVM	This study	0.7782	0.7740	0.7782	0.7758

In case of the CatBoost model, the proposed model achieved competitive yet more balanced performance compared to Tang et al. [65]. While the accuracy values were comparable (0.9008 vs. 0.90), the proposed model exhibited improved recall (0.9031 vs. 0.79) and a higher F1-score (0.9035 vs. 0.84). This suggests that the proposed CatBoost model maintains strong predictive capability while enhancing sensitivity to safety-related instances, which is critical in safety behavior modeling.

For the SVM model, the proposed approach showed notable improvement over the work of Yuan et al. [45]. Accuracy increased from 0.68 to 0.7782, and the F1-score rose from 0.66 to 0.7758. These results indicate that the proposed feature representation and training strategy substantially enhance SVM performance, making it more suitable for classifying complex safety behavior patterns.

Overall, the experimental results demonstrate that the proposed models consistently outperform or match the state-of-the-art approaches across all evaluated classifiers. The improvements are particularly evident in recall and F1-score, emphasizing the effectiveness of the proposed method in accurately identifying safety behavior while maintaining reliable classification performance.

This study contributes significantly to understanding WSB through XML techniques. By integrating ML models with interpretability XAI approaches, including PI, PDPs, LIME, and SHAP, this study not only identifies critical predictors of safety behavior but also reveals how these factors operate differently across behavioral levels. This methodological shift enables a more detailed and data-driven understanding of safety dynamics beyond what is achievable through conventional statistical analysis alone.

Previous studies have largely relied on traditional statistical methods such as SEM, regression analysis, and factor analysis to explore relationships between safety factors and workers' behavior [14,27]. For instance, Mohamed [52] and Newaz et al. [53] emphasized the role of organizational safety climate and management commitment, while Cigularov et al. [54] highlighted the importance of safety communication in fostering compliance. Although these studies provided essential foundational insights, they generally assumed linear or additive relationships among variables, which may restrict their ability to capture complex dependencies and nonlinear interactions in real-world safety systems.

In contrast, this study employs ML to uncover nonlinear patterns and conditional relationships that may be overlooked by traditional analytical approaches. While safety communication has been widely recognized as a critical determinant, XAI results reveal that its influence varies across different levels of safety behavior. Specifically, SC2 (open communication with management) emerges as the most influential factor for workers exhibiting low and moderate safety behavior, while a supportive environment (SE6) is identified as the dominant predictor for high-performing workers. These findings extend prior research by demonstrating that the relative importance of safety behavior determinants shifts with

the level of safety maturity. From the perspective of TPB [84], SC2 reflects subjective norms, which are particularly influential when attitudes and perceived control are not yet fully developed. In contrast, SE6 aligns with perceived behavioral control, which becomes more salient among workers with higher levels of safety performance. Similarly, the results are consistent with the SET, suggesting that management's openness in safety communication fosters reciprocal safe behavior among workers.

Furthermore, unlike SEM-based approaches that focus primarily on effect size and statistical significance, the ML-based framework highlights predictive influence and variable interaction. This allows for deeper insight into how risk perception, communication, and environmental support jointly shape safety behavior. The findings suggest that safety management strategies should be behavior-specific rather than uniform, with targeted interventions designed according to worker safety profiles. By offering a fine-grained understanding of predictor dominance, XML provides actionable intelligence that can enhance evidence-based safety policy development and organizational decision-making.

5. Conclusions

This study has adopted an AI-based model approach to identify key factors influencing safety behavior on building construction sites. An ML model for predicting WSB was developed to check whether it can determine the factors influencing safety behavior with a high predictive ability. The study commenced with data preprocessing, including distribution analysis, cleansing, and class balancing. Subsequently, a filter-based selection method, specifically the ANOVA-F test, was applied to determine the most relevant predictors of WSB. For model evaluation, several ML classifiers were employed, including RF, AdaBoost, LightGBM, CatBoost, DJ and SVM. The results indicate that RF achieved the highest performance across all evaluation metrics, with an accuracy of 0.9086, precision of 0.9110, recall of 0.9086, F1-score of 0.9079, and AUC of 0.9815. CatBoost and LightGBM showed competitive performance but remained inferior to RF.

Overall, the proposed approach demonstrates superior performance across multiple evaluation metrics compared with the existing state-of-the-art models. To interpret the ML models, model-agnostic techniques were utilized. The PI method identified "safety communication (SC2)" as the most influential feature in classifying safety behavior levels. PDPs found an advantageous link between SC2 and the likelihood of belonging to the medium conduct class. Additionally, both local and global SHAP analyses were conducted to generate comprehensive explanations. The results revealed that SC2 and "risk perception (RP4)" held first-order importance in modulating the relevance of features within the medium behavior class. Conversely, in the high behavior class, RP4 and "supportive environment (SE6)" predominated, with higher values of these factors positively influencing the model output.

5.1. Research Implications

The findings of this study offer important practical implications for enhancing safety management on building construction sites through the application of artificial intelligence (AI). By leveraging ML algorithms, this research successfully identifies primary determinants affecting WSB. A key contribution lies in the differentiation of predictor dominance across behavior levels, enabling the development of tiered, worker-profile-specific safety interventions rather than one-size-fits-all strategies. Accordingly, three tiers of intervention are proposed, each aligned with a distinct worker behavioral profile identified in the classification model.

For workers in the low safety behavior tier, SC2 (open communication with management) emerges as the most influential predictor. Interventions at this level should prioritize

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the establishment and reinforcement of structured safety communication mechanisms such as regular toolbox talks led by site supervisors, anonymous safety reporting systems, and open-door policies that allow workers to raise hazard concerns without fear of reprisal. These measures address the deficit in subjective norms, as conceptualized in the TPB analysis, while also activating the reciprocity mechanism articulated by SET.

For workers in the medium safety behavior tier, where both SC2 and RP4 emerge as dominant predictors, interventions should integrate enhanced communication practices with targeted risk awareness initiatives. Recommended measures include hazard simulation drills, structured near-miss reporting and review sessions, and the use of visual risk indicators in high-hazard work zones. These interventions aim to strengthen workers' perceptual sensitivity to risks, and to translate normative safety intentions into consistent behavioral vigilance.

For workers in the high safety behavior tier, SE6 (collective responsibility for workplace safety) is the most influential predictor. Interventions should therefore focus on reinforcing and sustaining a team-oriented safety culture. Effective strategies include the implementation of peer safety champion programs, team-level safety accountability metrics, collective recognition schemes for safety achievements, and group-based safety planning processes. These mechanisms reinforce the perceived behavioral control dimension of TPB by providing the workers with the social and organizational infrastructure necessary to sustain high levels of safety performance over time.

In addition, the interpretability XAI techniques—PI, PDPs, LIME and SHAP—proved to be helpful in revealing the varying influence of different factors on safety behavior. It implies that the developed models are not just "black boxes"; rather, they are interpretable decision-support tools that facilitate informed safety management. The findings further indicate that the application of AI in construction is not just about making predictions; it is more about cultivating a proactive, data-driven safety culture. By identifying high-risk workers and providing transparent explanations of the underlying contributing factors, organizations can roll out tailored training programs, enhance communication strategies, and deploy proactive safety interventions.

5.2. Limitations and Future Research Directions

This study relies on self-reported safety behavior data, which may not fully reflect actual safety performance due to potential biases such as social desirability bias and common method variance. Moreover, the absence of validation against objective indicators such as accident records or supervisor assessments implies that the relationship between predictors and real-world safety outcomes is inferred rather than directly verified. Future research should integrate self-reported data with objective performance indicators to establish a robust linkage between behavioral determinants and actual safety outcomes. In addition, the use of multi-method approaches, such as combining self-reports with observational data, may further reduce bias and enhance the robustness of findings.

Likewise, this study was conducted exclusively in a male-dominated culture; therefore, generalizability of the findings may be limited across different cultural contexts and female construction workers. Hence, further research is suggested to examine cross-cultural and gender-diverse samples to improve external validity. In Saudi Arabia, a high-power-distance, expatriate-dominant workforce shapes safety dynamics, and the strong influence of SC2 on low-behavior workers may have been amplified here. Individual factors such as risk perception are likely to dominate in egalitarian contexts. SE6 for high performers is likely more universal. The all-male sample limits transferability to female workers. Hence, cross-cultural evaluation in East Asia, Northern Europe, and Sub-Saharan Africa needs to be carried out for generalizability.

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While SHAP, LIME, and PDPs enhance model interpretability, each technique has inherent limitations that warrant critical consideration. SHAP assumes feature independence in the computation of Shapley values; however, in the presence of correlated features, SHAP can produce inconsistent or misleading attributions [23,48]. LIME provides local explanations that are sensitive to perturbation settings, and different parameter configurations may yield varying explanations for the same prediction, with no universally accepted standard for parameter selection [24]. Similarly, PDPs assume feature independence and average over the marginal distribution of other features; when features are correlated, this can result in unrealistic data extrapolation and may obscure heterogeneous effects [49].

To mitigate the aforesaid limitations, multiple XAI techniques (PI, PDPs, LIME, and SHAP) were employed in this study, and emphasis was placed on features exhibiting consistent importance across methods. Future research may consider accumulated local effects (ALE) plots as an alternative, as they address several of the limitations associated with PDPs under feature dependence.

Although multiple ML models were evaluated in this research, subsequent studies could benefit from examining more sophisticated methods, such as ensemble models, deep learning, neural networks, or hybrid ensemble strategies that can combine different algorithms. Yet, this study has expanded occupational safety research by providing a validated predictive model with practical relevance for both academia and the industry. It is likely to help construction organizations effectively decrease accident rates and promote safer workplaces through better understanding of WSB and by establishing a strong safety culture.

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Abbreviations

The following abbreviations are used in this manuscript:

AdaBoost	Adaptive Boosting
ANN	Artificial Neural Networks
AVE	Average Variance Extracted
CatBoost	Categorical Boosting
DJ	Decision Jungle
FPR	False Positive Rate
FN	False Negative
LightGBM	Light Gradient Boosting Machine
LIME	Local Interpretable Model-agnostic Explanations
MSC	Management Safety Commitment
PDP	Partial Dependence Plot
PI	Permutation Importance
RF	Random Forest
RP	Risk Perception
SA	Safety Attitude
SC	Safety Communication
SE	Supportive Environment
SET	Social Exchange Theory
SFL	Standardized Factor Loading
SHAP	SHapley Additive exPlanations
SMOTE	Synthetic Minority Oversampling Technique
SRP	Safety Rules and Procedures
SS	Social Support
ST	Safety Training
SVM	Support Vector Machine
TPB	Theory of Planned Behavior
TPR	True Positive Rate
WP	Work Pressure
WSB	Workers' Safety Behavior
WSI	Workers' Safety Involvement
XAI	Explainable Artificial Intelligence
XML	Explainable Machine Learning

References

1. Cabello, A.T.; Martínez-Rojas, M.; Carrillo-Castrillo, J.A.; Rubio-Romero, J.C. Occupational accident analysis according to professionals of different construction phases using association rules. *Saf. Sci.* **2021**, *144*, 105457. [CrossRef]
2. Xiang, Q.; Ye, G.; Liu, Y.; Goh, Y.M.; Wang, D.; He, T. Cognitive mechanism of construction workers' unsafe behavior: A systematic review. *Saf. Sci.* **2023**, *159*, 106037. [CrossRef]
3. International Labour Organization (ILO). Nearly Three Million Workers Die Every Year Due to Work-Related Accidents and Diseases. Available online: https://www.ilo.org/resource/news/nearly-3-million-people-die-work-related-accidents-and-diseases (accessed on 1 January 2023).
4. Li, Z.; Bao, X.; Sheng, Y.; Xia, Y. Research on unsafe behavior of construction workers under the bidirectional effect of formal rule awareness and conformity mentality. *Front. Psychol.* **2021**, *12*, 794394. [CrossRef] [PubMed]
5. Li, H.; Lu, M.; Hsu, S.-C.; Gray, M.; Huang, T. Proactive behavior-based safety management for construction safety improvement. *Saf. Sci.* **2015**, *75*, 107–117. [CrossRef]
6. Saurin, T.A. Safety inspections in construction sites: A systems thinking perspective. *Accid. Anal. Prev.* **2016**, *93*, 240–250. [CrossRef]
7. Maliha, M.N.; Abu Aisheh, Y.I.; Tayeh, B.A.; Almalki, A. Safety barriers identification, classification, and ways to improve safety performance in the architecture, engineering, and construction (AEC) industry: Review study. *Sustainability* **2021**, *13*, 3316. [CrossRef]

8. Mohajeri, M.; Ardeshir, A.; Malekitabar, H. Diagnostic intervention program based on construction workers' internal factors for persistent reduction of unsafe behavior. *Eng. Constr. Archit. Manag.* **2023**, *30*, 478–495. [CrossRef]
9. Mannering, F.; Bhat, C.R.; Shankar, V.; Abdel-Aty, M. Big data, traditional data and the tradeoffs between prediction and causality in highway-safety analysis. *Anal. Methods Accid. Res.* **2020**, *25*, 100113. [CrossRef]
10. Meng, Q.; Liu, W.; Li, Z.; Hu, X. Influencing factors, mechanism and prevention of construction workers' unsafe behaviors: A systematic literature review. *Int. J. Environ. Res. Public Health* **2021**, *18*, 2644. [CrossRef]
11. Deng, S.; Zhu, H.; Cai, Y.; Pan, Y. Group cognitive characteristics of construction workers' unsafe behaviors from personalized management. *Saf. Sci.* **2024**, *175*, 106492. [CrossRef]
12. Yang, J.; Ye, G.; Zhang, Z.; Liu, X.; Liu, Y. Linking construction noise to worker safety behavior: The role of negative emotion and regulatory focus. *Saf. Sci.* **2023**, *162*, 106093. [CrossRef]
13. Zhang, Z.; Guo, H.; Gao, P.; Wang, Y.; Fang, Y. Impact of owners' safety management behavior on construction workers' unsafe behavior. *Saf. Sci.* **2023**, *158*, 105944. [CrossRef]
14. Zahoor, H.; Chan, A.P.; Utama, W.P.; Gao, R.; Memon, S.A. Determinants of safety climate for building projects: SEM-based cross-validation study. *J. Constr. Eng. Manag.* **2017**, *143*, 05017005. [CrossRef]
15. Vithanage, S.C.; Sing, M.C.; Davis, P.; Newaz, M.T. Assessing the off-site manufacturing workers' influence on safety performance: A Bayesian network approach. *J. Constr. Eng. Manag.* **2022**, *148*, 04021185. [CrossRef]
16. Liu, W.; Zhao, T.; Zhou, W.; Tang, J. Safety risk factors of metro tunnel construction in China: An integrated study with EFA and SEM. *Saf. Sci.* **2018**, *105*, 98–113. [CrossRef]
17. Mei, Y.; Huang, J.; Liu, J.; Jia, L. A study of factors influencing construction workers' intention to share safety knowledge. *Buildings* **2024**, *14*, 440. [CrossRef]
18. Mohammadfam, I.; Ghasemi, F.; Kalatpour, O.; Moghimbeigi, A. Constructing a Bayesian network model for improving safety behavior of employees at workplaces. *Appl. Ergon.* **2017**, *58*, 35–47. [CrossRef]
19. Zhang, Z.; Li, H.; Guo, H.; Wu, Y.; Luo, Z. Causal inference of construction safety management measures towards workers' safety behaviors: A multidimensional perspective. *Saf. Sci.* **2024**, *172*, 106432. [CrossRef]
20. Shin, M.; Lee, H.-S.; Park, M.; Moon, M.; Han, S. A system dynamics approach for modeling construction workers' safety attitudes and behaviors. *Accid. Anal. Prev.* **2014**, *68*, 95–105. [CrossRef]
21. Ayhan, B.U.; Tokdemir, O.B. Accident analysis for construction safety using latent class clustering and artificial neural networks. *J. Constr. Eng. Manag.* **2020**, *146*, 04019114. [CrossRef]
22. Deng, S.; Ni, P.; Zhu, H.; Cai, Y.; Pan, Y. Artificial cognition to predict and explain the potential unsafe behaviors of construction workers. *J. Constr. Eng. Manag.* **2024**, *150*, 04024074. [CrossRef]
23. Hooker, G.; Mentch, L.; Zhou, S. Unrestricted permutation forces extrapolation: Variable importance requires at least one more model, or there is no free variable importance. *Stat. Comput.* **2021**, *31*, 82. [CrossRef]
24. Ribeiro, M.T.; Singh, S.; Guestrin, C. "Why should I trust you?" Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016; pp. 1135–1144. [CrossRef]
25. Zhang, L.; Liu, Y.; Chu, Z. The influence mechanism of owners' safety management behavior on construction workers' safety citizenship behavior. *Behav. Sci.* **2023**, *13*, 721. [CrossRef]
26. Khalid, U.; Sagoo, A.; Benachir, M. Safety Management System (SMS) framework development—Mitigating the critical safety factors affecting health and safety performance in construction projects. *Saf. Sci.* **2021**, *143*, 105402. [CrossRef]
27. Zahoor, H.; Chan, A.P.; Utama, W.P.; Gao, R.; Zafar, I. Modeling the relationship between safety climate and safety performance in a developing construction industry: A cross-cultural validation study. *Int. J. Environ. Res. Public Health* **2017**, *14*, 351. [CrossRef]
28. Vierendeels, G.; Reniers, G.; van Nunen, K.; Ponnet, K. An integrative conceptual framework for safety culture: The Egg Aggregated Model (TEAM) of safety culture. *Saf. Sci.* **2018**, *103*, 323–339. [CrossRef]
29. Chiaburu, D.S.; Harrison, D.A. Do peers make the place? Conceptual synthesis and meta-analysis of coworker effects on perceptions, attitudes, OCBs, and performance. *J. Appl. Psychol.* **2008**, *93*, 1082–1103. [CrossRef]
30. Bayounis, A.A. Impact of Mental and Physical Workloads, Stress, Fatigue and Situational Awareness on Safety Performance among Electrical Construction Projects Workers. Doctoral Dissertation, King Abdulaziz University, Jeddah, Saudi Arabia, 2020.
31. Kalteh, H.O.; Mortazavi, S.B.; Mohammadi, E.; Salesi, M. The relationship between safety culture and safety climate and safety performance: A systematic review. *Int. J. Occup. Saf. Ergon.* **2021**, *27*, 206–216. [CrossRef]
32. Ishdorj, S.; Ahn, C.R.; Park, M. Major factors influencing safety knowledge-sharing behaviors of construction field workers: Worker-to-worker level safety communication. *J. Constr. Eng. Manag.* **2024**, *150*, 04024021. [CrossRef]
33. Amirah, N.A.; Him, N.F.N.; Rashid, A.; Rasheed, R.; Zaliha, T.N.; Afthanorhan, A. Fostering a safety culture in manufacturing through safety behavior: A structural equation modelling approach. *J. Saf. Sustain.* **2024**, *1*, 108–116. [CrossRef]
34. Basahel, A.M. Safety leadership, safety attitudes, safety knowledge and motivation toward safety-related behaviors in electrical substation construction projects. *Int. J. Environ. Res. Public Health* **2021**, *18*, 4196. [CrossRef]

35. He, C.; Jia, G.; McCabe, B.; Chen, Y.; Zhang, P.; Sun, J. Psychological decision-making process of construction worker safety behavior: An agent-based simulation approach. *Int. J. Occup. Saf. Ergon.* **2023**, *29*, 141–153. [CrossRef] [PubMed]
36. Asad, M.; Kashif, M.; Sheikh, U.A.; Asif, M.U.; George, S.; Khan, G.U.H. Synergetic effect of safety culture and safety climate on safety performance in SMEs: Does transformation leadership have a moderating role? *Int. J. Occup. Saf. Ergon.* **2022**, *28*, 1858–1864. [CrossRef] [PubMed]
37. Shea, T.; De Cieri, H.; Vu, T.; Pettit, T. How is safety climate measured? A review and evaluation. *Saf. Sci.* **2021**, *143*, 105413. [CrossRef]
38. Thampi, A. *Interpretable AI: Building Explainable Machine Learning Systems*; Simon and Schuster: New York, NY, USA, 2022.
39. Shetty, S.H.; Shetty, S.; Singh, C.; Rao, A. Supervised machine learning: Algorithms and applications. In *Fundamentals and Methods of Machine and Deep Learning: Algorithms, Tools and Applications*; Wiley: Hoboken, NJ, USA, 2022; pp. 1–16. [CrossRef]
40. Esen, H.; Esen, M.; Ozsolak, O. Modelling and experimental performance analysis of solar-assisted ground source heat pump system. *J. Exp. Theor. Artif. Intell.* **2017**, *29*, 1–17. [CrossRef]
41. Tixier, A.J.-P.; Hallowell, M.R.; Rajagopalan, B.; Bowman, D. Application of machine learning to construction injury prediction. *Autom. Constr.* **2016**, *69*, 102–114. [CrossRef]
42. Choi, J.; Gu, B.; Chin, S.; Lee, J.-S. Machine learning predictive model based on national data for fatal accidents of construction workers. *Autom. Constr.* **2020**, *110*, 102974. [CrossRef]
43. Patel, D.; Jha, K. Neural network approach for safety climate prediction. *J. Manag. Eng.* **2015**, *31*, 05014027. [CrossRef]
44. Patel, D.; Jha, K. Evaluation of construction projects based on the safe work behavior of co-employees through a neural network model. *Saf. Sci.* **2016**, *89*, 240–248. [CrossRef]
45. Yuan, M.; Tang, T.; Zhao, S.; Xue, X.; Luo, B. The factors influencing safety compliance behavior among new-generation construction workers in China: A safety compliance behavior–artificial neural network model approach. *Buildings* **2024**, *14*, 3774. [CrossRef]
46. Gunning, D.; Aha, D. DARPA's explainable artificial intelligence (XAI) program. *AI Mag.* **2019**, *40*, 44–58. [CrossRef]
47. Arrieta, A.B.; Díaz-Rodríguez, N.; Del Ser, J.; Bennetot, A.; Tabik, S.; Barbado, A.; García, S.; Gil-López, S.; Molina, D.; Benjamins, R. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Inf. Fusion* **2020**, *58*, 82–115. [CrossRef]
48. Debeer, D.; Strobl, C. Conditional Permutation Importance Revisited. *BMC Bioinform.* **2020**, *21*, 307. [CrossRef]
49. Friedman, J.H. Greedy function approximation: A gradient boosting machine. *Ann. Stat.* **2001**, *29*, 1189–1232. [CrossRef]
50. Lundberg, S.M.; Lee, S.-I. A unified approach to interpreting model predictions. *arXiv* **2017**, arXiv:1705.07874. [CrossRef]
51. Hartono, N.T.P.; Thapa, J.; Tiihonen, A.; Oviedo, F.; Batali, C.; Yoo, J.J.; Liu, Z.; Li, R.; Marrón, D.F.; Bawendi, M.G. How machine learning can help select capping layers to suppress perovskite degradation. *Nat. Commun.* **2020**, *11*, 4172. [CrossRef] [PubMed]
52. Mohamed, S. Safety climate in construction site environments. *J. Constr. Eng. Manag.* **2002**, *128*, 375–384. [CrossRef]
53. Newaz, M.T.; Davis, P.; Jefferies, M.; Pillay, M. The psychological contract: A missing link between safety climate and safety behaviour on construction sites. *Saf. Sci.* **2019**, *112*, 9–17. [CrossRef]
54. Cigularov, K.P.; Chen, P.Y.; Rosecrance, J. The effects of error management climate and safety communication on safety: A multi-level study. *Accid. Anal. Prev.* **2010**, *42*, 1498–1506. [CrossRef]
55. Man, S.S.; Chan, A.H.S.; Alabdulkarim, S.; Zhang, T. The effect of personal and organizational factors on the risk-taking behavior of Hong Kong construction workers. *Saf. Sci.* **2021**, *136*, 105155. [CrossRef]
56. Pilanawithana, N.M. *Developing Resilience for Safety Management Systems*; University of Sydney: Sydney, Australia, 2022.
57. Chen, Y.; McCabe, B.; Hyatt, D. Impact of individual resilience and safety climate on safety performance and psychological stress of construction workers: A case study of the Ontario construction industry. *J. Saf. Res.* **2017**, *61*, 167–176. [CrossRef]
58. Guo, B.H.; Yiu, T.W.; González, V.A. Predicting safety behavior in the construction industry: Development and test of an integrative model. *Saf. Sci.* **2016**, *84*, 1–11. [CrossRef]
59. Gyekye, S.A.; Salminen, S. Are "good soldiers" safety conscious? An examination of the relationship between organizational citizenship behaviors and perception of workplace safety. *Soc. Behav. Personal.* **2005**, *33*, 805–820. [CrossRef]
60. Pallant, J. *SPSS Survival Manual: A Step by Step Guide to Data Analysis Using IBM SPSS*; Routledge: London, UK, 2020.
61. Wang, D.; Wang, X.; Xia, N. How safety-related stress affects workers' safety behavior: The moderating role of psychological capital. *Saf. Sci.* **2018**, *103*, 247–259. [CrossRef]
62. Hair, J.F.; Babin, B.; Anderson, R.; Black, W. *Multivariate Data Analysis*, 7th ed.; Pearson: Harlow, UK, 2014.
63. Bagozzi, R.P.; Fornell, C.; Larcker, D.F. Canonical correlation analysis as a special case of a structural relations model. *Multivar. Behav. Res.* **1981**, *16*, 437–454. [CrossRef]
64. Cheung, C.M.; Zhang, R.P. How organizational support can cultivate a multilevel safety climate in the construction industry. *J. Manag. Eng.* **2020**, *36*, 04020014. [CrossRef]
65. Tang, T.; Liu, Z.; Yuan, M.; Guo, Y.; Lin, X.; Li, J. Exploring organizational and individual determinants of construction workers' safety behavior: An interpretable machine learning approach. *Buildings* **2026**, *16*, 191. [CrossRef]

66. Kovačević, M.; Crnoja, A.; Bulajić, B.; Petronijević, P. Data-driven framework for predicting airborne sound insulation of recycled rubber–polyurethane composite panels. *Appl. Sci.* **2026**, *16*, 2410. [CrossRef]
67. Kovačević, M.; Hadzima-Nyarko, M.; Petronijević, P.; Vasiljević, T.; Radomirović, M. Comparative analysis of machine learning models for predicting interfacial bond strength of fiber-reinforced polymer-concrete. *Computation* **2025**, *13*, 17. [CrossRef]
68. Chawla, N.V.; Bowyer, K.W.; Hall, L.O.; Kegelmeyer, W.P. SMOTE: Synthetic minority over-sampling technique. *J. Artif. Intell. Res.* **2002**, *16*, 321–357. [CrossRef]
69. Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Prettenhofer, P.; Weiss, R.; Dubourg, V. Scikit-learn: Machine learning in Python. *J. Mach. Learn. Res.* **2011**, *12*, 2825–2830.
70. Bishop, C.M.; Nasrabadi, N.M. *Pattern Recognition and Machine Learning*; Springer: New York, NY, USA, 2006; Volume 4.
71. Cheng, X. A comprehensive study of feature selection techniques in machine learning models. *Insights Comput. Signals Syst.* **2024**, *1*, 65–78. [CrossRef]
72. El Touati, Y.; Slimane, J.B.; Saidani, T. Adaptive method for feature selection in the machine learning context. *Eng. Technol. Appl. Sci. Res.* **2024**, *14*, 14295–14300. [CrossRef]
73. Hancock, J.T.; Khoshgoftaar, T.M.; Johnson, J.M. Evaluating classifier performance with highly imbalanced big data. *J. Big Data* **2023**, *10*, 42. [CrossRef]
74. Alvarez, S.A. *An Exact Analytical Relation Among Recall, Precision, and Classification Accuracy in Information Retrieval*; Technical Report BCCS-02-01; Boston College: Boston, MA, USA, 2002; pp. 1–22.
75. Raschka, S. An overview of general performance metrics of binary classifier systems. *arXiv* **2014**, arXiv:1410.5330. [CrossRef]
76. Derczynski, L. Complementarity, F-score, and NLP evaluation. In Proceedings of the 10th International Conference on Language Resources and Evaluation (LREC'16), Portorož, Slovenia, 23–28 May 2016; pp. 261–266.
77. Huang, J.; Ling, C.X. Using AUC and accuracy in evaluating learning algorithms. *IEEE Trans. Knowl. Data Eng.* **2005**, *17*, 299–310. [CrossRef]
78. Zhou, S.; Lei, Y.; Zhang, Z.-X.; Luo, X.; Aladejare, A.; Ozoji, T. Estimating dynamic compressive strength of rock subjected to freeze-thaw weathering by data-driven models and non-destructive rock properties. *Nondestruct. Test. Eval.* **2025**, *40*, 116–139. [CrossRef]
79. Bentéjac, C.; Csörgő, A.; Martínez-Muñoz, G. A comparative analysis of gradient boosting algorithms. *Artif. Intell. Rev.* **2021**, *54*, 1937–1967. [CrossRef]
80. Shotton, J.; Sharp, T.; Kohli, P.; Nowozin, S.; Winn, J.; Criminisi, A. Decision jungles: Compact and rich models for classification. *Adv. Neural Inf. Process. Syst.* **2013**, *26*, 1–9.
81. Awad, M.; Khanna, R. Support vector machines for classification. In *Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers*; Springer: New York, NY, USA, 2015; pp. 39–66. [CrossRef]
82. Ribeiro, M.T.; Singh, S.; Guestrin, C. Model-agnostic interpretability of machine learning. *arXiv* **2016**, arXiv:1606.05386. [CrossRef]
83. Khater, T.; Tawfik, H.; Sowdagar, S.; Singh, B. Interpretable models for ML-based classification of obesity. In Proceedings of the 2023 7th International Conference on Cloud and Big Data Computing, Manchester, UK, 17–19 August 2023; pp. 40–47. [CrossRef]
84. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **1991**, *50*, 179–211. [CrossRef]

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Using Safety Accountability to Enhance Construction Safety Performance: The Mediating Roles of Safety Monitoring and Safety Learning Under Inclusive Leadership

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Abstract

Safety performance remains a persistent challenge in the construction industry due to hazardous working conditions, dynamic site environments, and complex organizational structures. Despite regulatory advances and technical safety controls, accident rates remain high, suggesting that formal mechanisms alone are insufficient. Addressing this gap, this study examines safety accountability as a central organizational mechanism and investigates how it influences construction workers' safety performance through behavioral processes and leadership conditions. Drawing on accountability theory and social learning theory, we propose a moderated parallel mediation model in which safety monitoring and safety learning function as mediators, while inclusive leadership behavior serves as a contextual moderator. Data were collected from 629 construction workers employed in large-scale projects in Istanbul and Ankara, Türkiye, using a two-wave survey design to mitigate common method bias. Hypotheses were tested using confirmatory factor analysis and Hayes' PROCESS macro. The results indicate that safety accountability does not exert a significant direct effect on safety performance; rather, its influence is fully transmitted through safety monitoring and safety learning, with monitoring emerging as the stronger mediating mechanism. Moreover, inclusive leadership behavior significantly strengthens the accountability-driven pathways leading to improved safety outcomes. By integrating accountability structures, behavioral processes, and leadership context, this study advances construction safety research and provides evidence-based guidance for enhancing occupational safety performance in high-risk construction environments.

Keywords: safety accountability; safety performance; safety monitoring; safety learning; inclusive leadership; construction safety

1. Introduction

The construction industry is widely recognized as one of the most hazardous sectors globally, characterized by complex work environments, dynamic site conditions, and a high incidence of occupational injuries and fatalities [1]. Despite continuous improvements in safety regulations, training programs, and technological interventions, safety performance in construction projects remains uneven and often unsatisfactory [2,3]. This persistent challenge has prompted scholars and practitioners to move beyond technical safety controls and explore organizational and behavioral factors that shape workers' safety-related actions [4]. Within this evolving stream of research, safety accountability

has emerged as a critical mechanism for influencing individual behavior and fostering collective responsibility for safety outcomes [5]. Safety accountability refers to the extent to which individuals and organizations are held responsible for adhering to safety standards, reporting unsafe conditions, and taking corrective actions when risks arise. In theory, accountability systems should motivate workers to comply with safety procedures and discourage unsafe behaviors by clarifying expectations and consequences [6]. However, empirical evidence from construction contexts suggests that accountability alone does not automatically translate into improved safety performance. In many projects, accountability mechanisms are implemented in a formal or punitive manner, focusing on fault-finding rather than learning, which limits their effectiveness and may even suppress proactive safety behavior [7].

A growing body of research indicates that safety performance improvements depend not only on accountability structures but also on the processes through which accountability is enacted in daily work practices [5,8]. In particular, safety monitoring and safety learning have been identified as two essential behavioral mechanisms that enable organizations to convert safety expectations into observable performance outcomes. Safety monitoring allows organizations to detect deviations from safety standards and respond promptly to emerging risks, while safety learning facilitates the accumulation and dissemination of safety knowledge through experience, reflection, and feedback [2]. Yet, these mechanisms are often examined in isolation, leaving a limited understanding of how they simultaneously and jointly operate within accountability-driven safety systems. Moreover, the effectiveness of accountability, monitoring, and learning processes is strongly influenced by leadership behavior. In construction settings, where hierarchical structures and productivity pressures are prevalent, leadership styles that discourage participation or open communication can undermine safety initiatives [9]. Inclusive leadership, characterized by openness, accessibility, and encouragement of employee involvement, has recently gained attention as a leadership approach capable of enhancing psychological safety and fostering constructive safety dialog [10]. Recent safety research suggests that leadership behaviors promoting voice and participation strengthen learning-oriented safety climates; however, empirical evidence explicitly positioning inclusive leadership as a boundary condition in accountability-based safety models remains limited in construction contexts [11–13].

The existing literature therefore reveals three specific and interrelated gaps. First, although safety accountability has been associated with improved compliance, there is insufficient empirical clarification of the behavioral mechanisms through which accountability translates into measurable safety performance outcomes in construction projects [5,14]. Second, prior studies typically examine safety monitoring or safety learning independently, rather than testing them as parallel mediating processes within a single integrated model [15,16]. Third, while leadership has been widely studied in relation to safety culture and safety climate, limited research has examined inclusive leadership as a contextual boundary condition shaping the effectiveness of accountability-driven safety processes among construction workers [17–19]. Addressing these gaps is essential for advancing theory and offering actionable guidance to construction managers operating in high-risk environments.

Drawing on accountability theory and social learning theory, this study proposes that safety accountability influences safety performance indirectly through safety monitoring and safety learning. Accountability theory suggests that individuals regulate their behavior more carefully when expectations and responsibilities are clearly defined, while social learning theory explains how behaviors evolve through observation, feedback, and shared experiences [20]. Inclusive leadership is positioned as a contextual factor that enhances these processes by creating an environment in which workers feel valued, supported, and

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encouraged to engage in safety-related communication [17]. Together, these theoretical perspectives provide a robust foundation for examining a double-mediated–moderated model of safety performance. Accordingly, the purpose of this study is to examine how safety accountability affects safety performance among construction workers through the mediating roles of safety monitoring and safety learning, and to investigate whether inclusive leadership behavior strengthens or weakens these relationships. By empirically testing this integrated model, the study seeks to clarify the conditions under which accountability mechanisms are most effective in improving safety outcomes.

This study contributes to construction safety and occupational health research in three important ways. First, it develops and tests an integrated model that simultaneously examines safety monitoring and safety learning as parallel mediators linking safety accountability to safety performance, thereby extending prior single-mediator approaches. Second, it positions inclusive leadership as a contextual boundary condition that shapes the effectiveness of accountability mechanisms, offering a more nuanced explanation of when accountability translates into improved safety outcomes. Third, the study provides empirical evidence from large-scale construction projects in Turkey, a context characterized by rapid urban development, complex subcontracting structures, and regulatory enforcement variability, thereby extending safety accountability research beyond frequently studied Western settings.

The remainder of this paper proceeds by reviewing the relevant literature and developing hypotheses, followed by a description of the research methodology, presentation of the empirical results, discussion of the findings, and concluding implications for theory and practice.

2. Theoretical Framework and Hypotheses Development

2.1. Accountability Theory and Social Learning Theory

This study is theoretically grounded in accountability theory and social learning theory, which together provide a robust explanatory lens for understanding how safety accountability translates into safety performance through behavioral and social mechanisms in construction settings. The present study anchors accountability theory in its broader organizational foundations, where accountability is conceptualized as a social and evaluative process through which individuals anticipate scrutiny and regulate their behavior accordingly [5,21]. Accountability theory posits that individuals are more likely to align their actions with organizational expectations when they perceive clear responsibility for outcomes, combined with the possibility of evaluation and consequences [6]. In organizational contexts, accountability systems clarify "who is responsible for what," thereby encouraging compliance, diligence, and self-monitoring [22].

Within construction environments, safety accountability signals that safety is not merely a formal requirement, but a shared obligation embedded in daily work routines. Recent construction safety research suggests that accountability mechanisms are particularly effective when they move beyond punitive control and instead promote ownership, transparency, and proactive engagement with safety practices [2,10]. However, accountability theory alone does not fully explain how responsibility perceptions are converted into sustained safety performance. This limitation is especially evident in construction projects, where safety behaviors are shaped by ongoing interactions, experiential learning, and situational cues.

Social learning theory, originally developed by Bandura [23], complements accountability theory by explaining how individuals acquire, reinforce, and modify behaviors through observation, modeling, feedback, and reciprocal interactions within a social context. According to social learning principles, behavior is shaped not only by formal rules

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but also by cognitive processing, peer influence, and observed consequences. From this perspective, safety-related behaviors are learned not only through written procedures but also through continuous exposure to monitoring practices, supervisory feedback, and shared responses to safety incidents.

Integrating social learning theory into the accountability–safety relationship allows for a deeper understanding of the mediating roles of safety monitoring and safety learning. Safety monitoring creates visible feedback loops that reinforce accountability expectations, while safety learning enables workers to internalize safety knowledge and adapt behaviors based on past experiences and collective reflection [24]. Recent empirical evidence from construction safety studies highlights that organizations with strong learning-oriented safety systems are better positioned to transform accountability into meaningful performance improvements [3,25]. The combined application of accountability theory and social learning theory is therefore conceptually appropriate for this study. Accountability theory explains the motivational foundation of safety responsibility, while social learning theory elucidates the behavioral and cognitive processes through which accountability is enacted and sustained over time. Importantly, both theories acknowledge the influence of contextual factors, such as leadership behavior, in shaping how accountability cues are interpreted and acted upon. Inclusive leadership, by fostering openness, trust, and participation, strengthens social learning processes and enhances the effectiveness of accountability mechanisms [26]. By integrating these two theoretical perspectives, this study provides a coherent framework for explaining why safety accountability alone may be insufficient and how its impact on safety performance is realized through learning and monitoring processes embedded within a supportive leadership context.

2.2. Safety Accountability and Safety Performance

Safety performance refers to the extent to which construction workers comply with established safety procedures, avoid unsafe behaviors, and actively contribute to accident prevention and risk reduction [2,8,27]. In high-risk construction environments characterized by physical hazards, time pressure, and subcontracting complexity, safety performance depends not only on formal safety systems but also on how responsibility is distributed and perceived among organizational members [28,29].

From an accountability perspective, when individuals perceive that safety-related behaviors are clearly defined, monitored, and associated with meaningful consequences, they are more likely to regulate their conduct in accordance with organizational expectations [5,6,30]. Accountability clarifies "who is responsible for what," thereby reducing ambiguity and reinforcing safety as a non-negotiable priority. Such clarity can increase vigilance, procedural compliance, and risk awareness.

However, empirical research indicates that accountability does not always guarantee sustained improvements in safety performance, particularly when accountability is perceived as punitive or symbolic rather than developmental [7]. This suggests that while safety accountability may exert a direct motivational influence on safety performance, its effectiveness may also depend on complementary behavioral mechanisms that translate responsibility perceptions into durable safe practices.

Accordingly:

H1. *Safety accountability positively influences safety performance.*

2.3. Safety Accountability and Safety Learning

Safety learning refers to the continuous acquisition, sharing, and application of safety-related knowledge derived from experience, feedback, and incident analysis [31]. In con-

struction projects where site conditions evolve rapidly and hazards vary across tasks, learning plays a central role in enhancing adaptive capacity and situational awareness [32,33].

Safety accountability contributes to safety learning by legitimizing reflective practices and reinforcing the expectation that workers engage in knowledge exchange and improvement activities. When responsibility for safety is clearly articulated and evaluated, workers are more likely to report near misses, participate in safety meetings, and reflect on procedural weaknesses [34]. Through this process, accountability serves as a motivational catalyst, while learning functions as the cognitive and behavioral mechanism through which safety competence is strengthened.

Therefore:

H2. *Safety accountability positively influences safety learning.*

2.4. Safety Learning and Safety Performance

Safety learning enhances safety performance by strengthening hazard recognition, procedural adherence, and adaptive responses to emerging risks [24]. Workers who internalize lessons from prior incidents are better equipped to anticipate potential dangers and adjust their behavior accordingly [35].

Moreover, learning-oriented safety systems foster collective awareness and shared understanding of risks, thereby reinforcing behavioral consistency across teams [36]. In this sense, safety learning represents a critical pathway through which accountability expectations may be transformed into sustained performance outcomes rather than short-term compliance.

Thus:

H3. *Safety learning positively influences safety performance.*

2.5. Safety Accountability and Safety Monitoring

Safety monitoring involves systematic inspection, observation, and feedback mechanisms designed to ensure adherence to safety standards and detect unsafe conditions in real time [37]. In complex construction environments, monitoring enables early identification of hazards and corrective intervention.

Accountability strengthens monitoring by reinforcing attentiveness and responsibility for safety outcomes [6]. When safety roles are clearly assigned and performance is evaluated, workers and supervisors are more likely to engage in proactive inspection, reporting, and follow-up behaviors [38]. Monitoring therefore operationalizes accountability by converting responsibility expectations into observable safety oversight practices.

Accordingly:

H4. *Safety accountability positively influences safety monitoring.*

2.6. Safety Monitoring and Safety Performance

Effective safety monitoring directly contributes to improved safety performance by reducing unsafe acts and increasing compliance [2,39]. Continuous feedback loops enable organizations to correct deviations before incidents escalate.

By providing visible enforcement and reinforcement of safety standards, monitoring ensures that accountability mechanisms are enacted in daily operations rather than remaining abstract principles.

Thus:

H5. *Safety monitoring positively influences safety performance.*

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2.7. The Mediating Role of Safety Learning

Although accountability establishes responsibility and expectations, learning equips workers with the knowledge and adaptive skills necessary to perform tasks safely. Without learning, accountability may generate surface-level compliance; with learning, it fosters sustained behavioral change and risk anticipation [40,41].

Safety learning therefore functions as a mediating mechanism linking accountability to safety performance by translating motivational signals into internalized competence.

Accordingly:

H6. *Safety learning mediates the relationship between safety accountability and safety performance.*

2.8. The Mediating Role of Safety Monitoring

Safety monitoring serves as another behavioral pathway through which accountability influences performance. By reinforcing oversight and corrective feedback, monitoring ensures that accountability cues are enacted through observable safety behaviors [42,43].

Through continuous evaluation and feedback loops, monitoring strengthens the behavioral consistency necessary for translating responsibility perceptions into measurable safety outcomes.

Therefore:

H7. *Safety monitoring mediates the relationship between safety accountability and safety performance.*

2.9. The Moderating Role of Inclusive Leadership

Inclusive leadership is characterized by openness, accessibility, and encouragement of employee voice [26,44]. In construction settings where hierarchical structures and productivity pressures may suppress communication, inclusive leaders foster psychological safety and participatory engagement [11,17].

When leaders promote openness and involvement, accountability cues are more likely to be interpreted as supportive and developmental rather than punitive [45,46]. Under high inclusive leadership, workers are more inclined to engage actively in monitoring and learning processes, thereby amplifying the effectiveness of accountability mechanisms. Conversely, under low inclusive leadership, accountability may lead to minimal compliance without fostering proactive safety behaviors.

Thus:

H8. *Inclusive leadership moderates the relationship between safety accountability and safety monitoring, such that the relationship is stronger under high inclusive leadership.*

H9. *Inclusive leadership moderates the relationship between safety accountability and safety learning, such that the relationship is stronger under high inclusive leadership.*

H10. *Inclusive leadership moderates the relationship between safety accountability and safety performance, such that the relationship is stronger under high inclusive leadership.*

To enhance clarity and conciseness, Table 1 summarizes all proposed hypotheses and their corresponding relationships within the conceptual framework.

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Table 1. Summary of Hypotheses.

Hypothesis	Proposed Relationship
H1	Safety accountability → Safety performance
H2	Safety accountability → Safety learning
H3	Safety learning → Safety performance
H4	Safety accountability → Safety monitoring
H5	Safety monitoring → Safety performance
H6	Safety learning mediates SA → SP
H7	Safety monitoring mediates SA → SP
H8	Inclusive leadership moderates SA → SM
H9	Inclusive leadership moderates SA → SL
H10	Inclusive leadership moderates SA → SP

2.10. Control Variables: Firm and Employee Characteristics

This study incorporates education and gender as employee-level control variables to account for potential confounding influences on safety-related behaviors and performance outcomes. Education has been shown to influence safety awareness, hazard perception, and compliance with established safety procedures, particularly in construction environments characterized by task variability and physical risk exposure [7,47]. Workers with higher educational attainment may process safety information more effectively and demonstrate greater engagement with learning and monitoring mechanisms, thereby potentially influencing safety performance [48].

Gender is included as a control variable due to documented differences in safety attitudes, reporting behavior, and risk-taking tendencies across occupational settings [37,49]. Prior research suggests that gender may shape responses to accountability systems and leadership practices, which in turn could affect safety engagement [50]. By controlling for these demographic characteristics, the study enhances internal validity and ensures that the hypothesized relationships are not spuriously attributed to individual differences.

2.11. Research Model

As illustrated in Figure 1, the proposed research model positions safety accountability as the independent variable, safety learning and safety monitoring as parallel mediators, inclusive leadership behavior as a moderator, and safety performance as the dependent variable. The model reflects a double-mediated–moderated framework, capturing both the behavioral mechanisms and contextual boundary conditions through which accountability influences safety outcomes.

Specifically, the model proposes a direct effect of safety accountability on safety performance (H1), indirect effects through safety learning (H6) and safety monitoring (H7), and moderating effects of inclusive leadership behavior on key structural paths (H8–H10). All hypothesized direct, mediated, and moderating relationships are summarized in Table 1 and visually represented in Figure 1 to ensure structural alignment and conceptual clarity.

By integrating accountability theory and social learning theory, the model provides a structured explanation of how responsibility perceptions (accountability), behavioral processes (learning and monitoring), and leadership context (inclusive leadership) jointly shape safety performance in high-risk construction environments.

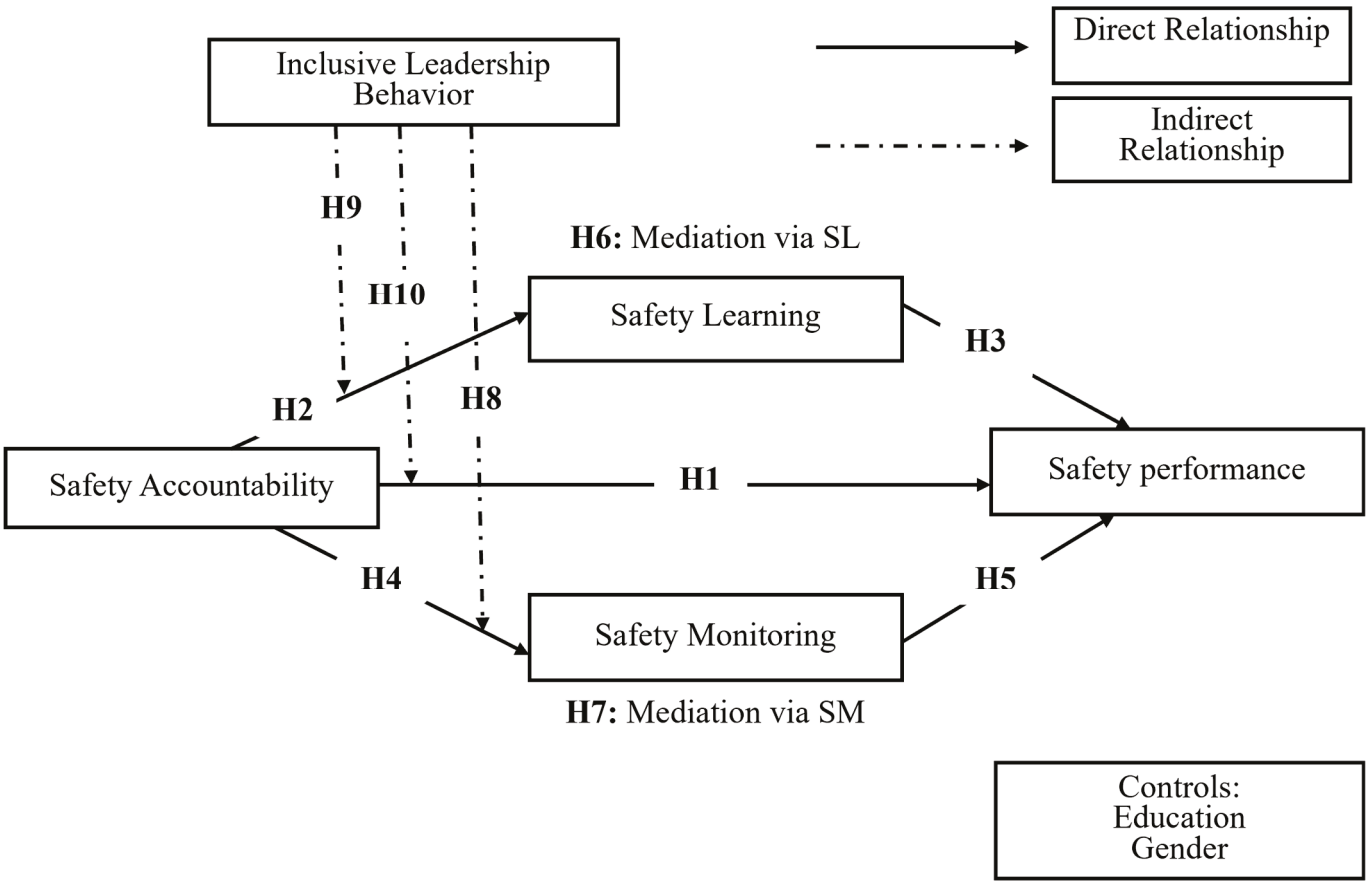

Figure 1. Conceptual research model.

3. Methods

3.1. Sample and Data Collection

This study adopted a quantitative cross-sectional research design to examine the relationships among safety accountability, safety monitoring, safety learning, inclusive leadership behavior, and safety performance within the Turkish construction sector. Data were collected from employees working on large and medium-scale construction projects located in Istanbul and Ankara, Türkiye [51]. A non-probability convenience sampling approach was employed due to the practical constraints associated with accessing geographically dispersed construction sites and project-based workforces. While probability sampling was not feasible, access was formally secured through project management approval, thereby enabling structured and controlled data collection [52].

Survey administration was conducted on-site during scheduled safety briefings and break periods. Trained research assistants distributed the questionnaires directly to participants, and supervisors were not present during completion in order to reduce evaluation apprehension and social desirability bias. No financial or material incentives were offered. Participation was voluntary, and respondents were informed that their responses would remain anonymous and used solely for academic purposes. No personally identifiable information was collected.

To mitigate common method variance, the survey was administered in two temporal waves following the procedural remedies recommended by Podsakoff et al. [53]. In the first wave, participants completed measures of safety accountability, safety monitoring, and safety learning. Three weeks later, the second wave assessed inclusive leadership behavior and safety performance. This temporal separation reduced the likelihood that respondents would rely on cognitive consistency biases when answering related constructs [54,55].

A total of 815 questionnaires were distributed in both paper-based and electronic formats. Of these, 661 responses were returned. After excluding incomplete questionnaires and responses with substantial missing data, 629 valid responses were retained, resulting in a response rate of 77.18%. Respondents were required to meet three inclusion criteria: (1) full-time employment status, (2) a minimum of three years of construction-related work experience, and (3) at least one year of tenure with their current organization. These criteria ensured that participants possessed sufficient exposure to safety systems and leadership practices to provide informed responses.

Table 2 presents the detailed demographic characteristics of the respondents. The demographic composition of the sample reflects the structural characteristics of the Turkish construction workforce. Of the 629 respondents, 611 (97.14%) identified as male and 18 (2.86%) identified as female. Biological sex (male/female) was self-reported and used as a control variable in the analysis. Although female participation was limited, this distribution aligns with national labor statistics indicating that the construction sector in Türkiye remains overwhelmingly male-dominated [56,57].

Table 2. Respondents' characteristics.

Characteristics	Classification	Frequency	Proportion (%)
Gender	Male	611	97.14
	Female	18	2.86
Education	Below high school	141	22.42
	High school	301	47.85
	Bachelor degree	101	16.06
	Others	86	13.67
Marital status	Married	201	31.96
	Single	379	60.25
	Prefer not to disclose	49	7.79
Job roles	Construction workers	431	68.52
	Non-construction personnel	168	26.71
	Legal staff	30	4.77
Experience	3–7	186	29.57
	8–12	101	16.06
	13–17	252	40.06
	18–22	43	6.84
	Above 22	47	7.47
	Total	629	100%

With respect to professional roles, 431 respondents (68.52%) were construction workers engaged in manual or trade-related tasks, 168 (26.71%) held technical or supervisory roles, and 30 (4.77%) were administrative or legal personnel associated with project operations. The predominance of site-based workers ensures that the data primarily reflect frontline safety experiences rather than purely administrative perspectives.

Regarding work experience, 252 respondents (40.06%) reported between 13 and 17 years of experience, 186 (29.57%) reported 3–7 years, and 101 (16.06%) reported 8–12 years, with the remainder exceeding 17 years. Overall, more than 70% of participants had at least eight years of professional experience, indicating a mature and experienced workforce sample.

Given the total sample size of 629 respondents, the estimated margin of error at a 95% confidence level is approximately $\pm 3.9\%$ under conservative assumptions of a large population, suggesting adequate statistical precision. Additionally, exploratory subgroup

comparisons across job roles and experience categories revealed no substantive structural differences in the key relationships, supporting the stability of the proposed model across respondent groups.

Finally, it is important to situate the study within the Turkish regulatory context. Construction safety practices in Türkiye are governed by Occupational Health and Safety Law No. 6331, which mandates employer responsibility for worker training, hazard communication, and on-site supervision [58,59]. Mandatory safety training and supervisory oversight form the institutional foundation upon which accountability, monitoring, and learning mechanisms operate, reinforcing the contextual relevance of the present investigation.

3.2. Measurement Instrument and Administration

The survey instrument consisted of two sections. The first section collected demographic information, including education and gender. The second section measured the five core constructs: safety accountability, safety performance, safety monitoring, safety learning, and inclusive leadership behavior. In total, the questionnaire included 36 measurement items across all constructs.

All constructs were measured using a five-point Likert-type scale ranging from 1 = strongly disagree to 5 = strongly agree, ensuring consistency across variables. The questionnaire was administered in person at construction sites during scheduled safety meetings, with the assistance of site supervisors who facilitated access but did not influence responses. Participation was voluntary and anonymous.

All items were adopted and adapted from previously validated scales in the safety and organizational behavior literature, thereby enhancing content validity.

Safety accountability was measured using 15 items adapted from [60]. An example item is: "What I do is noticed by others in my organization."

Safety performance was measured using 6 items from [27]. An example item is: "I use the correct safety procedures for carrying out my job."

Safety monitoring was measured using 3 items from [31], such as: "Is alert to safety behavior in the team."

Safety learning was measured using 3 items from [31], including: "Sees unsafe behavior as an opportunity for learning."

Inclusive leadership behavior was measured using 9 items adapted from [61], for example: "My supervisor is open to hearing new ideas."

All scales were originally developed in English and were translated into Turkish following a back-translation procedure to ensure semantic equivalence [62]. Two bilingual experts independently translated and back-translated the items, and discrepancies were resolved through discussion.

Prior to the main data collection, a pilot test was conducted with 30 construction workers to assess clarity and comprehensibility of the items. Minor wording adjustments were made accordingly.

Reliability and validity of the constructs were assessed through confirmatory factor analysis (CFA). Cronbach's alpha values for all constructs exceeded the recommended threshold of 0.70. Composite reliability (CR) and average variance extracted (AVE) also met established criteria, indicating satisfactory internal consistency and convergent validity. The complete list of measurement items is presented in Table 3.

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Table 3. Measurement of variables.

Construct	Variable	Number of Substances	Source
Independent	Safety Accountability	SA1: What I do is noticed by others in my organization. SA2: If I make a mistake, I will be caught. SA3: I am constantly watched to see if I follow my organization's safety policies and procedures. SA4: Anyone outside my organization can tell whether I'm doing well in my safety job. SA5: My errors can be easily spotted outside my organization. SA6: People outside my organization are interested in my job performance. SA7: The outcomes of my work are rigorously evaluated. SA8: My work efforts are rigorously evaluated. SA9: I expect to receive frequent feedback from the management. SA10: I could not easily get away with making a false statement to justify my performance. SA11: I am always required to follow strict safety policies or procedures. SA12: I am not allowed to make excuses to avoid blame in my organization. SA13: If I perform well in safety work, I will be rewarded. SA14: Good effort on my part will ultimately be rewarded. SA15: If I do my safety management job well, my organization will benefit from it.	[60]
Dependent	Safety Performance	SP1: I use all the necessary safety equipment to do my job. SP2: I use the correct safety procedures for carrying out my job. SP3: I ensure the highest levels of safety when I carry out my job. SP4: I promote the safety program within the organization. SP5: I put in extra effort to improve the safety of the workplace. SP6: I voluntarily carry out tasks or activities that help to improve workplace safety.	[27]
Mediator	Safety Monitoring	SM1: Is alert to safety behavior in the team. SM2: Scans the environment for unsafe actions by the team. SM3: Let the subordinates know if they are working unsafely	[31]
Mediator	Safety Learning	SL1: Encourages new ways of thinking about safety. SL2: Sees unsafe behavior as an opportunity for learning. SL3: Actively seeks opportunities to learn about new safety protocols and practices	[31]
Moderator	Inclusive Leadership Behavior	ILB1: My supervisor is open to hearing new ideas ILB2: My supervisor is attentive to new opportunities to improve work processes ILB3: My supervisor is open to discussing the desired goals and new ways to achieve them ILB4: My supervisor is available for consultation on problems ILB5: My supervisor is an ongoing 'presence' in this team, someone who is readily available. ILB6: My supervisor is available for safety questions. ILB7: My supervisor is ready to listen to safety requests. ILB8: My supervisor always encourages subordinates on emerging issues. ILB9: My supervisor is accessible for discussing emerging problems.	[61]

3.3. Analytical Procedures

The collected data were analyzed using SPSS 26 and AMOS 24. A two-step analytical approach was adopted [63,64]. First, confirmatory factor analysis (CFA) was conducted to assess the measurement model, including internal consistency reliability, convergent validity, and discriminant validity of the constructs [65]. Second, the structural relationships were tested using Hayes' PROCESS macro for SPSS [66].

To examine the proposed mediation effects (H2–H7), PROCESS Model 4 was employed. Model 4 estimates parallel mediation effects by testing whether the independent variable (safety accountability) influences the dependent variable (safety performance) indirectly through multiple mediators (safety learning and safety monitoring). Specifically, Model 4 tested:

- The direct effect of safety accountability on safety performance (H1);
- The effect of safety accountability on safety learning (H2);
- The effect of safety accountability on safety monitoring (H4);
- The effect of safety learning on safety performance (H3);
- The effect of safety monitoring on safety performance (H5);
- The indirect (mediated) effects through safety learning (H6) and safety monitoring (H7).

To examine the moderating and conditional process effects (H8–H10), PROCESS Model 8 was used. Model 8 estimates moderated mediation by allowing the moderator (inclusive leadership behavior) to interact with the independent variable in predicting both the mediators and the dependent variable. In the present study, Model 8 tested:

- The interaction between safety accountability and inclusive leadership in predicting safety monitoring (H8);
- The interaction between safety accountability and inclusive leadership in predicting safety learning (H9);
- The interaction between safety accountability and inclusive leadership in predicting safety performance (H10).

Bootstrapping with 5000 resamples was employed to generate bias-corrected confidence intervals for all direct, indirect, and interaction effects. An effect was considered statistically significant when the 95% confidence interval did not include zero [67].

3.4. Common Method Bias

Given that data were collected using a self-reported survey design, common method bias (CMB) may pose a potential threat to validity [53]. CMB refers to systematic measurement error arising from the use of a single data source or measurement method, which may inflate or deflate observed relationships among constructs [68,69].

To mitigate and detect CMB, both procedural and statistical remedies were implemented. Procedurally, temporal separation was introduced by administering the survey in two waves, separating measurement of predictors and outcomes. In addition, anonymity was emphasized, no identifying information was collected, and respondents were assured that there were no right or wrong answers [70,71]. These steps were taken to reduce evaluation apprehension and response consistency bias.

Statistically, Harman's single-factor test was conducted [72]. The unrotated exploratory factor analysis revealed that the largest single factor accounted for 40.11% of the total variance, which is below the commonly accepted 50% threshold, suggesting that CMB is unlikely to be a serious concern [73].

Furthermore, a theoretically unrelated marker variable was included to assess potential method variance. The correlations between the marker variable and the main constructs

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were very low and non-significant ($r < 0.03$), indicating that shared method variance did not substantially bias the results [74].

Taken together, the procedural and statistical assessments suggest that common method bias does not materially threaten the validity of the findings.

4. Results

4.1. Reliability and Validity Assessment

Prior to hypothesis testing, a confirmatory factor analysis (CFA) was conducted using AMOS 24 to evaluate the measurement model. The objective was to assess internal consistency reliability, convergent validity, discriminant validity, and overall model fit before proceeding to structural analysis [65]. The results are presented in Table 4.

Table 4. Summary of measurement model.

Variables	Item Codes	λ	α	AVE	CR	Skewness	Kurtosis
Safety Accountability (SA)			0.948	0.564	0.951		
	SA1	0.732				−0.572	0.018
	SA2	0.786				−0.690	0.332
	SA3	0.763				−0.673	0.116
	SA4	0.747				−0.825	0.425
	SA5	0.747				−0.904	0.644
	SA6	0.745				−0.676	0.060
	SA7	0.737				−0.709	0.245
	SA8	0.789				−0.565	−0.282
	SA9	0.706				−0.974	0.958
	SA10	0.809				−0.490	−0.090
	SA11	0.682				−0.743	0.566
	SA12	0.747				−0.579	−0.082
	SA13	0.732				−0.490	−0.435
	SA14	0.741				−0.381	−0.479
	SA15	0.761				−0.530	0.025
Safety Monitoring (SM)			0.908	0.781	0.914		
	SM1	0.927				−0.652	0.347
	SM2	0.926				−0.744	0.511
	SM3	0.790				−0.691	0.406
Safety Learning (SL)			0.825	0.625	0.833		
	SL1	0.757				−1.675	−2.966
	SL2	0.854				−1.092	−1.984
	SL3	0.756				−0.813	0.658

Table 4. *Cont.*

Variables	Item Codes	λ	α	AVE	CR	Skewness	Kurtosis
Inclusive Leadership Behavior (ILB)			0.961	0.735	0.961		
	ILB1	0.828				−0.308	−0.526
	ILB2	0.822				−0.646	0.205
	ILB3	0.833				−0.545	−0.376
	ILB4	0.840				−0.246	−0.544
	ILB5	0.885				−0.444	−0.566
	ILB6	0.874				−0.544	−0191
	ILB7	0.876				−0.245	−0.901
	ILB8	0.874				−0.373	−0.432
	ILB9	0.881				−0.445	−0.800
Safety Performance (SP)			0.956	0.787	0.957		
	SP1	0.857				−0.504	0.716
	SP2	0.886				−0.356	−0.717
	SP3	0.926				−0.433	0.753
	SP4	0.903				−0.512	−0.430
	SP5	0.896				−0.418	−0.644
	SP6	0.854				−0.630	0.299

Internal consistency reliability was examined using Cronbach's alpha (α) and composite reliability (CR). All constructs demonstrated strong reliability, with Cronbach's alpha values ranging from 0.825 to 0.961, exceeding the recommended threshold of 0.70 [75,76]. Similarly, composite reliability values ranged from 0.833 to 0.961, further confirming adequate construct reliability.

Convergent validity was assessed using standardized factor loadings and average variance extracted (AVE). All standardized loadings were statistically significant and ranged from 0.682 to 0.927, exceeding the recommended minimum threshold of 0.60. The AVE values ranged from 0.564 to 0.787, surpassing the 0.50 criterion [77,78], indicating that each construct explains more than half of the variance of its indicators.

Discriminant validity was evaluated using the Fornell–Larcker criterion. As shown in Table 5, the square root of the AVE for each construct (diagonal elements) exceeded the corresponding inter-construct correlations, supporting adequate discriminant validity [77].

Table 5. Discriminant validity, correlations, and descriptive statistics.

Variables	M	SD	SA	SM	SL	ILB	SP
SA	5.424	0.930	(0.751)				
SM	5.675	0.968	0.472 **	(0.884)			
SL	5.723	1.003	0.494 **	0.486 **	(0.791)		
ILB	5.529	0.960	0.509 **	0.428 **	0.505 **	(0.857)	
SP	5.661	0.954	0.552 **	0.494 **	0.601 **	0.499 **	(0.887)

Note: ** correlation is significant at 0.01, two-tailed. Diagonal values (in brackets) represent the square root of AVE.

Multicollinearity was examined using the variance inflation factor (VIF). All VIF values were below 3.0, which is well under the conservative threshold of 3.3 suggested by Kock [79], indicating that collinearity does not threaten the estimation results.

To assess data normality, skewness and kurtosis statistics were examined. Skewness values ranged between 0.245 and 1.675, and kurtosis ranged between 0.018 and 2.966, both within acceptable ranges (± 2 for skewness and ± 3 for kurtosis) as recommended by Lei and Lomax [80]. These results indicate that the distributional properties of the data satisfy normality assumptions for maximum likelihood estimation.

Finally, model fit indices indicated an acceptable overall fit of the measurement model (CMIN/df = 2.229; CFI = 0.941; GFI = 0.921; TLI = 0.936; IFI = 0.939; NFI = 0.938), suggesting that the proposed factor structure adequately represents the observed data.

4.2. Direct and Mediation Analysis

The direct and mediation hypotheses were tested using Hayes' PROCESS Model 4 [66], which estimates parallel mediation effects. All coefficients reported are unstandardized regression coefficients (B) with corresponding standard errors (SE) and 95% confidence intervals (CI).

First, as shown in Table 6, the direct relationship between safety accountability and safety performance (H1) was examined. The results indicate that safety accountability did not significantly predict safety performance (B = 0.110, SE = 0.056, t = 1.946, p = 0.052). Therefore, H1 was not supported.

Table 6. Direct and Mediation Results (PROCESS Model 4).

Hypothesis	Path	B	SE	*t*-Value	*p*-Value	95% CI (LL, UL)	R^2
H1	SA → SP	0.110	0.056	1.946	0.052	[−0.001, 0.220]	0.333
H2	SA → SL	0.874	0.048	18.168	<0.001	[0.779, 0.921]	0.372
H3	SL → SP	0.132	0.055	2.404	0.016	[0.024, 0.241]	0.378
H4	SA → SM	0.855	0.047	18.400	<0.001	[0.764, 0.946]	—
H5	SM → SP	0.322	0.057	5.644	<0.001	[0.209, 0.434]	—
H6	SA → SL → SP	0.115	—	—	—	[0.026, 0.204]	—
H7	SA → SM → SP	0.275	—	—	—	[0.184, 0.368]	—

Note: LL = lower limit; UL = upper limit; CI = confidence interval. All indirect effects were tested using 5000 bootstrap samples.

Second, safety accountability significantly predicted safety learning (H2) (B = 0.874, SE = 0.048, t = 18.168, $p < 0.001$), providing support for H2. In addition, safety learning positively influenced safety performance (H3) (B = 0.132, SE = 0.055, t = 2.404, p = 0.016), supporting H3.

Third, safety accountability significantly predicted safety monitoring (H4) (B = 0.855, SE = 0.047, t = 18.400, $p < 0.001$), supporting H4. Furthermore, safety monitoring positively influenced safety performance (H5) (B = 0.322, SE = 0.057, t = 5.644, $p < 0.001$), supporting H5.

The mediation hypotheses were evaluated using bootstrapping with 5000 resamples to generate bias-corrected 95% confidence intervals [67,81]. The indirect effect of safety accountability on safety performance through safety learning (H6) was significant (B = 0.115, 95% CI [0.026, 0.204]), supporting H6. Similarly, the indirect effect through safety monitoring (H7) was significant (B = 0.275, 95% CI [0.184, 0.368]), supporting H7.

Because the direct effect of safety accountability on safety performance became non-significant after including the mediators, the findings indicate full mediation, whereby

safety accountability influences safety performance entirely through safety monitoring and safety learning.

4.3. Moderation Analysis

The moderation hypotheses (H8–H10) were tested using Hayes' PROCESS Model 8 [66], which estimates moderated mediation effects by allowing inclusive leadership behavior to interact with safety accountability in predicting both the mediators and the dependent variable. All coefficients reported are unstandardized regression coefficients (B) with corresponding standard errors (SE) and 95% confidence intervals (CI). Continuous variables were mean-centered prior to computing interaction terms, and education and sex (biological classification) were included as control variables in all models.

In Model 1 of Table 7, where safety monitoring was specified as the outcome variable, safety accountability significantly predicted safety monitoring (B = 0.272, SE = 0.041, $t = 6.641$, $p < 0.001$, 95% CI [0.192, 0.353]). The interaction term between safety accountability and inclusive leadership was also significant (B = 0.102, SE = 0.031, $t = 3.337$, $p = 0.001$, 95% CI [0.042, 0.161]), providing support for H8. Simple slope analysis indicated that the relationship between safety accountability and safety monitoring was weaker at low levels of inclusive leadership (−1 SD; B = 0.186, $p < 0.001$) and stronger at high levels (+1 SD; B = 0.344, $p < 0.001$). Figure 2 illustrates this interaction pattern. Neither education nor sex significantly predicted safety monitoring ($p > 0.05$), suggesting that the moderation effect is robust across demographic groups.



Figure 2. Interaction effect of inclusive leadership behavior on the safety accountability-safety monitoring link.

Table 7. Moderation Results (PROCESS Model 8).

Paths	B	S.E.	*t*-Value	*p*-Value	95% CI		R^2
					LL	UL	
Model 1: Safety Monitoring							
SA → SM	0.272	0.041	6.641	0.000	0.192	0.353	0.689
ILB → SM	0.756	0.033	23.276	0.000	0.692	0.820	
H8: SA × ILB → SM	0.102	0.031	3.337	0.001	0.042	0.161	
Co: Education → SM	0.047	0.052	0.904	0.775	−0.095	0.067	
Co: Gender → SM	0.019	0.028	0.679	0.865	−0.100	0.059	
The conditional direct effect of SA on SM at levels of ILB							
ILB (−1 SD)	0.186	0.045	3.699	0.000	0.087	0.285	
ILB (Mean)	0.265	0.041	6.420	0.000	0.184	0.346	
ILB (+1 SD)	0.344	0.050	7.679	0.000	0.256	0.433	
Model 2: Safety Learning							
SA → SL	0.309	0.045	6.859	0.000	0.220	0.397	0.649
ILB → SL	0.731	0.036	20.544	0.000	0.661	0.801	
H9: SA × ILB → SL	0.114	0.033	3.411	0.000	0.048	0.180	
Co: Education → SL	0.066	0.039	1.692	0.162	−0.216	0.059	
Co: Gender → SL	0.024	0.042	0.571	0.804	−0.099	0.048	
The conditional direct effect of SA on SL at levels of ILB							
ILB (−1 SD)	0.212	0.055	3.699	0.000	0.103	0.320	
ILB (Mean)	0.300	0.045	6.420	0.000	0.211	0.389	
ILB (+1 SD)	0.389	0.049	7.679	0.000	0.292	0.486	
Model 3: Safety Performance							
SA → SP	0.028	0.034	2.696	0.007	0.025	0.157	
SM → SP	0.207	0.040	5.226	0.000	0.129	0.285	
SL → SP	0.329	0.101	3.265	0.001	0.131	0.527	
ILB → SP	1.292	0.089	0.154	0.878	−0.162	0.189	
H10: SA × ILB → SP	0.122	0.036	3.425	0.001	0.052	0.192	
Co: Education → SP	0.018	0.029	0.620	0.304	−0.119	0.029	
Co: Gender → SP	0.031	0.033	0.939	0.206	−0.102	0.051	
The conditional direct effect of SA on SP at different levels of ILB							
ILB (−1 SD)	0.093	0.057	0.405	0.685	−0.107	0.024	
ILB (Mean)	0.050	0.061	1.602	0.109	−0.082	0.124	
ILB (+1 SD)	0.021	0.052	2.088	0.046	0.089	0.169	

Note: All coefficients are unstandardized (B). Bootstrap samples = 5000. LL = lower limit; UL = upper limit; Co = control variables.

In Model 2, where safety learning was treated as the dependent variable, safety accountability significantly predicted safety learning (B = 0.309, SE = 0.045, t = 6.859, $p < 0.001$, 95% CI [0.220, 0.397]). The interaction between safety accountability and inclusive leadership was significant (B = 0.114, SE = 0.033, t = 3.411, $p < 0.001$, 95% CI [0.048, 0.180]), supporting H9. At low inclusive leadership (−1 SD), the effect of safety accountability on safety learning was weaker (B = 0.212, $p < 0.001$), whereas at high inclusive leadership

(+1 SD), the effect was stronger (B = 0.389, $p < 0.001$). The interaction effect is presented in Figure 3. Education and sex did not significantly predict safety learning ($p > 0.05$).



Figure 3. Interaction effect of inclusive leadership behavior on the safety accountability-safety learning link.

In Model 3, which examined safety performance as the dependent variable, safety accountability had a significant direct effect on safety performance (B = 0.128, SE = 0.034, $t = 2.696$, $p = 0.007$, 95% CI [0.025, 0.157]). The interaction term between safety accountability and inclusive leadership was also significant (B = 0.122, SE = 0.036, $t = 3.425$, $p = 0.001$, 95% CI [0.052, 0.192]), supporting H10. Simple slope analysis revealed that the relationship between safety accountability and safety performance was non-significant at low levels of inclusive leadership (B = 0.093, $p = 0.685$) but became significant at high levels (B = 0.169, $p = 0.046$), indicating that inclusive leadership strengthens the positive effect of accountability on performance. This interaction is illustrated in Figure 4. As in the previous models, education and sex remained non-significant predictors ($p > 0.05$), indicating that the moderation results are not driven by demographic differences.

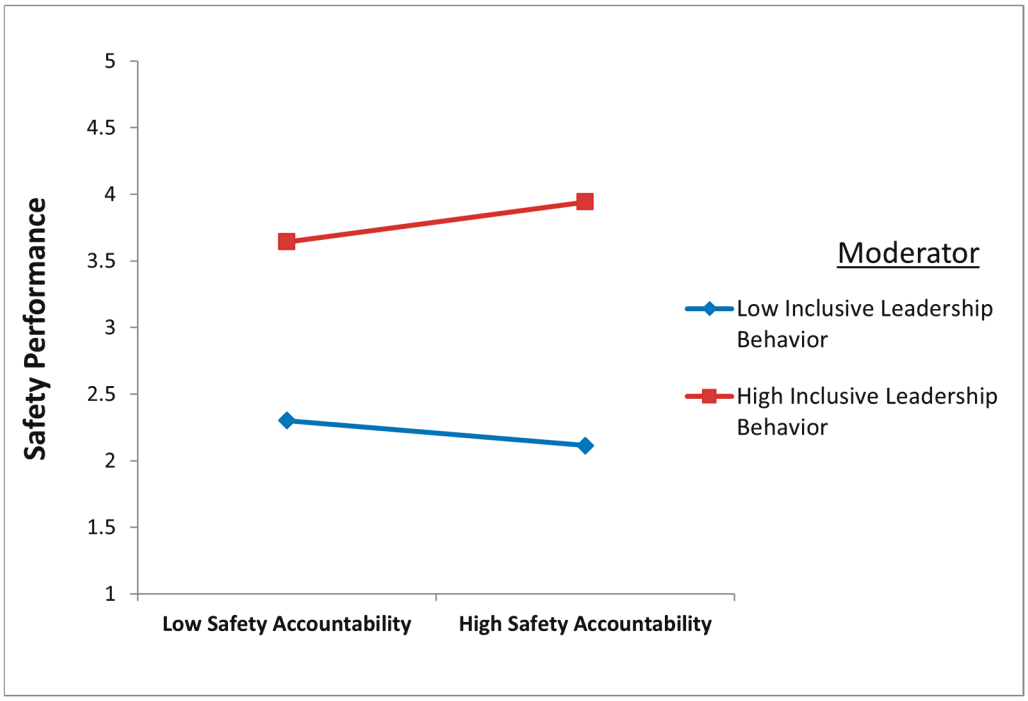

Figure 4. Interaction effect of inclusive leadership behavior on the safety accountability-safety performance link.

5. Discussion and Implications

5.1. Discussion of Findings

This study demonstrates that safety accountability, by itself, does not directly enhance safety performance in construction settings. Although accountability clarifies roles and expectations, the findings indicate that accountability must operate through concrete behavioral mechanisms to influence performance outcomes. The non-significant direct relationship suggests that accountability becomes effective only when translated into observable safety processes [82].

This result helps clarify previously mixed evidence reported in construction safety research [5,7]. While accountability is often assumed to drive compliance [6], the present findings indicate that formal accountability structures alone may remain symbolic unless embedded within active monitoring and learning systems. Thus, the study highlights the distinction between declarative accountability and enacted accountability within daily site operations.

Second, the results reveal that safety monitoring and safety learning fully mediate the relationship between safety accountability and safety performance. Safety monitoring emerged as the primary mechanism through which accountability influences safety outcomes. Continuous observation, feedback, and corrective actions appear to transform accountability expectations into real-time behavioral adjustments [83]. In dynamic construction environments, where risks evolve rapidly, such monitoring mechanisms play a decisive role in preventing unsafe acts.

Safety learning also contributed significantly to safety performance. Learning processes enabled workers to internalize safety standards, reflect on incidents, and adapt practices accordingly. While monitoring reinforces compliance, learning supports behavioral adaptation and long-term safety improvement [31]. These findings support arguments in prior occupational health literature that effective safety systems combine control-oriented and developmental mechanisms [2,37], yet the present study empirically demonstrates their simultaneous mediating roles within an accountability framework.

Third, inclusive leadership behavior was found to function as a critical boundary condition. Accountability translated into improved safety performance only under conditions of high inclusive leadership. When leaders demonstrated openness, accessibility, and support, accountability strengthened both safety monitoring and safety learning [84]. Conversely, under low inclusive leadership, accountability mechanisms failed to produce meaningful safety gains.

This pattern aligns with social learning principles [17,85], suggesting that leadership behaviors shape how organizational expectations are interpreted and enacted. However, the present findings extend prior work by showing that inclusive leadership does not merely influence safety directly, but conditions the effectiveness of accountability systems themselves.

Overall, the study advances construction safety research by demonstrating that sustainable improvements in safety performance emerge when accountability is operationalized through monitoring and learning processes and supported by inclusive leadership. Rather than treating accountability as a standalone compliance mechanism, the findings position it as a catalytic force that requires behavioral and leadership integration to generate meaningful occupational health outcomes.

5.2. Theoretical Implications

This study offers three focused theoretical contributions to the construction safety and occupational health literature.

First, the findings refine accountability theory by demonstrating that safety accountability does not directly predict safety performance, but instead operates through behavioral mechanisms. The non-significant direct effect and significant indirect effects suggest that accountability functions as a distal governance signal rather than an immediate behavioral driver. This finding challenges assumptions that formal accountability structures alone improve safety outcomes and supports a process-based understanding of safety systems [5–7].

Second, the study advances social learning perspectives in construction safety by empirically establishing safety monitoring and safety learning as parallel mediating mechanisms. Rather than treating monitoring and learning as independent safety practices, the results show that they jointly translate accountability into performance outcomes. Monitoring reinforces behavioral expectations through feedback and control, while learning supports cognitive adaptation and knowledge internalization [3]. This integrated mediation model provides a more nuanced explanation of how safety systems operate in dynamic and high-risk environments.

Third, the findings extend leadership–safety theory by identifying inclusive leadership as a boundary condition that determines when accountability becomes effective. Accountability translated into improved safety performance only under high levels of inclusive leadership, indicating that leadership behavior shapes how accountability cues are interpreted and enacted. This contribution moves beyond examining direct leadership effects and instead positions inclusive leadership as an enabling mechanism within accountability-based safety systems [10,17].

Collectively, these contributions offer a more parsimonious and mechanism-focused explanation of safety performance in construction, emphasizing the interaction between governance structures, behavioral processes, and leadership context.

5.3. Practical Implications

The findings of this study suggest that construction firms should rethink how safety accountability systems are implemented in practice.

First, because safety accountability did not directly improve safety performance, organizations should avoid relying solely on formal rules or punitive controls. Accountability mechanisms must be translated into daily behavioral processes. Practically, this means embedding accountability within structured safety monitoring systems, such as systematic site inspections, real-time feedback, and supervisor-led hazard observations. These practices ensure that accountability expectations become observable and actionable rather than symbolic.

Second, the full mediation results indicate that safety monitoring and safety learning are the mechanisms through which accountability produces performance gains. Therefore, firms should institutionalize both control-based and learning-based practices. Monitoring mechanisms (e.g., routine safety audits, peer reporting systems) reinforce compliance, while structured learning mechanisms (e.g., post-incident reviews, near-miss analysis meetings, cross-crew knowledge sharing) support behavioral adaptation and long-term safety improvement. Treating monitoring and learning as complementary rather than isolated initiatives is essential for sustained occupational health outcomes.

Third, the moderation findings demonstrate that accountability becomes effective only under high inclusive leadership. Construction managers and site supervisors should therefore be trained in inclusive leadership behaviors, including openness to employee input, accessibility during safety concerns, and encouragement of worker voice. Without such leadership behaviors, accountability systems may fail to translate into improved safety performance.

Finally, from an industry perspective, the results support an integrated safety management approach that aligns accountability structures, behavioral processes, and leadership practices. Rather than focusing exclusively on regulatory compliance, firms should design safety systems that simultaneously reinforce responsibility, encourage learning, and cultivate supportive leadership climates. Such alignment is more likely to generate meaningful and sustainable improvements in safety performance.

5.4. Limitations and Future Research Directions

Despite its contributions, this study has several limitations that should be acknowledged. First, the cross-sectional design restricts causal inference, and future research should adopt longitudinal or time-lagged designs to better capture the dynamic relationships among accountability, leadership, and safety outcomes. Second, although procedural remedies were implemented, reliance on self-reported measures may introduce common method variance and social desirability bias. Future studies could incorporate objective safety indicators (e.g., accident records, near-miss data) and multi-source assessments. Importantly, the sample composition presents structural imbalances that limit subgroup inference. The sample was predominantly male, and certain job roles (e.g., construction workers) were overrepresented relative to supervisory or specialist positions. In addition, experience categories were unevenly distributed. These imbalances restrict the ability to generalize findings across gender groups, professional roles, and experience levels, and caution is warranted when interpreting subgroup effects. Future research should employ more stratified sampling approaches to ensure balanced representation across demographic and occupational categories.

Furthermore, the study was conducted exclusively at construction sites in Ankara and Istanbul, two large metropolitan areas characterized by complex project structures and formalized safety systems. As a result, the findings may reflect safety dynamics typical of large-scale, urban construction projects. Construction settings in less urbanized regions or smaller-scale projects may differ in organizational hierarchy, leadership proximity, regulatory enforcement, and resource availability. Therefore, generalizability beyond

major metropolitan contexts should be approached cautiously. Future research should replicate the proposed model in rural areas, smaller firms, and diverse project types to assess contextual boundary conditions and enhance external validity.

6. Conclusions

This study examined how safety accountability influences safety performance in construction projects through safety monitoring and safety learning, and under the boundary condition of inclusive leadership behavior. The findings demonstrate that safety accountability does not directly improve safety performance; rather, its influence is fully transmitted through monitoring and learning mechanisms. Safety monitoring emerged as the stronger mediator, highlighting the importance of real-time oversight and corrective feedback, while safety learning contributed through knowledge internalization and behavioral adaptation. Moreover, inclusive leadership was found to strengthen the effectiveness of accountability-driven safety processes, indicating that leadership behavior determines whether accountability translates into meaningful performance outcomes.

The study contributes to construction safety research by advancing a mechanism-based explanation of how accountability systems operate in high-risk environments. Rather than treating accountability as a standalone compliance tool, the findings position it as a governance signal that requires behavioral enactment and supportive leadership to generate safety improvements. At the same time, the results should be interpreted in light of methodological limitations, including the cross-sectional design, self-reported measures, subgroup imbalances, and the metropolitan context of Ankara and Istanbul. Future research should replicate and extend this framework across diverse project types and organizational settings to further validate its applicability and strengthen the evidence base for integrated safety management systems.

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References

1. Dodoo, J.E.; Al-Samarraie, H. A Systematic Review of Factors Leading to Occupational Injuries and Fatalities. *J. Public Health* **2023**, *31*, 99–113. [CrossRef]
2. Awolusi, I.; Marks, E.; Hallowell, M. Wearable Technology for Personalized Construction Safety Monitoring and Trending: Review of Applicable Devices. *Autom. Constr.* **2018**, *85*, 96–106. [CrossRef]
3. Dodoo, J.E.; Al-Samarraie, H.; Alzahrani, A.I.; Lonsdale, M.; Alalwan, N. Digital Innovations for Occupational Safety: Empowering Workers in Hazardous Environments. *Workplace Health Saf.* **2024**, *72*, 84–95. [CrossRef]
4. Swieai, W.; Alzubi, A.B.; Aljuhmani, H.Y.; Topal, H. Unpacking the Role of Proactive Personality in Enhancing Safety Behavior: A Moderated Mediation Model in Turkish Healthcare Organizations. *J. Health Organ. Manag.* **2025**, 1–29. [CrossRef] [PubMed]

5. Sha, Y.; Zhang, Y.; Zhang, Y. How Safety Accountability Impacts the Safety Performance of Safety Managers: A Moderated Mediating Model. *J. Saf. Res.* **2024**, *89*, 160–171. [CrossRef] [PubMed]
6. Nadeem, M.A.; Surienty, L.; Haque, M.M. Impact of Organization Decision Making Styles and Safety Accountability on Occupational Health and Safety Implementation: The Moderating Role of Mimetic Motives. *Front. Public Health* **2022**, *10*, 1004767. [CrossRef]
7. Al-Arnous, A.B.; Abdelwahed, N.A.A. The Impact of the Implementation of Safety Measures on Frontline Workers' Safety Accountability: A Saudi Arabian Case Study of a Well Intervention Business Model. *Safety* **2022**, *8*, 82. [CrossRef]
8. Slil, E.; Iyiola, K.; Alzubi, A.; Aljuhmani, H.Y. Impact of Safety Leadership and Employee Morale on Safety Performance: The Moderating Role of Harmonious Safety Passion. *Buildings* **2025**, *15*, 186. [CrossRef]
9. Senthamizh Sankar, S.; Anandh, K.S. Building Safer Workplaces: Unveiling the Impact of Safety Leadership Styles in the Construction Industry. *Adm. Sci.* **2024**, *14*, 212. [CrossRef]
10. Giri, M.K. Teacher Retention in Private Schools: A Narrative Inquiry into Principals' Leadership. Doctoral Dissertation, Kathmandu University, Kavrepalanchok, Nepal, 2025.
11. Jiang, S.; Ma, G.; Wang, D.; Jia, J. How Inclusive Leadership Influences Voice Behavior in Construction Project Teams: A Social Identity Perspective. *Proj. Manag. J.* **2023**, *54*, 116–131. [CrossRef]
12. Paul, J.; Pilbeam, C.; Smallwood, A. Safety Voice Concept Clean-up: Examining the Voice That Challenges Us to Be Safer. *Saf. Sci.* **2025**, *191*, 106931. [CrossRef]
13. Lee, S.E.; Dahinten, V.S. Psychological Safety as a Mediator of the Relationship Between Inclusive Leadership and Nurse Voice Behaviors and Error Reporting. *J. Nurs. Scholarsh.* **2021**, *53*, 737–745. [CrossRef]
14. Cheng, R.; Zhao, Z.; Sheng, S.; Sun, H. When Zodiac Year and Disaster Echoes Meet Accountability: Dual Moderators in Emergency Management Prioritization. *Research Square* (preprint). 2025. Available online: https://www.researchsquare.com/article/rs-6866868/v1 (accessed on 27 February 2026).
15. Chatburn, E.; Macrae, C.; Carthey, J.; Vincent, C. Measurement and Monitoring of Safety: Impact and Challenges of Putting a Conceptual Framework into Practice. *BMJ Qual. Saf.* **2018**, *27*, 818–826. [CrossRef] [PubMed]
16. Winge, S.; Albrechtsen, E.; Arnesen, J. A Comparative Analysis of Safety Management and Safety Performance in Twelve Construction Projects. *J. Saf. Res.* **2019**, *71*, 139–152. [CrossRef] [PubMed]
17. Junwen, M.; Libing, C. The Influence of Inclusive Leadership Styles on the Safety Behaviors of New Generation High Altitude Railway Construction Workers. *Sci. Rep.* **2025**, *15*, 10706. [CrossRef] [PubMed]
18. Qasim, S.; Usman, M.; Ghani, U.; Khan, K. Inclusive Leadership and Employees' Helping Behaviors: Role of Psychological Factors. *Front. Psychol.* **2022**, *13*, 888094. [CrossRef]
19. Kusumawardani, K.A.; Arquisola, M.J.; Amin, G.; Restiawati, M. Inclusive Leadership and Workers' Safety Behaviour during Covid-19 Pandemic. *Evid.-Based HRM A Glob. Forum Empir. Scholarsh.* **2023**, *11*, 465–482. [CrossRef]
20. Bandura, A. Human Agency in Social Cognitive Theory. *Am. Psychol.* **1989**, *44*, 1175–1184. [CrossRef]
21. Frink, D.D.; Klimoski, R.J. Advancing Accountability Theory and Practice: Introduction to the Human Resource Management Review Special Edition. *Hum. Resour. Manag. Rev.* **2004**, *14*, 1–17. [CrossRef]
22. Hall, A.T.; Frink, D.D.; Buckley, M.R. An Accountability Account: A Review and Synthesis of the Theoretical and Empirical Research on Felt Accountability. *J. Organ. Behav.* **2017**, *38*, 204–224. [CrossRef]
23. Bandura, A. *Social Learning Theory*; Prentice-Hall: Englewood Cliffs, NJ, USA, 1977; ISBN 978-0-13-816744-8.
24. Nwagbala, D.C.; Park, J.Y. A Study of the Foremen's Influence on the Safety Behavior of Construction Workers Based on Cognitive Theory. *Buildings* **2023**, *13*, 1792. [CrossRef]
25. Ayouz, H.; Alzubi, A.; Iyiola, K. Using Benevolent Leadership to Improve Safety Behaviour in the Construction Industry: A Moderated Mediation Model of Safety Knowledge and Safety Training and Education. *Int. J. Occup. Saf. Ergon.* **2025**, *31*, 167–180. [CrossRef]
26. Bhuttah, T.M.; Xusheng, Q.; Abid, M.N.; Sharma, S. Enhancing Student Critical Thinking and Learning Outcomes through Innovative Pedagogical Approaches in Higher Education: The Mediating Role of Inclusive Leadership. *Sci. Rep.* **2024**, *14*, 24362. [CrossRef] [PubMed]
27. Neal, A.; Griffin, M.A. A Study of the Lagged Relationships among Safety Climate, Safety Motivation, Safety Behavior, and Accidents at the Individual and Group Levels. *J. Appl. Psychol.* **2006**, *91*, 946–953. [CrossRef]
28. Chan, A.P.C.; Guan, J.; Choi, T.N.Y.; Yang, Y.; Wu, G.; Lam, E. Improving Safety Performance of Construction Workers through Learning from Incidents. *Int. J. Environ. Res. Public Health* **2023**, *20*, 4570. [CrossRef] [PubMed]
29. Al-Naser, N.K.; Al-Tabtabai, H. The Impact of Safety Violations on Construction Project Performance: A Case Study of the ADFA Project. *J. Eng. Res.* **2025**, *13*, 3037–3050. [CrossRef]
30. McCall, J.R.; Pruchnicki, S. Just Culture: A Case Study of Accountability Relationship Boundaries Influence on Safety in HIGH-Consequence Industries. *Saf. Sci.* **2017**, *94*, 143–151. [CrossRef]

31. Griffin, M.A.; Hu, X. How Leaders Differentially Motivate Safety Compliance and Safety Participation: The Role of Monitoring, Inspiring, and Learning. *Saf. Sci.* **2013**, *60*, 196–202. [CrossRef]
32. Kadher, Y.; Alzubi, A.; Berberoğlu, A.; Öz, T. Perceived Leadership Support, Safety Citizenship, and Employee Safety Behavior in the Construction Industry: The Role of Safety Learning. *Buildings* **2024**, *14*, 3260. [CrossRef]
33. Yazdi, M. The Impact of Leadership on Fostering a Safety-Oriented Organizational Culture. In *Safety-Centric Operations Research: Innovations and Integrative Approaches: A Multidisciplinary Approach to Managing Risk in Complex Systems*; Yazdi, M., Ed.; Springer Nature: Cham, Switzerland, 2025; pp. 31–50. ISBN 978-3-031-82934-5.
34. Yeboah, M.A.; Kalvei, M.; Ansong, L.O.; Ansong, A. Responsible Leadership and Workplace Safety: Do Safety Culture and Safety Motivation Matter? *Asia-Pac. J. Bus. Adm.* **2024**, *17*, 285–302. [CrossRef]
35. Carmeli, A.; Gittell, J.H. High-Quality Relationships, Psychological Safety, and Learning from Failures in Work Organizations. *J. Organ. Behav.* **2009**, *30*, 709–729. [CrossRef]
36. Edmondson, A. Psychological Safety and Learning Behavior in Work Teams. *Adm. Sci. Q.* **1999**, *44*, 350–383. [CrossRef]
37. Curcuruto, M.; Griffin, M.A. Upward Safety Communication in the Workplace: How Team Leaders Stimulate Employees' Voice through Empowering and Monitoring Supervision. *Saf. Sci.* **2023**, *157*, 105947. [CrossRef]
38. Wang, Y.; Liu, T.; Zhao, W.; Qian, Y.; He, M. How the Project Manager Influences Construction Workers' Safety Behaviors: The Linking Roles of Safety Intervention and Safety Motivation. *Eng. Constr. Archit. Manag.* **2025**, 1–22. [CrossRef]
39. Shaikh, A.Y.; Osei-Kyei, R.; Hardie, M. A Critical Analysis of Safety Performance Indicators in Construction. *Int. J. Build. Pathol. Adapt.* **2020**, *39*, 547–580. [CrossRef]
40. Tews, M.J.; Burke-Smalley, L.A. Enhancing Training Transfer by Promoting Accountability in Different Work Contexts: An Integrative Framework. In *The Cambridge Handbook of Workplace Training and Employee Development*; Brown, K.G., Ed.; Cambridge Handbooks in Psychology; Cambridge University Press: Cambridge, UK, 2017; pp. 201–227, ISBN 978-1-107-08598-5.
41. Smith, M. *How Safety and Accountability Build Work Culture*; Work Wallet: Derby, UK, 2024.
42. AlShemeili, H.; Davidson, R.; Khalid, K. Impact of Empowering Leadership on Safety Behavior and Safety Climate: Mediating and Moderating Role of Safety Monitoring. *J. Eng. Des. Technol.* **2022**, *22*, 1282–1305. [CrossRef]
43. Kandola, R.; Curcuruto, M.; Griffin, M.; Morgan, J.I. The Influence of Organisational Safety Climate on Group Safety Outcomes: The Mediation Role of Supervisor Safety Communication and Monitoring. In *Proceedings of the Advances in Safety Management and Human Factors*; Arezes, P.M.F.M., Ed.; Springer International Publishing: Cham, Switzerland, 2019; pp. 35–46.
44. Yang, J.; Wang, Y.; Huang, H.; Han, J.; Zhou, Y. How Can Inclusive Leadership Motivate Employee Voice? A Cross-Level Study from Psychological Capital and Internal Social Capital Perspective. *BMC Psychol.* **2025**, *13*, 1249. [CrossRef]
45. Zeng, H.; Zhao, L.; Zhao, Y. Inclusive Leadership and Taking-Charge Behavior: Roles of Psychological Safety and Thriving at Work. *Front. Psychol.* **2020**, *11*, 62. [CrossRef]
46. Guo, Y.; Zhu, Y.; Zhang, L. Inclusive Leadership, Leader Identification and Employee Voice Behavior: The Moderating Role of Power Distance. *Curr. Psychol.* **2022**, *41*, 1301–1310. [CrossRef]
47. Chan, A.P.C.; Guan, J.; Choi, T.N.Y.; Yang, Y. Moderating Effects of Individual Learning Ability and Resilient Safety Culture on the Relationship between the Educational Level and Safety Performance of Construction Workers. *Buildings* **2023**, *13*, 3026. [CrossRef]
48. Karimi, H.; Taghaddos, H. The Influence of Craft Workers' Educational Attainment and Experience Level in Fatal Injuries Prevention in Construction Projects. *Saf. Sci.* **2019**, *117*, 417–427. [CrossRef]
49. Cordellieri, P.; Baralla, F.; Ferlazzo, F.; Sgalla, R.; Piccardi, L.; Giannini, A.M. Gender Effects in Young Road Users on Road Safety Attitudes, Behaviors and Risk Perception. *Front. Psychol.* **2016**, *7*, 1412. [CrossRef]
50. Sjöberg Forssberg, K.; Vänje, A.; Parding, K. Bringing in Gender Perspectives on Systematic Occupational Safety and Health Management. *Saf. Sci.* **2022**, *152*, 105776. [CrossRef]
51. Ali, M.; Iyiola, K.; Alzubi, A.; Aljuhmani, H.Y. Using Safety-Specific Transformational Leadership to Improve Safety Behavior Among Construction Workers: Exploring the Role of Knowledge Sharing and Psychological Safety. *Buildings* **2025**, *15*, 3340. [CrossRef]
52. Etikan, I.; Musa, S.A.; Alkassim, R.S. Comparison of Convenience Sampling and Purposive Sampling. *Am. J. Theor. Appl. Stat.* **2016**, *5*, 1–4. [CrossRef]
53. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef]
54. Elkhweildi, M.; Vetbuje, B.; Alzubi, A.B.; Aljuhmani, H.Y. Leading with Green Ethics: How Environmentally Specific Ethical Leadership Enhances Employee Job Performance Through Communication and Engagement. *Sustainability* **2025**, *17*, 7923. [CrossRef]
55. Aljuhmani, H.Y.; Emeagwali, O.L.; Ababneh, B. The Relationships between CEOs' Psychological Attributes, Top Management Team Behavioral Integration and Firm Performance. *Int. J. Organ. Theory Behav.* **2021**, *24*, 126–145. [CrossRef]

56. Arslan, G.; Kivrak, S. The Lower Employment of Women in Turkish Construction Sector. *Build. Environ.* **2004**, *39*, 1379–1387. [CrossRef]
57. Gumusburun Ayalp, G.; Yüksel Deniz, E. Identifying the Factors Hindering Stakeholder Management in Construction with Structural Equation Modeling. *Buildings* **2026**, *16*, 15. [CrossRef]
58. Çabuk, A. Occupational Hazards in Veterinary Practice: A 15-Year Review of Türkiye's Official Injury and Disease Data (2008–2023). *Int. Arch. Occup. Environ. Health* **2025**, *98*, 743–755. [CrossRef]
59. Isik, V. From Worker Health to Occupational Health and Safety in Turkey: A History of Paradigm Change. *Labor. Hist.* **2026**, *67*, 108–122. [CrossRef]
60. Han, Y.; Perry, J.L. Employee Accountability: Development of a Multidimensional Scale. *Int. Public Manag. J.* **2020**, *23*, 224–251. [CrossRef]
61. Carmeli, A.; Reiter-Palmon, R.; Ziv, E. Inclusive Leadership and Employee Involvement in Creative Tasks in the Workplace: The Mediating Role of Psychological Safety. *Creat. Res. J.* **2010**, *22*, 250–260. [CrossRef]
62. Brislin, R.W. The Wording and Translation of Research Instruments. In *Field Methods in Cross-Cultural Research*; Cross-cultural research and methodology series; Sage Publications, Inc.: Thousand Oaks, CA, USA, 1986; Volume 8, pp. 137–164, ISBN 978-0-8039-2549-6.
63. Nasr, E.; Emeagwali, O.L.; Aljuhmani, H.Y.; Al-Geitany, S. Destination Social Responsibility and Residents' Environmentally Responsible Behavior: Assessing the Mediating Role of Community Attachment and Involvement. *Sustainability* **2022**, *14*, 14153. [CrossRef]
64. Anderson, J.C.; Gerbing, D.W. Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychol. Bull.* **1988**, *103*, 411–423. [CrossRef]
65. Byrne, B.M. *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming*, 3rd ed.; Routledge: London, UK, 2016.
66. Hayes, A.F. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, 3rd ed.; Methodology in the social sciences; The Guilford Press: New York, NY, USA; London, UK, 2022.
67. Hayes, A.F.; Rockwood, N.J. Regression-Based Statistical Mediation and Moderation Analysis in Clinical Research: Observations, Recommendations, and Implementation. *Behav. Res. Ther.* **2017**, *98*, 39–57. [CrossRef] [PubMed]
68. Zhang, W.; Yuan, G.; Xue, R.; Han, Y.; Taylor, J.E. Mitigating Common Method Bias in Construction Engineering and Management Research. *J. Constr. Eng. Manag.* **2022**, *148*, 04022089. [CrossRef]
69. Ashergawi, M.; Aljuhmani, H.Y.; Alzubi, A.B. Empowering Green Innovation Through Artificial Intelligence: The Strategic Role of Organizational Agility and Technological Readiness in the Turkish Construction Sector. *Eng. Manag. J.* **2026**, 1–21. [CrossRef]
70. Chang, S.-J.; van Witteloostuijn, A.; Eden, L. From the Editors: Common Method Variance in International Business Research. *J. Int. Bus. Stud.* **2010**, *41*, 178–184. [CrossRef]
71. Rihal, J.; Alzubi, A.; Aljuhmani, H.Y.; Berberoğlu, A. From Ethics to Ecology: How Ethical Leadership Drives Environmental Performance through Green Organizational Identity and Culture. *PLoS ONE* **2025**, *20*, e0336608. [CrossRef]
72. Harman, H.H. *Modern Factor Analysis*, 3rd ed., Revised; University of Chicago Press: Chicago, IL, USA, 1976.
73. Rajhi, M.; Aljuhmani, H.Y. Fostering Sustainable Innovation Through Communication Quality: The Sequential Role of Trust in Leadership and Organizational Commitment in Team-Based Enterprises. *Sustainability* **2026**, *18*, 554. [CrossRef]
74. Lindell, M.K.; Whitney, D.J. Accounting for Common Method Variance. *J. Appl. Psychol.* **2001**, *86*, 114–121. [CrossRef] [PubMed]
75. Nunnally, J.C. *Psychometric Theory*, 2nd ed.; McGraw-Hill Companies: New York, NY, USA, 1978.
76. Farnana, K.; Alzubi, A.B.; Aljuhmani, H.Y.; Khadem, A. Fostering a Green Workplace: How Responsible Leadership Inspires Voluntary Green Behavior through Perceived Insider Status and Green Work Climate. *Kybernetes* **2026**, 1–31. [CrossRef]
77. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
78. Enbaia, E.; Alzubi, A.; Iyiola, K.; Aljuhmani, H.Y. The Interplay Between Environmental Ethics and Sustainable Performance: Does Organizational Green Culture and Green Innovation Really Matter? *Sustainability* **2024**, *16*, 10230. [CrossRef]
79. Kock, N. Common Method Bias: A Full Collinearity Assessment. In *Partial Least Squares Path Modeling*; Springer: New York, NY, USA, 2017; pp. 245–257.
80. Lei, M.; Lomax, R.G. The Effect of Varying Degrees of Nonnormality in Structural Equation Modeling. *Struct. Equ. Model. A Multidiscip. J.* **2005**, *12*, 1–27. [CrossRef]
81. Al-Geitany, S.; Aljuhmani, H.Y.; Emeagwali, O.L.; Nasr, E. Consumer Behavior in the Post-COVID-19 Era: The Impact of Perceived Interactivity on Behavioral Intention in the Context of Virtual Conferences. *Sustainability* **2023**, *15*, 8600. [CrossRef]
82. Brye, S. *How Workplace Safety and Accountability Shape a Positive Culture*; The Safety Geek: Ocala, FL, USA, 2023.
83. Provan, D.J.; Woods, D.D.; Dekker, S.W.A.; Rae, A.J. Safety II Professionals: How Resilience Engineering Can Transform Safety Practice. *Reliab. Eng. Syst. Saf.* **2020**, *195*, 106740. [CrossRef]

84. Ahmed, F.; Zhao, F.; Faraz, N.A.; Qin, Y.J. How Inclusive Leadership Paves Way for Psychological Well-being of Employees during Trauma and Crisis: A Three-wave Longitudinal Mediation Study. *J. Adv. Nurs.* **2021**, *77*, 819–831. [CrossRef]
85. Al'Ararah, K.; Çağlar, D.; Aljuhmani, H.Y. Mitigating Job Burnout in Jordanian Public Healthcare: The Interplay between Ethical Leadership, Organizational Climate, and Role Overload. *Behav. Sci.* **2024**, *14*, 490. [CrossRef] [PubMed]

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Article

A Musculoskeletal Simulation Study to Evaluate the Influence of Postural and Anthropometric Variability on Intervertebral Loads During Manual Lifting in Construction

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Abstract

Computational simulation is a valuable tool for advancing personalized ergonomics. This study evaluated the ability of musculoskeletal simulation to estimate individual lumbar loading during manual lifting tasks representative of construction activities. Fifty-six Colombian adults were recruited to reflect national anthropometric distributions and grouped by BMI and stature. Participants performed two standardized lifting tasks with a 10 kg load: symmetric lifting from the floor to xiphoid height and lateral lifting from a 0.40 m surface to shoulder height with contralateral transfer. Whole-body kinematics and ground reaction forces were processed in OpenSim software using the validated model to estimate L5–S1 compression and shear forces. Results showed a moderate association between lumbar compression and body weight, while shear forces exhibited low correlations with kinematic variables. Subject-specific scaled models revealed substantial inter-individual differences in lumbar loading related to lifting technique and anthropometric characteristics, highlighting the potential of musculoskeletal simulation for personalized risk assessment in construction.

Keywords: load lifting; musculoskeletal simulations; anthropometric variability; postural variability

1. Introduction

Manual materials handling is a major occupational hazard strongly associated with the development of musculoskeletal disorders, particularly in the lumbar spine [1–3]. The prevalence of low back pain is estimated to be 4.36 times higher among workers engaged in heavy lifting compared to their non-lifting counterparts [4], a factor strongly correlated with prolonged occupational absenteeism [5]. The substantial economic and human costs derived from these injuries underline the need to continue investigating lumbar spine

disorders, especially in sectors with high physical demands such as the construction industry [6–9].

In the construction industry, manual load handling is one of the leading causes of musculoskeletal injury throughout workers' occupational lives [10,11]. These tasks, typically characterized by repetitive lifting and asymmetric postures involving trunk flexion and rotation, substantially increase biomechanical demands on the lumbar spine. This risk is particularly pronounced in low- and middle-income countries, where limited mechanization, labor informality, and insufficient training promote the systematic adoption of biomechanically unfavorable lifting strategies in construction work [12–14].

Risk assessment for manual lifting frequently employs observational methods. Despite their expediency, these tools are inherently subjective and often demonstrate poor agreement with objective in vitro biomechanical measures [15]. For manual lifting tasks, the global standard is the NIOSH Lifting Equation, which calculates risk based on load characteristics, including weight, location, displacement, and grip type [16]. A significant limitation of this approach is its reliance on sex as the primary individual variable, neglecting subject-specific anthropometry and individual lifting kinematics [17]. On the other hand, these analyses are predominantly static and do not account for inertial effects, thereby underestimating the compressive and shear forces at the L5–S1 segment [18,19].

Given that posture and individual anthropometry influence lifting techniques, the ability to estimate risk on an individual basis would enhance our understanding of why some individuals develop injuries while others do not [20].

To determine the forces generated in the spine during lifting, the reference method involves in vivo studies, which are invasive and impractical for large populations [15, 21,22]. In recent years, the emergence of musculoskeletal simulation has provided a valuable alternative for studying the variability of human movement [21,23–25]. However, few studies have utilized this capability to estimate compressive and shear forces in a representative population reflecting the variability in weight and height of a region, particularly in relation to common tasks performed in construction sites in developing countries, such as lifting loads from the floor and raising them from a surface to shoulder height.

Platforms such as OpenSim v4.4 (SIMTK, NIH, USA), in addition to being open-source, provide the capability to conduct dynamic analyses [26–28] using full-body models like the Full Body Lifting model [29,30]. This, combined with its ability to scale models to individual anthropometry, facilitates a realistic estimation of lumbar forces during movements such as the lifts [19].

Therefore, the objective of this study was to verify the use of musculoskeletal simulation to estimate the risk of lumbar injury during two lifting tasks involving a 10 kg load, utilizing personalized models of Colombian subjects in OpenSim. This approach considered their anthropometric and kinematic variability while performing the tasks. This study will provide data to support ergonomic interventions aimed at reducing the risk of occupational injuries in this and similar populations.

2. Materials and Methods

A correlational study was conducted with Colombian subjects to analyze how anthropometric parameters (weight, height, BMI) and posture variability at lift initiation (range of motion (ROM) of the hip, knee, and trunk) influence spinal loading. The dependent variables were the compressive, anteroposterior and mediolateral shear forces at the L5–S1 segment. The research protocol was approved by the Ethics Committee of the Universidad del Valle. All participants provided written informed consent prior to any procedures.

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2.1. Population

Sixty (60) Colombian male adults aged 18 to 44 years were recruited through an open call directed to the university community. The invitation was disseminated through institutional communication channels, including email lists, social media, and direct academic communication, allowing voluntary participation from the university community. As a result of this open call, approximately 160 volunteers attended the laboratory for an initial screening.

During this stage, eligibility criteria were verified. Inclusion criteria were being between 18 and 44 years old, not presenting any health condition that could limit the performance of manual lifting tasks, and agreeing to voluntary participation in the study. The study focused on male participants to reduce variability associated with sex-related anthropometric differences and to reflect typical anthropometric profiles reported in occupational lifting studies.

Participants were subsequently classified according to body mass index (BMI) and height percentiles reported for the Colombian population in the ACOPLA-95 anthropometric study [31], which provides reference distributions for the Colombian working population. Based on these criteria, an intentional stratified sampling approach was used to represent different anthropometric profiles.

Four subjects were excluded due to errors in the musculoskeletal simulations, resulting in a final sample of 56 subjects. To ensure anthropometric variability, 37 subjects of average stature (1.68–1.70 m) were classified by body mass index (BMI) as follows: 9 underweight (BMI < 18.5 kg/m^2), 8 normal weight (18.5–24.9 kg/m^2), 10 overweight (25–29.9 kg/m^2), and 10 obese (>30 kg/m^2). Additionally, 9 normal-weight participants with heights at the 5th percentile (<1.60 m) and 10 with heights at the 95th percentile (>1.79 m) were included.

2.2. Data Collection

In a controlled environment, two manual lifts evidenced in construction works were replicated. In the first, participants were asked to lift a load of 10 kg from the floor to the height of the xiphoid process. To ensure symmetry during the lifting task, footprints were marked on the floor to guide foot placement. In the second, the load was positioned 0.4 m anterior to the centroid of the footprints. In the second task, they were asked to lift the same load from a surface located 0.4 m above the floor to the shoulder (Figure 1).

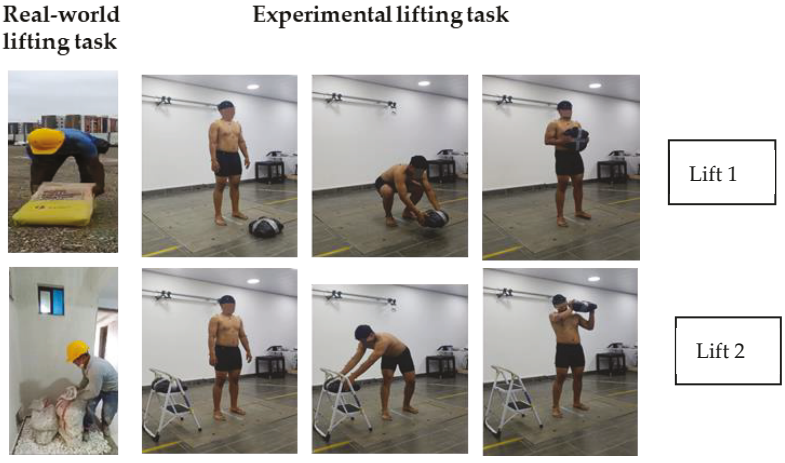

Figure 1. Experimental setup.

During each lift, 3D motion was recorded using an eight-camera Motive system (Optitrack, NaturalPoint Inc.,Corvallis, OR, USA) at 100 Hz. Thirty-nine reflective markers were placed on each participant to capture body kinematics. Simultaneously, ground

reaction forces were measured using a P6000 force platform (BTS Bioengineering Corp., Milan, Italy) at 1000 Hz. Kinematic and kinetic data were integrated into the Smart Analyzer system (BTS Bioengineering Corp., Milan, Italy). A 6 Hz Butterworth low-pass filter was applied. The data were then exported in C3D format and processed in the open-source musculoskeletal simulation software OpenSim v4.4 to compute compressive and shear forces at the L5–S1 segment.

2.3. Musculoskeletal Simulation Model

The full-body musculoskeletal model (LFB) developed by Erika Beaucage-Gauvreau [29] was utilized in this study. This model comprises 30 segments, 29 degrees of freedom, and 238 musculotendinous actuators, specifically targeting the trunk musculature. It has been validated for lifting tasks, demonstrating differences of less than 4% compared with measurements from vertebral body implants, a correlation of r = 0.85 with the measured activation of the erector spinae, and a strong correlation of r = 0.90 with in vivo measurements of intradiscal pressures [29].

The model was scaled to each participant's height and body mass using the OpenSim scaling tool. This process involves adjusting a generic musculoskeletal model to fit a specific subject by utilizing the distances between experimental and virtual markers, ensuring an accurate representation of the individual's anatomy. Additionally, a scaling factor was applied to account for the difference between the subject's height and that considered in the original LFB model (Figure 2). The lifted weight was represented as a distributed mass applied to both hands. Subsequently, inverse kinematics, inverse dynamics, and static optimization analyses were performed, ensuring that the residual actuator forces remained low relative to the phenomenon under study. This guarantees that the stabilization forces we manipulate contribute minimally compared with the forces computed by the model itself. Through this process, the anterior–posterior and mediolateral shear forces, as well as the compressive forces acting on the L5–S1 segment, were obtained for each subject (Figure 3).

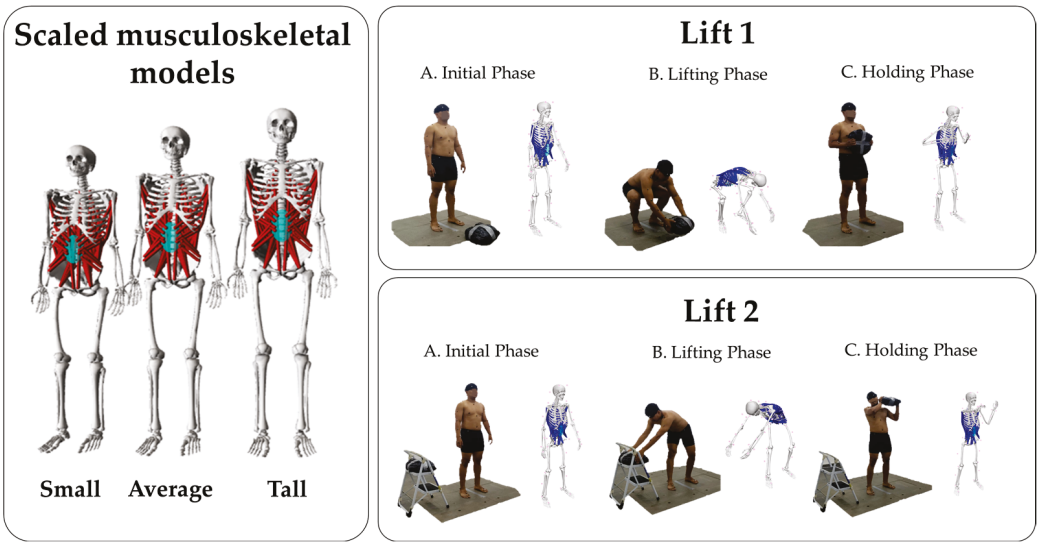

Figure 2. FLB musculoskeletal scaled models for the small, average, and tall subjects.

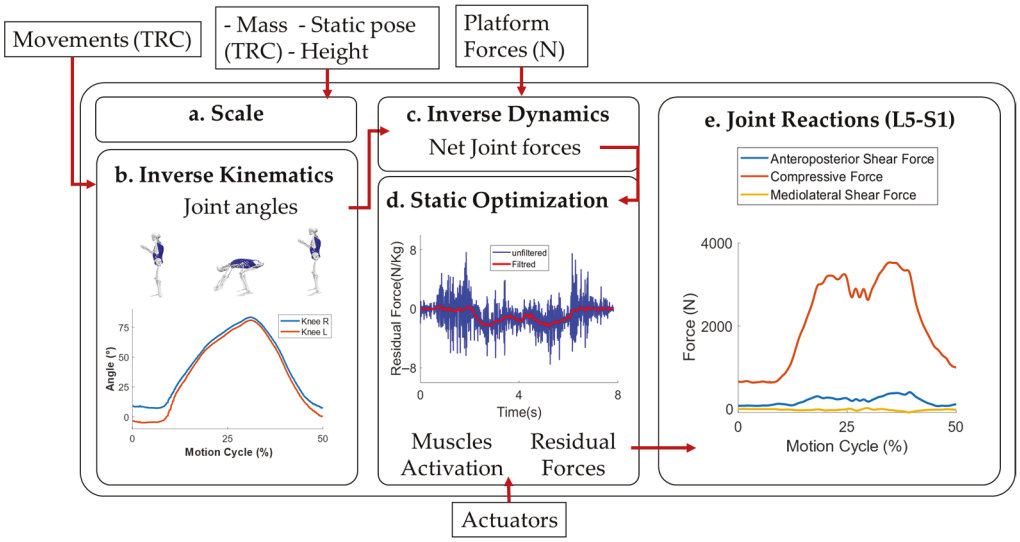

Figure 3. OpenSim workflow to determine the joint reaction forces. TRC—Track Row Column motion capture file containing 3D marker trajectories.

2.4. Verification of the Computational Model with Theoretical Analysis

As an additional verification of the data, the compressive forces obtained in task 1 (standard symmetrical lifting) were compared with those from the theoretical weightlifting model [32] (Figure 4), which is briefly described below:

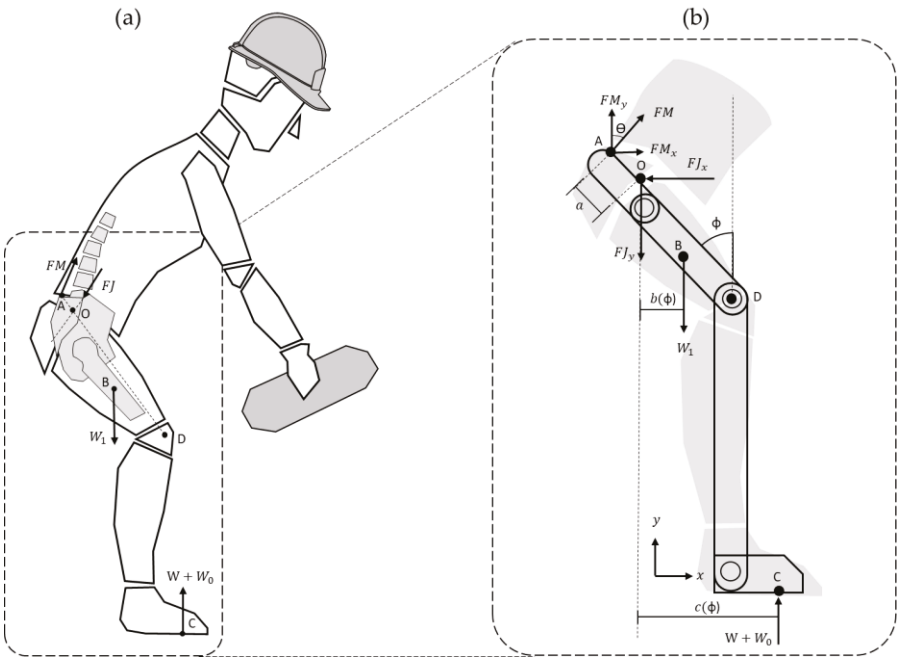

Figure 4. (**a**) Representation of the lifting activity and Forces acting on the lower body, and (**b**) Free-body diagram. Based on the modeling approach described in [32].

In this approach, two degrees of freedom were considered: pelvis flexion (θ) and knee flexion (ϕ). The force generated by the erector spinae muscles was expressed as a function of anthropometric and task related parameters, including body weight (W), lower-limb segment weight (W_1), total leg length (L), the maximum horizontal distance between the sacro lumbar reference point O and the load application point C (L_h), the erector spinae

moment arm about O, and the external load (W_o). The sacrolumbar joint reaction force (F_J) was estimated as:

$$F_J = \sqrt{\left(F_M sin\theta\right)^2 + \left(F_M cos\theta - \ W_1 + (W + W_0)\right)^2}, \quad (1)$$

where

$$F_M = \frac{(L_h \ sin\phi)(W + W_0) - (kL \ sin\phi)W_1}{a}. \quad (2)$$

Under no-load conditions, the theoretical predictions showed good agreement with musculoskeletal model results (Figure 5).

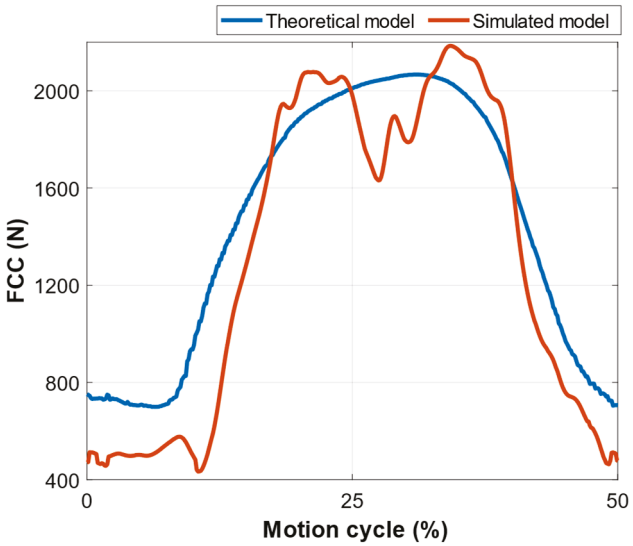

Figure 5. Comparative Theoretical Model [32] vs. Musculoskeletal Model.

2.5. Statistical Analysis

Levene's test confirmed the homogeneity of variances among groups for all analyzed forces with p-values larger than the significance level, α = 0.05. The normality of each variable was assessed using the Lilliefors test, a modification of the Kolmogorov–Smirnov test. Based on these results, bivariate correlations were computed for all variables. When both variables followed a normal distribution, the Pearson correlation coefficient was applied; otherwise, the Spearman rank coefficient was used.

For the study of group comparisons, the assumptions of normality and homogeneity were assessed within each group. All groups showed homogeneity of variances (Levene's test) and normality was evaluated using the Shapiro–Wilk test. Variables meeting both assumptions were analyzed using ANOVA, while non-normal variables were analyzed using Kruskal–Wallis. For variables showing significant differences in the global test, post hoc pairwise comparisons were performed using Tukey–Kramer after ANOVA and Dunn–Sidak after Kruskal–Wallis. These methods adjust the p-values for multiple comparisons.

3. Results

3.1. Descriptive Findings

Descriptive analysis revealed distinct anthropometric and biomechanical profiles across the study groups (Table 1). Height-stratified normal weight groups exhibited the expected variations in stature (ranging from 1.60 ± 0.01 m in the low-height group to 1.80 ± 0.02 m in the tall group) while maintaining similar BMI values (~23 kg m^{-2}). On the

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other hand, body-mass defined groups showed the anticipated progression in BMI, from underweight (19.7 ± 1.3 kg m^{-2}) to obesity (32.9 ± 3.2 kg m^{-2}).

Table 1. Anthropometric, kinematic, and kinetic data by study group.

Group	Variable	*n*	Anthropometric Parameters		
			Weight (kg)	**Height (m)**	**BMI (kg/m^2)**
Normal weight	average height	8	66.5 ± 3.5	1.7 ± 0.03	23.1 ± 1
	Tall	10	77.5 ± 6.6	1.8 ± 0.02	23.7 ± 1.8
	Short	9	58.5 ± 3.3	1.6 ± 0.01	23.2 ± 1.4
Average height	Under-weight	9	56.1 ± 4.1	1.7 ± 0.02	19.7 ± 1.3
	Over-weight	10	76.64 ± 3.5	1.68 ± 0.01	27.05 ± 0.9
	Obese	10	94.87 ± 7.5	1.7 ± 0.02	32.87 ± 3.2
	p value		<0.001 [1]	<0.001 [1]	<0.001 [1]

[1] Variables that did not meet the normality assumption (marked [1] in the table) were analyzed using the Kruskal–Wallis test instead of ANOVA.

Musculoskeletal simulation evidenced the expected differences between the lifting tasks: Lift 1 followed a flexion-dominant strategy (knee flexion ≈ 117–126°, hip flexion ≈ 124–143°), whereas Lift 2 showed markedly reduced knee and hip flexion (≈26–49° and ≈44–68°, respectively) together with a rotational component, including higher trunk rotation (≈45–51° vs. ≈2–5° in Lift 1) and greater relative L5–S1 rotation (≈1.7–4.0° vs. ≈0.49–0.70°).

Regarding anthropometric grouping, only two variables exhibited significant between-group differences: hip flexion in Lift 1 ($p = 0.02$), with the largest contrast between normal-weight, short-statured participants (143.3 ± 12.87°) and the obese group (124.42 ± 10°), and relative L5–S1 rotation in Lift 2 ($p < 0.001$), most notably between normal-weight, short-statured participants (4.0 ± 0.6°) and the normal-weight, average-height group (1.7 ± 1.31°) (Table 2).

Table 2. Kinematic parameters.

Group	Variable	Kinematic Parameters											
		Knee Flexion (°)		**Hip Flexion (°)**		**Trunk Flexion (°)**		**L5–S1 Relative Flexion (°)**		**Trunk Rotation (°)**		**L5–S1 Relative Rotation (°)**	
		Lift 1	**Lift 2**	**Lift 1**	**Lift 2**	**Lift 1**	**Lift 2**	**Lift 1**	**Lift 2**	**Lift 1**	**Lift 2**	**Lift 1**	**Lift 2**
Normal weight	average height	122.1 ± 21.2	48.9 ± 41.9	125.7 ± 14.5	67.9 ± 36.2	67.9 ± 14.7	63.7 ± 5.7	5.5 ± 2.2	4.5 ± 1.5	2.6 ± 1.7	50.6 ± 7.4	1 ± 0.6	1.7 ± 1.3
	Tall	119.8 ± 21.3	47 ± 16.8	131.5 ± 13.9	56.7 ± 14.9	70.4 ± 15.6	61.9 ± 8.8	5.3 ± 2.8	4.9 ± 1.7	4.8 ± 8.8	46.3 ± 9.7	0.7 ± 0.6	2.8 ± 0.9
	Short	117.2 ± 25.7	26.4 ± 13.8	143.3 ± 12.9	45.4 ± 16.5	70 ± 15	60.1 ± 5.2	4 ± 2	4.1 ± 1	2.6 ± 2	46 ± 5.1	0.6 ± 0.5	4 ± 0.6
Average height	Under-weight	119.9 ± 18.8	42.3 ± 19.6	130.2 ± 10.3	62.5 ± 26.3	74.8 ± 11.2	63.2 ± 5.6	6.3 ± 2.3	4.3 ± 1.5	3.6 ± 2.2	49.1 ± 7.5	0.5 ± 0.4	2.5 ± 1.1
	Over-weight	126.1 ± 21.9	33.4 ± 15.1	137 ± 12.7	55.4 ± 13	62.9 ± 15.2	60.8 ± 3.7	3.6 ± 2.4	3.6 ± 1.6	2.4 ± 1.7	45.3 ± 5.9	0.5 ± 0.3	3.4 ± 0.7
	Obese	118.3 ± 14.3	33.8 ± 10.7	124.4 ± 10	44.3 ± 13	70.6 ± 11.5	61.2 ± 5.8	6.1 ± 2.2	5.3 ± 2.2	1.4 ± 1.4	47.6 ± 3.3	0.5 ± 0.3	3.5 ± 0.6
	p value	0.82 [1]	0.12 [1]	0.02	0.21 [1]	0.41 [1]	0.78 [1]	0.09 [1]	0.29	0.24 [1]	0.68	0.28	<0.001 [1]

[1] Variables that did not meet the normality assumption (marked [1] in the table) were analyzed using the Kruskal–Wallis test instead of ANOVA.

According to the compressive force reference of 3400 N established in the NIOSH lifting guidelines, which is considered the Action Limit (AL) safe for the majority of the population [16], Lift 1 showed a significantly higher likelihood of approaching or exceeding this threshold compared to Lift 2. Overall, approximately 65% of participants exceeded the Action Limit during Lift 1, while only about 5% did so in Lift 2. For Lift 1, the proportion of participants exceeding the 3400 N Action Limit varied across anthropometric groups. Among normal weight participants, 20% of short individuals and 80% of tall individuals exceeded the threshold. Among participants of average height, 55.6% of underweight or

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normal weight individuals, 80% of overweight individuals, and 100% of obese participants exceeded the limit. This clearly highlights the greater risk associated with Lift 1 compared to Lift 2, due both to the lifting technique and anthropometry, with the likelihood of exceeding the Action Limit increasing progressively with body mass and stature. Tall, overweight, and obese participants are particularly at risk (Figure 6a).

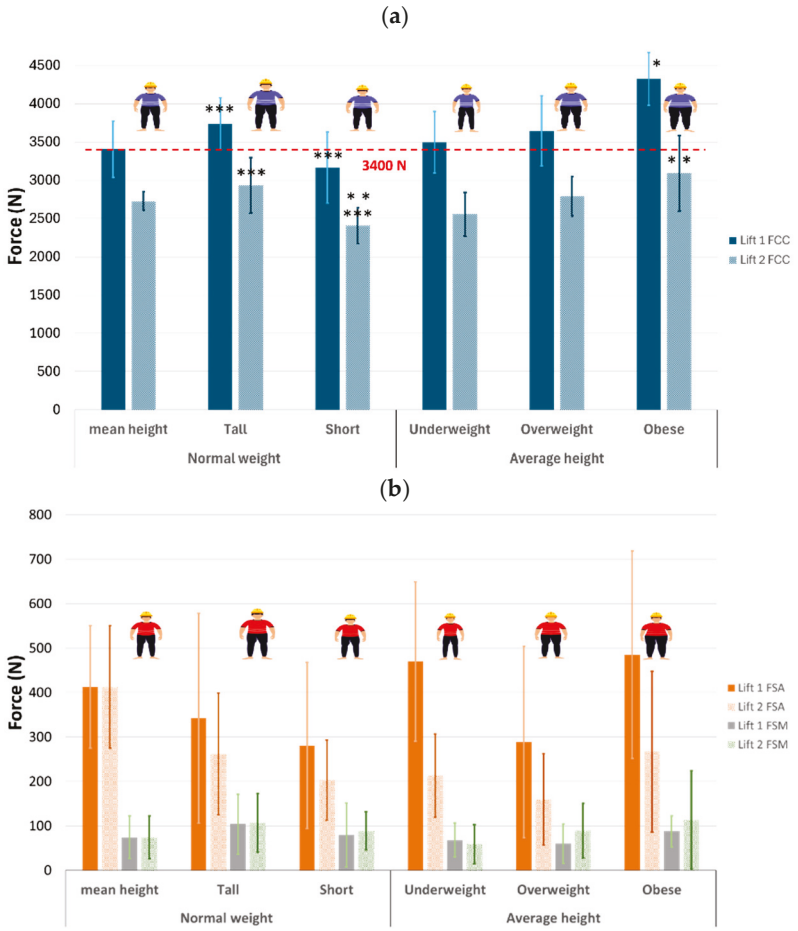

Figure 6. Peak joint reaction forces in the L5-S1 joint during the lifting tasks. (**a**) Compression Force. (**b**) Shear Force. FCC—Compressive Force, FSA—Shear Force Anterior, FSM—Shear Force Mediolateral. (*) Indicates a significant difference compared to all other groups. (**) and (***) indicate significant differences between the specific groups marked.

Anterior–posterior shear force is higher than mediolateral shear force across all groups. Lift 1 generally produces higher shear than Lift 2, with the largest decrease in the anterior–posterior direction. Taller and mean height normal weight participants show greater anterior–posterior shear than shorter participants, while mediolateral shear changes only slightly. Across body mass categories, anterior–posterior shear increases from underweight to overweight and is highest in obesity, whereas mediolateral shear remains comparatively low with smaller differences between groups (Figure 6b).

3.2. Correlation Analysis

For the Lift 1, compressive force at L5–S1 showed a moderate and statistically significant association with body weight (r = 0.49), whereas the correlation with body mass index was notably weaker (r = 0.25). By contrast, anterior shear force was more strongly related to lumbo-pelvic kinematics, exhibiting a strong association with relative L5–S1 segment flexion (r = 0.77) and a moderate correlation with hip flexion angle (r = 0.56). Collinearity was also observed between hip flexion and lumbar flexion (r = 0.76), while medio-lateral

shear force and arm length showed no significant correlations with other model variables ($r < 0.10$) (Figure 7).

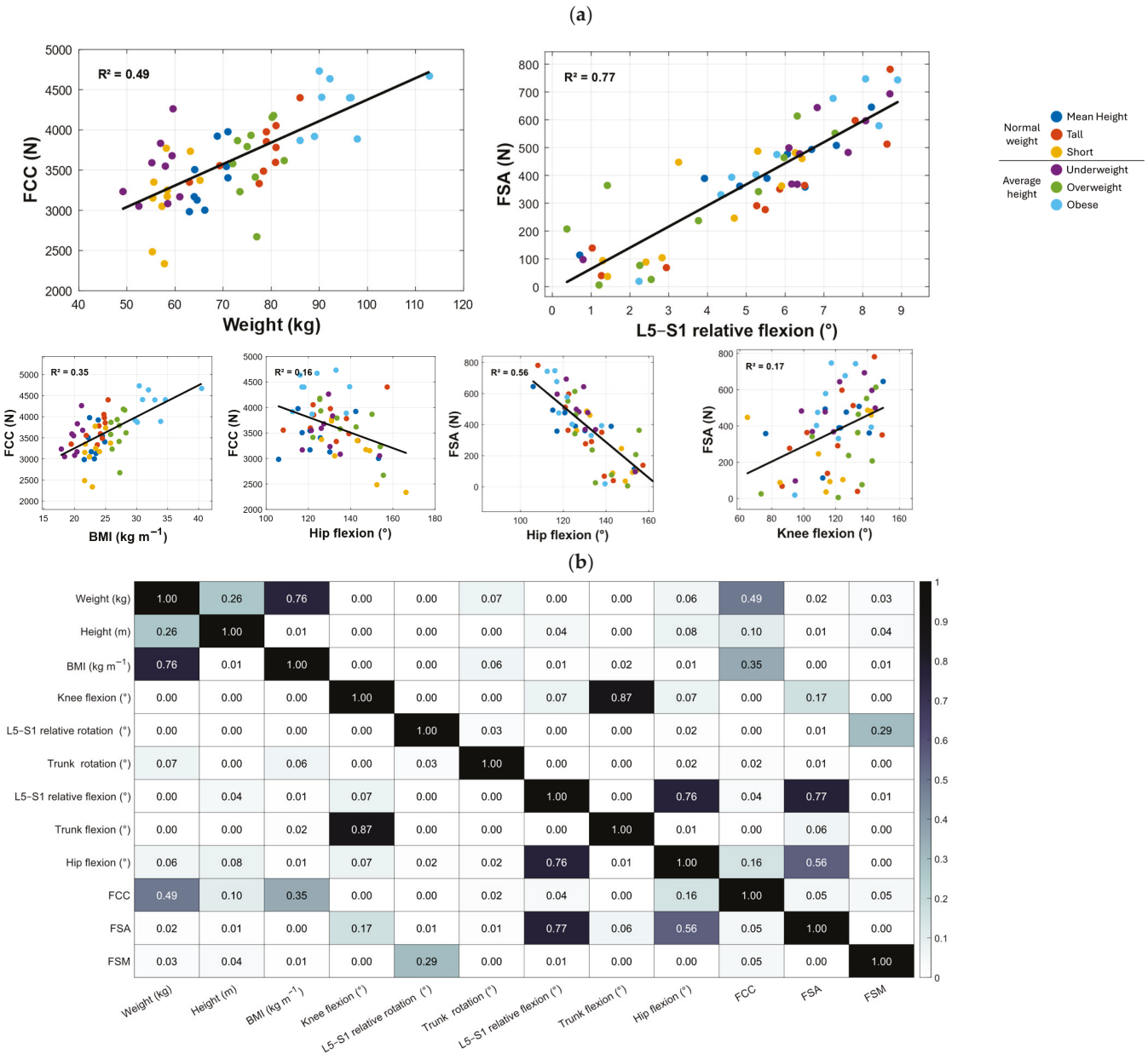

Figure 7. Correlation analysis Lift 1. (**a**) Univariate correlation with a black trend line and R^2, (**b**) correlation matrix. When both variables showed a normal distribution, the Pearson correlation coefficient was applied; otherwise, the Spearman coefficient was used. The results were presented through a correlation matrix and a heatmap (R^2), highlighting statistically significant associations ($p < 0.05$).

Correlation results for Lift 2 indicate that compressive force (FCC) was primarily associated with anthropometric measures, most notably body weight (r = 0.45) and, to a lesser extent, BMI (r = 0.25), while exhibiting near-null correlations with the kinematic variables. In contrast, shear force (FSA) was largely independent of anthropometry and most kinematic measures but showed a strong association with relative L5–S1 flexion (r = 0.78) and a weak relationship with hip flexion (r = 0.27) (Figure 8).

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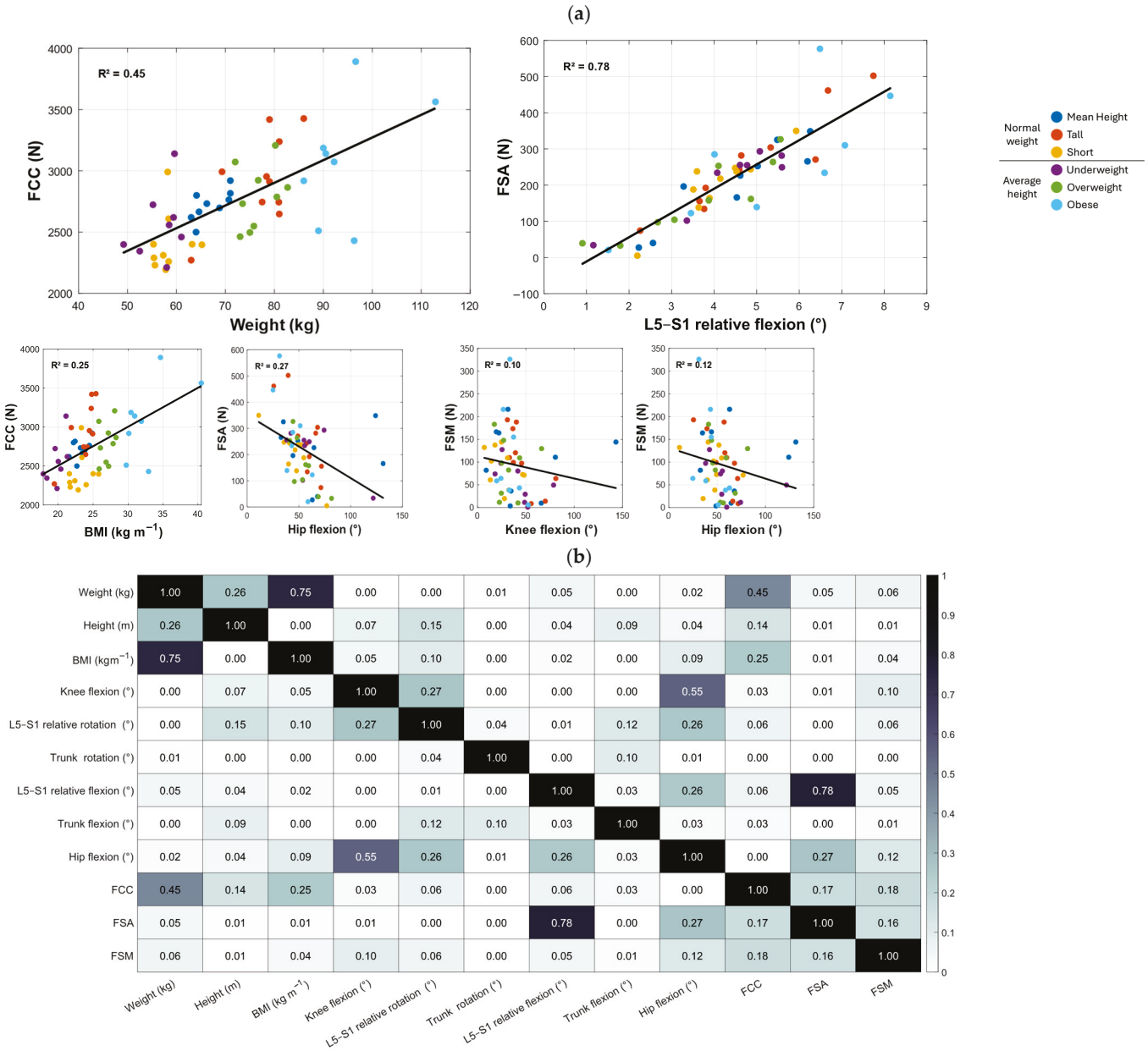

Figure 8. Correlation analysis Lift 2. (**a**) Univariate correlation, with a black trend line and R^2, (**b**) correlation matrix. When both variables showed a normal distribution, the Pearson correlation coefficient was applied; otherwise, the Spearman coefficient was used. The results were presented through a correlation matrix and a heatmap (R^2), highlighting statistically significant associations ($p < 0.05$).

4. Discussion

This study shows that musculoskeletal simulation, using a Full Body Lifting model, can estimate subject-specific lumbar spine loading during lifting by integrating individual anthropometry, posture, and kinematics. The research focused on two lifting tasks common in construction in developing countries where mechanical aid is limited and task execution depends largely on the worker. In this context, the findings question the adequacy of conventional risk assessment tools based on population averages, which may obscure relevant variability in exposure that, on construction sites, often contributes to fatigue accumulation, overexertion, and injury risk. Overall, the results support incorporating individual morphological and kinematic variability into ergonomic evaluations [20,33,34].

Task demands explained most of the kinematic differences observed between the lifting tasks, while anthropometry influenced only specific aspects of the movement pattern. In Lift 1 (symmetric lifting of a 10-kg load from the floor), participants adopted a flexion-dominant strategy characterized by knee and hip flexion with minimal trunk rotation, consistent with classical sagittal-plane lifting patterns in which symmetry reduces rotational demands on the lumbar spine [28,35]. In contrast, Lift 2, which involved lateral load pickup and transfer toward the contralateral shoulder, was characterized by reduced lower-limb involvement and an increased rotational component, reflected in greater trunk rotation and relative L5–S1 rotation. This transition toward an asymmetric strategy, widely reported in lateral lifting and cross-body transfer tasks, arises from spatial constraints and non-frontal load placement, shifting demand toward the transverse plane and increasing lumbosacral involvement [12,35,36].

The results indicate that L5–S1 compressive forces are driven mainly by body weight, whereas anterior shear forces relate more to movement strategy. L5–S1 compressive force, linked to disc degeneration risk [37,38], showed a moderate association with body weight (R^2 = 0.49 in lift 1 and 0.45 in lift 2), consistent with the role of head–arms–trunk (HAT) mass in axial spinal loading [39]. BMI showed a weaker correlation (R^2 = 0.35 in lift 1 and 0.25 in lift 2), suggesting absolute body mass may better reflect compressive loading than a composite index. Compressive force was not significantly related to the analyzed kinematic variables, indicating limited influence of posture and strategy on axial loading under the tested conditions.

By contrast, anteroposterior shear force appeared more dependent on kinematics. The strongest association was between relative L5–S1 flexion and anterior shear, followed by hip flexion, in both lifting, pointing to the role of lumbosacral control in managing shear. This is more relevant for Lift 2, where asymmetry and cross-body transfer are inherent: exposure depends not only on overall trunk rotation but also on how much rotation occurs at L5–S1. Proposed anteroposterior shear limits remain debated (about 500–1000 N depending on frequency and duration). In this single-lift condition, mean shear remained below 500 N, but values near 700 N in some individuals suggest potential risk under repetitive or sustained loading [40].

The absence of significant correlations in mediolateral shear is consistent with the previously described technical differences between the two lifts. While Lift 1 was dominated by the sagittal plane and thus inherently limited in terms of lateral forces, Lift 2 integrated sagittal and transverse movements without the pronounced lateral inclinations typically responsible for triggering such loads. This lack of frontal-plane asymmetry maintained shear forces at reduced levels that remained independent of individual anthropometric variability. However, it is important to consider that the muscle coactivation required to stabilize the trunk against potential lateral tilting can increase total compressive forces, even when mediolateral shear remains low [41].

Anthropometric group differences were limited and task-dependent, suggesting that participants converged on similar task-level motor solutions; however, anthropometry still modulated where the movement was accommodated, i.e., whether task demands were resolved relatively more through hip/lower-limb contributions or through greater lumbosacral segmental participation. In manual material handling, body size variables such as stature and body mass have been linked to measurable changes in kinematics during demanding lifting tasks, even when sex- or broad category-based differences are small, supporting the view of anthropometry as a modifier of inter-segmental motion distribution rather than a sole determinant of the global pattern [42,43]. Ergonomically, these findings support preventive approaches that move beyond body size classifications alone and instead account for how morphology interacts with mechanical constraints and

task repetition to localize exposure at specific spinal segments (e.g., L5–S1), particularly in asymmetric tasks where lumbopelvic loading can increase meaningfully [44].

For prevention in low-mechanization construction settings, the findings support the need for a combined preventive approach integrating task design, work organization, and worker-focused interventions. To reduce compressive risk, priority should be given to lowering external demands and cumulative exposure by controlling load magnitude and lifting frequency, reducing horizontal reach, improving coupling, and organizing materials to minimize floor-level lifts. Recent evidence indicates that such task-level modifications can substantially reduce lumbar compressive forces, even in contexts where mechanical aids are scarce [45,46]. Given the observed association between body weight and L5–S1 compression, workplace health initiatives targeting physical conditioning and body-weight management may effectively complement engineering and administrative controls, particularly among workers exposed to frequent manual lifting [47,48].

To mitigate shear forces in asymmetric tasks such as Lift 2, preventive priorities include limiting combined trunk flexion and rotation and avoiding rotation concentrated at the L5–S1 segment. Recent biomechanical studies show that feasible interventions, such as step-turning strategies, reducing lateral or cross-body reaches, and positioning pick-up and set-down points closer to the frontal plane, can significantly decrease lumbosacral shear forces without compromising task efficiency [28,49]. These measures are especially relevant in construction environments characterized by spatial constraints, high work pace, and operational variability.

Comparison with the NIOSH 3400 N limit showed heterogeneous risk: although exceedances were more frequent in the obese group, peaks above the limit also occurred in normal-weight, underweight, and overweight individuals. This supports risk assessments that account for individual variability in construction contexts shaped by repetition, fatigue, and changing site conditions. Integrating musculoskeletal modeling with multivariate analysis supports a shift toward more individualized and preventive ergonomic strategies in resource-constrained settings [20,33].

From an occupational risk assessment perspective, musculoskeletal simulation effectively complements conventional ergonomic tools by accounting for individual biomechanical variability often overlooked by generalized exposure metrics. By integrating subject-specific anthropometry and movement strategies, these models provide direct estimates of spinal loads, enhancing the identification of high-risk conditions in dynamic environments such as construction. Consequently, incorporating biomechanical simulation into ergonomic evaluations facilitates targeted interventions, including task redesign and optimized load positioning, specifically aimed at mitigating compressive and shear forces at the lumbosacral segment [14,19].

Study Limitations

The interpretation of these findings must be contextualized within certain methodological limitations inherent to computational simulations. The use of static optimization for muscle force calculation is a common simplification used to resolve muscle indeterminacy; however, this technique assumes the system minimizes antagonistic co-contraction. As a result, net muscle force and joint stiffness may be underestimated, since active co-contraction forces, which are critical for spinal stability, are not fully represented in the model. This limitation may affect compressive and shear forces differently, with shear forces potentially being more sensitive to the absence of co-contraction [50]. However, it has been shown that static optimization provides reasonable agreement with in vivo measurements of muscle activation and spinal loads for quasi-static or low-speed lifting tasks, as was the case for the tasks evaluated in this study [29]. For faster or more dynamic movements, underestimation

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of forces and activations would likely be more pronounced, emphasizing that the validity of SO is task-dependent.

On the other hand, this study utilized marker-based scaling in OpenSim, a robust approach for ensuring kinematic consistency across subjects. While this method effectively normalizes segmental lengths, it assumes a proportional mass distribution. According to Ghezelbash et al. (2016) [51], body mass and its distribution are important factors in estimating spinal loads; therefore, future studies could enhance model biofidelity by incorporating subject-specific center of mass (CoM) shifts, particularly in cases of abdominal obesity. Nevertheless, since the evaluated population did not include individuals with morbid obesity or severe abdominal obesity, the linear scaling used may be suitable for comparing motor strategies and relative loading patterns.

Furthermore, the study design was limited to a two-lifting task. This simplification limits the generalizability of the results to real-world work environments, which are predominantly asymmetric, often involve trunk twisting, and are repetitive in nature. The lack of correlation observed for mediolateral shear force, for instance, is the direct consequence of this task design limitation. Finally, while a broad range of weight categories was covered, the sample size may not fully capture the complexity of anthropometric and kinematic variability observed in broader occupational populations. Nonetheless, the model's ability to clearly dissociate anthropometric and kinematic contributions to spinal loads supports its utility as an objective-oriented research tool in occupational ergonomics.

5. Conclusions

Musculoskeletal simulation enabled individualized estimation of L5–S1 loading during construction-relevant lifting and exposed a clear dissociation between the determinants of compression and shear. L5–S1 compression was predominantly explained by body weight ($R^2 = 0.41$), whereas anteroposterior shear was primarily governed by movement strategy, with the strongest association observed for relative L5–S1 flexion and a secondary contribution from hip flexion. Exceedances of the NIOSH 3400 N action limit occurred across all BMI categories, revealing substantial exposure heterogeneity that is obscured by population-averaged assessment tools. These findings support a dual-factor ergonomic framework in which both morphology (mass) and subject-specific kinematics are essential to characterize lumbar spine risk, particularly in low-mechanization construction tasks. Likewise, it highlights the importance of computational simulation in the field of personalized ergonomics.

However, it is essential to develop future research focused on optimizing musculoskeletal simulation models to enable a more accurate representation of the anthropometric characteristics of workers, as well as the assessment of other work activities conducted in the construction sector, given the high biomechanical demands of the tasks performed there.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on reasonable request from the corresponding author. Due to ethical restrictions related to human participant data, the datasets are not publicly available.

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References

1. Dreischarf, M.; Rohlmann, A.; Graichen, F.; Bergmann, G.; Schmidt, H. In vivo loads on a vertebral body replacement during different lifting techniques. *J. Biomech.* **2016**, *49*, 890–895. [CrossRef] [PubMed]
2. Kuiper, J.I.; Burdorf, A.; Verbeek, J.H.A.M.; Frings-Dresen, M.H.W.; van der Beek, A.J.; Viikari-Juntura, E.R.A. Epidemiologic evidence on manual materials handling as a risk factor for back disorders: A systematic review. *Int. J. Ind. Ergon.* **1999**, *24*, 389–404. [CrossRef]
3. Jahn, A.; Andersen, J.H.; Christiansen, D.H.; Seidler, A.; Dalbøge, A. Occupational mechanical exposures as risk factor for chronic low-back pain: A systematic review and meta-analysis. *Scand. J. Work Environ. Health* **2023**, *49*, 453–465. [CrossRef]
4. Khairunnisa; Tamtomo, D.G.; Murti, B. Meta-analysis of the effect of heavy lifting on low back pain among health workers. *Indones. J. Med.* **2024**, *9*, 388–397. [CrossRef]
5. Iwakiri, K.; Miki, K.; Sasaki, T. Effect of manual handling weight for lifting and carrying on the severity of acute occupational low back pain. *Int. Arch. Occup. Environ. Health* **2025**, *98*, 507–513. [CrossRef] [PubMed]
6. Buchbinder, R.; van Tulder, M.; Öberg, B.; Costa, L.M.; Woolf, A.; Schoene, M.; Turner, J.A. Low back pain: A call for action. *Lancet* **2018**, *391*, 2384–2388. [CrossRef]
7. Hartvigsen, J.; Hancock, M.J.; Kongsted, A.; Louw, Q.; Ferreira, M.L.; Genevay, S.; Woolf, A. What low back pain is and why we need to pay attention. *Lancet* **2018**, *391*, 2356–2367. [CrossRef]
8. Ferreira, M.L.; de Luca, K.; Haile, L.M.; Steinmetz, J.D.; Culbreth, G.T.; Cross, M.; GBD 2021 Low Back Pain Collaborators. Global, regional, and national burden of low back pain, 1990–2020, its attributable risk factors, and projections to 2050: A systematic analysis of the Global Burden of Disease Study 2021. *Lancet Reg. Health Eur.* **2023**, *32*, 100698. [CrossRef]
9. Chen, X.; Hou, L.; Zhang, Y.; Luo, S.; Dong, B. The accuracy of the Ishii score chart in predicting sarcopenia in the elderly community in Chengdu. *BMC Geriatr.* **2021**, *21*, 296. [CrossRef]
10. Hess, J.A.; Hecker, S.; Weinstein, M.; Lunger, M. A participatory ergonomics intervention to reduce risk factors for low-back disorders in concrete laborers. *Appl. Ergon.* **2004**, *35*, 427–441. [CrossRef]
11. Park, J.; Kim, Y. Association of exposure to a combination of ergonomic risk factors with musculoskeletal symptoms in Korean workers. *Int. J. Environ. Res. Public Health* **2020**, *17*, 9456. [CrossRef]
12. Gómez-Salazar, L.; Ordoñez-Hernandez, C.A.; Martínez, L.A.; Terán, B.S. Riesgo al levantar cargas: Mucho más que biomecánica. Investigación con metodología mixta en una pequeña empresa constructora de Colombia. *Arch. Prev. Riesgos Labor.* **2025**, *28*, 70–88. [CrossRef]
13. García Zambrano, J. Desórdenes músculo-esqueléticos (DME) y su incidencia en la salud de los trabajadores de la construcción. *Rev. San Gregorio* **2019**, *1*, 118–129. [CrossRef]
14. Ishwarya, G.K.A.; Rajkumar, D. Analysis of ergonomic risk factors in the construction industry. *Mater. Today Proc.* **2021**, *37*, 2415–2418. [CrossRef]
15. Brandl, C.; Bender, A.; Schmachtenberg, T.; Dymke, J.; Damm, P. Comparing risk assessment methods for work-related musculoskeletal disorders with in vivo joint loads during manual materials handling. *Sci. Rep.* **2024**, *14*, 6041. [CrossRef]

16. Waters, T.R.; Putz-Anderson, V.; Garg, A. *Applications Manual for the Revised NIOSH Lifting Equation*; National Institute for Occupational Safety and Health (NIOSH): Cincinnati, OH, USA, 1994.
17. Fox, R.R.; Lu, M.L.; Occhipinti, E.; Jaeger, M. Understanding outcome metrics of the revised NIOSH lifting equation. *Appl. Ergon.* **2019**, *79*, 102897. [CrossRef]
18. Boocock, M.; Naudé, Y.; Saywell, N.; Mawston, G. Obesity as a risk factor for musculoskeletal injury during manual handling tasks: A systematic review and meta-analysis. *Saf. Sci.* **2024**, *176*, 106548. [CrossRef]
19. Allaire, B.T.; Johannesdottir, F.; Bouxsein, M.L.; Anderson, D.E. Physiological and anthropometric factors associated with spine loading estimates from imaging-based subject-specific musculoskeletal models. *JOR Spine* **2025**, *8*, e70059. [CrossRef]
20. Armstrong, D.; Fischer, S.L. Evaluating the prospective benefit of considering movement variability in ergonomic risk assessment. *Theor. Issues Ergon. Sci.* **2025**, *26*, 544–563. [CrossRef]
21. Dreischarf, M.; Shirazi-Adl, A.; Arjmand, N.; Rohlmann, A.; Schmidt, H. Estimation of loads on human lumbar spine: A review of in vivo and computational model studies. *J. Biomech.* **2016**, *49*, 833–845. [CrossRef] [PubMed]
22. Bender, A.; Schmidt, H.; Wellner, D.L.; Duda, G.N.; Brandl, C.; Damm, P. In vivo load on knee, hip and spine during manual materials handling with two lifting techniques. *J. Biomech.* **2024**, *163*, 111963. [CrossRef]
23. Wang, S.; Zhao, D.; Tang, M.; Sun, S.; Zhang, X. OpenSim-based human musculoskeletal modeling and force measurement device design. In Proceedings of the 17th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC 2025), Hangzhou, China, 23–24 August 2025; pp. 148–151. [CrossRef]
24. Zaman, R.; Arefeen, A.; Quarnstrom, J.; Barman, S.; Yang, J.; Xiang, Y. Optimization-based biomechanical lifting models for manual material handling: A comprehensive review. *Proc. Inst. Mech. Eng. Part H J. Eng. Med.* **2022**, *236*, 1273–1287. [CrossRef]
25. Denayer, M.; Alfio, E.; Díaz, M.A.; Sartori, M.; De Groote, F.; De Pauw, K.; Verstraten, T. A PRISMA systematic review through time on predictive musculoskeletal simulations. *J. Neuroeng. Rehabil.* **2025**, *22*, 149. [CrossRef]
26. Quiñones Preciado, J.A.; Arango, S.P.; Garcia, L.M.; Salazar, L.G. Modelos musculoesqueléticos de columna lumbar de OpenSim en el análisis de levantamientos de cargas: Una revisión sistemática exploratoria. *Rev. Colomb. Salud Ocup.* **2025**, *15*, e-11817.
27. von Arx, M.; Liechti, M.; Connolly, L.; Bangerter, C.; Meier, M.L.; Schmid, S. From stoop to squat: A comprehensive analysis of lumbar loading among different lifting styles. *Front. Bioeng. Biotechnol.* **2021**, *9*, 769117. [CrossRef] [PubMed]
28. Skals, S.; Bláfoss, R.; de Zee, M.; Andersen, L.L.; Andersen, M.S. Effects of load mass and position on the dynamic loading of the knees, shoulders and lumbar spine during lifting: A musculoskeletal modelling approach. *Appl. Ergon.* **2021**, *96*, 103491. [CrossRef]
29. Beaucage-Gauvreau, E.; Robertson, W.S.P.; Brandon, S.C.E.; Fraser, R.; Freeman, B.J.C.; Graham, R.B.; Jones, C.F. Validation of an OpenSim full-body model with detailed lumbar spine for estimating lower lumbar spine loads during symmetric and asymmetric lifting tasks. *Comput. Methods Biomech. Biomed. Eng.* **2019**, *22*, 451–464. [CrossRef]
30. Molinaro, D.D.; King, A.S.; Young, A.J. Biomechanical analysis of common solid waste collection throwing techniques using OpenSim and an EMG-assisted solver. *J. Biomech.* **2020**, *104*, 109704. [CrossRef]
31. Estrada, J.M.; Camacho, J.P.A.; Restrepo, M.C.T.; Parra, C.M.M. Parámetros antropométricos de la población laboral colombiana. *Rev. Salud Pública* **1995**, *32*, 64–78. Available online: https://www.redalyc.org/pdf/120/12058127011.pdf (accessed on 11 January 2023).
32. Özkaya, N.; Leger, D.; Goldsheyder, D.; Nordin, M. *Fundamentals of Biomechanics*; Springer: New York, NY, USA, 2012. Available online: https://link.springer.com/content/pdf/10.1007/978-3-319-44738-4.pdf (accessed on 2 December 2024).
33. Graziosi, F.; Bonfiglioli, R.; Decataldo, F.; Violante, F.S. Criteria for assessing exposure to biomechanical risk factors: A research-to-practice guide—Part 1: General issues and manual material handling. *Life* **2024**, *14*, 1398. [CrossRef] [PubMed]
34. Hadjipavlou, A.G.; Tzermiadianos, M.N.; Bogduk, N.; Zindrick, M.R. The pathophysiology of disc degeneration: A critical review. *J. Bone Jt. Surg. Br. Vol.* **2008**, *90*, 1261–1270. [CrossRef]
35. Kingma, I.; Faber, G.S.; van Dieën, J.H. How to lift a box that is too large to fit between the knees. *Ergonomics* **2010**, *53*, 1228–1238. [CrossRef] [PubMed]
36. Russo, F.; Papalia, G.F.; Vadalà, G.; Fontana, L.; Iavicoli, S.; Papalia, R.; Denaro, V. The effects of workplace interventions on low back pain in workers: A systematic review and meta-analysis. *Int. J. Environ. Res. Public Health* **2021**, *18*, 12614. [CrossRef] [PubMed]
37. Inoue, N.; Espinoza Orías, A.A. Biomechanics of intervertebral disc degeneration. *Orthop. Clin. N. Am.* **2011**, *42*, 487–499. [CrossRef]
38. McMorran, J.G.; Gregory, D.E. The influence of axial compression on the cellular and mechanical function of spinal tissues; emphasis on the nucleus pulposus and annulus fibrosus: A review. *J. Biomech. Eng.* **2021**, *143*, 050802. [CrossRef]
39. Chaffin, D.B.; Andersson, G.B.J.; Martin, B.J. *Occupational Biomechanics*, 4th ed.; Wiley: Hoboken, NJ, USA, 2006.
40. Gallagher, S.; Marras, W.S. Tolerance of the lumbar spine to shear: A review and recommended exposure limits. *Clin. Biomech.* **2012**, *27*, 973–978. [CrossRef]
41. Marras, W.S.; Granata, K.P. Spine loading during trunk lateral bending motions. *J. Biomech.* **1997**, *30*, 697–703. [CrossRef]

42. Nematimoez, M.; Bangerter, C.; von Arx, M.; Liechti, M.; Schmid, S. Gender and body height discriminate spinal movement patterns during lifting and lowering tasks. *Ergonomics* **2025**, *68*, 1–13. [CrossRef] [PubMed]
43. Kranz, C.; Lee, K.; Jadhav, P.; Vestlin, L.; Barker, M.; Jacques, A.; Netto, K. Kinematic and perceptual responses in heavy lifting and pulling: Are there differences between males and females? *Appl. Ergon.* **2021**, *90*, 103274. [CrossRef]
44. Kim, H.-K.; Zhang, Y. Estimation of lumbar spinal loading and trunk muscle forces during asymmetric lifting tasks: Application of whole-body musculoskeletal modelling in OpenSim. *Ergonomics* **2017**, *60*, 563–576. [CrossRef]
45. Coenen, P.; Gouttebarge, V.; van der Burght, A.S.A.M.; van Dieën, J.H.; Frings-Dresen, M.H.W.; van der Beek, A.J.; Burdorf, A. The effect of lifting during work on low back pain: A health impact assessment based on a meta-analysis. *Occup. Environ. Med.* **2014**, *71*, 871–877. [CrossRef] [PubMed]
46. Santos, W.; Rojas, C.; Isidoro, R.; Lorente, A.; Dias, A.; Mariscal, G.; Lorente, R. Efficacy of ergonomic interventions on work-related musculoskeletal pain: A systematic review and meta-analysis. *J. Clin. Med.* **2025**, *14*, 3034. [CrossRef] [PubMed]
47. Lucha-López, M.O.; Hidalgo-García, C.; Monti-Ballano, S.; Márquez-Gonzalvo, S.; Ferrández-Laliena, L.; Müller-Thyssen-Uriarte, J.; Lucha-López, A.C. Body mass index and its influence on chronic low back pain in the Spanish population: A secondary analysis from the European Health Survey (2020). *Biomedicines* **2023**, *11*, 2175. [CrossRef] [PubMed]
48. Shiri, R.; Coggon, D.; Falah-Hassani, K. Exercise for the prevention of low back pain: Systematic review and meta-analysis of controlled trials. *Am. J. Epidemiol.* **2018**, *187*, 1093–1101. [CrossRef]
49. Harvey, E.J.; Pinder, J.A.; Haslam, R.A.; Dainty, A.R.J.; Gibb, A.G. The use of actor-based immersive health and safety inductions: Lessons from the Thames Tideway Tunnel megaproject. *Appl. Ergon.* **2020**, *82*, 102955. [CrossRef]
50. Lerchl, T.; Nispel, K.; Baum, T.; Bodden, J.; Senner, V. Multibody models of the thoracolumbar spine: A review on applications, limitations, and challenges. *Bioengineering* **2023**, *10*, 202. [CrossRef]
51. Ghezelbash, F.; Shirazi-Adl, A.; Arjmand, N.; El-Ouaaid, Z.; Plamondon, A. Subject-specific biomechanics of trunk: Musculoskeletal scaling, internal loads and intradiscal pressure estimation. *Biomech. Model. Mechanobiol.* **2016**, *15*, 1699–1712. [CrossRef]

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Ergonomic Risk and Musculoskeletal Disorders in Construction: Assessing Job-Related Determinants in the U.S. Workforce

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Abstract

Musculoskeletal disorders (MSDs) remain one of the most persistent occupational health challenges in the U.S. construction industry, where physically demanding tasks such as heavy lifting, kneeling, and working in awkward postures contribute to elevated injury rates. This study aims to identify significant job-related determinants of MSDs in construction-sector occupations. By integrating publicly available datasets from the Survey of Occupational Injuries and Illnesses (SOII) and the Occupational Information Network (O*NET) datasets, a stepwise multiple regression analysis was conducted on 344 occupation-condition observations representing 86 construction occupations, yielding a final model that explained 49% of the variance. Ten significant predictors of MSD events were identified and classified as either risk amplifiers or mitigators. Amplifiers included factors such as exposure to noise, disease, hazardous conditions, and time pressure, all of which heightened MSD risk, while mitigators—such as reduced cramped-space exposure and regulated work environments—were associated with lower risk. MSDs resulting from sprains, strains, or tears accounted for 62.8% of all cases, frequently leading to days away from work (36.3%) or job restrictions (26.5%). The findings underscore that ergonomic risk in construction extends beyond physical strain to include scheduling, equipment design, and work organization. These results provide actionable insights for employers and safety professionals to redesign tools, optimize task rotation, and implement realistic work pacing strategies, ultimately reducing MSD incidence and improving productivity in this high-risk sector.

Keywords: musculoskeletal disorders; ergonomics; occupational characteristics; construction-sector

1. Introduction

Musculoskeletal disorders (MSDs) are one of the most pervasive and costly occupational health challenges in the U.S. construction industry [1–4]. MSDs are injuries or pain affecting muscles, joints and tendons [5–7]. These pains can decrease a worker's flexibility, coordination, and balance, increasing their risk of falling. Construction workers who suffer from MSDs can have reduced work ability, and the symptoms are likely to recur if not treated properly [8–10]. Unlike many other sectors, construction work requires continuous engagement in high-force, high-exertion tasks such as lifting heavy materials, working in awkward positions, operating vibrating machinery, and navigating unpredictable environments, including elevated work surfaces, confined spaces, or partially completed

structures [11–14]. These biomechanical demands place construction workers at disproportionately higher risk of MSDs affecting the lower back, shoulders, knees, and upper extremities [15–20]. National surveillance data consistently show that MSD rates in the construction industry exceed those of most other industries, contributing to substantial lost work time, long-term disability, and escalating workers' compensation costs [21,22].

MSD-related workers' compensation claims account for approximately 30% of all claims, with direct costs reaching $20 billion annually and total costs, including lost productivity, estimated at $54 billion [23,24]. In 2015 alone, 264 million lost workdays were attributed to back and neck pain, resulting in $131.8 billion in lost annual earnings [25]. In 2016, low back pain was identified as the leading cause of years of disability in the U.S., followed by other musculoskeletal disorders, neck pain, osteoarthritis, and rheumatoid arthritis [26]. In 2022, the National Safety Council reported that workplace MSDs resulted in direct costs exceeding $50 billion, with the average compensation cost per strain injury reaching $37,185 [27].

Common construction tasks require workers to adopt postures such as kneeling, squatting, and stooping, which contribute to the development of musculoskeletal disorders [28–32]. A substantial body of ergonomics research has documented specific physical risk factors in construction—such as repetitive overhead work, kneeling on hard surfaces, forceful exertion, and prolonged static postures—as key contributors to MSD development [12,33–35]. Additionally, task-based studies highlight that vibration exposure from power tools, heavy PPE burden, and environmental challenges, such as temperature extremes, further exacerbate musculoskeletal strain [10,36,37]. However, although these studies provide valuable insights into task-level exposures, construction work is highly fragmented and varied across trades, worksites, and job roles. As a result, current ergonomic recommendations are often generic, inconsistent across occupations, or difficult to apply uniformly in dynamic construction settings.

A critical gap remains in the construction ergonomics literature: limited quantitative evidence linking standardized, occupation-level descriptors to MSD outcomes across the full range of U.S. construction occupations. Most existing studies focus on individual trades (e.g., roofers, electricians, masons) or specific tasks (e.g., drywall installation, scaffold assembly), leaving little understanding of which job attributes across the entire construction-sector workforce consistently predict MSD risk. Furthermore, the interplay of environmental exposures (noise, disease, hazardous conditions), organizational pressures (time pressure, scheduling), and ergonomic constraints (cramped workspaces, PPE) have rarely been analyzed using integrated occupational datasets.

This limitation is consequential for both researchers and practitioners. Without a unified view of risk across occupations, it is difficult for employers, safety managers, and policy makers to prioritize interventions or allocate ergonomic resources effectively. The construction sector, characterized by tight production schedules, subcontracting layers, and varying levels of worker training, would benefit from a data-driven understanding of which occupational descriptors amplify or mitigate MSD risk.

To address this gap, the present study applies a quantitative modeling approach to U.S. construction-sector occupations using standardized datasets from the Survey of Occupational Injuries and Illnesses (SOII) and the Occupational Information Network (O*NET).

By analyzing 86 construction occupations and 344 detailed observations, this study aims to:

1. Identify statistically significant job-related determinants of MSD events within the construction sector.

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2. Classify those determinants as ergonomic risk amplifiers or mitigators using occupation-level descriptors.
3. Provide evidence-based insights that can inform targeted ergonomic interventions, task redesign, and safety management practices explicitly tailored to construction work environments.

Through these contributions, this study offers a comprehensive, occupation-centered understanding of MSD risk in construction—moving beyond task-based ergonomics to uncover broader patterns that can support safer, more sustainable construction workforce practices.

2. Materials and Methods

2.1. Study Approach

This study was designed to identify which occupational characteristics within the U.S. construction sector are most closely associated with the occurrence of MSD events. Rather than beginning with a broad occupational dataset and narrowing down, this study adopted a sector-focused approach by isolating all occupations classified under the Construction and Extraction major group (Standard Occupational Classification (SOC) code 47). The analytical framework centers on determining how construction-specific job attributes—captured through standardized occupational descriptors—relate to variation in MSD incidence across trades. This study followed the terms and definitions of injury facts provided by the National Safety Council [38].

2.2. Data Sources and Sector Extraction

Three publicly available national datasets were combined:

1. Survey of Occupational Injuries and Illnesses (SOII): The U.S. Bureau of Labor Statistics (BLS) Survey of Occupational Injuries and Illnesses (SOII) supplied annual counts of MSD ergonomic-related reported injuries [21]. These data were filtered to include only North American Industry Classification System (NAICS) and SOC combinations corresponding to construction occupations.
2. Occupational Information Network (O*NET): Job characteristics were obtained from the U.S. Department of Labor' Occupational Information Network (O*NET), which provides standardized numerical ratings for physical demands, environmental exposures, and work context factors [39]. Only O*NET entries matching SOC codes beginning with "47" were retained.
3. BLS Occupational Employment Statistics: Employment totals and wage data were incorporated from BLS Occupational Employment Statistics to contextualize injury counts relative to workforce size [40].

The datasets were aligned based on their occupational identifiers. After removing duplicates and incomplete entries, the final analytic file contained 86 construction occupations and 344 occupation-condition observations, each representing a unique combination of job role and MSD profile.

2.3. Variables and Coding

The categorical moderators were numerically coded to facilitate regression analysis. Following established industry definitions, MSD_outcome was coded as 0 for events resulting in job transfer or restriction (DJTR) and 1 for those resulting in days away from work (DAFW). Similarly, MSD_symptoms was coded as 0 for injuries involving general soreness or pain and 1 for injuries classified as sprains, strains, or tears. The 43 occupational characteristics from O*NET served as continuous numerical predictors, measured on a progressive scale from 0 (no occurrence/importance) to 100 (continual occurrence/extreme

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importance). These descriptors reflect ergonomic exposures relevant to construction, such as cramped workspaces, hazardous conditions, noise environments, or PPE requirements.

To account for differences in skill and training requirements within construction occupations, the O*NET's Job Zone classifications were recoded into a five-point numeric scale (0–4). This scale represents the following educational benchmarks: (0) no High School Diploma or General Educational Development (GED) credential; (1) High School Diploma or GED; (2) Associate Degree (AA/AS); (3) Bachelor's Degree; and (4) Master's Degree or higher.

It should be noted that O*NET descriptors represent occupation-level aggregated averages rather than task-specific or individual-level exposures. As such, variability in work activities, task sequencing, and exposure intensity among workers within the same occupation may not be fully captured. This aggregation introduces the potential for ecological inference, whereby associations observed at the occupational level may not directly reflect individual worker risk. Consequently, the findings of this study should be interpreted as characterizing relative differences in MSD risk across construction occupations rather than predicting individual-level injury outcomes. Future research should incorporate task-level exposure measurements, wearable sensor data, or observational methods to validate and refine the occupation-level patterns identified here.

2.4. Analytical Procedure

All data preparation, matching, and statistical analyses were performed using SAS® 9.4 (SAS Institute Inc., Cary, NC, USA). Prior to analysis, MSD counts were log-transformed to address skewness and satisfy the assumption of normality. Subsequently, a stepwise multiple regression procedure was then used to identify which occupational descriptors significantly predicted MSD frequency.

The model-building process proceeded as follows:

1. Moderator Variables Entered First: MSD outcome type, MSD symptom type, and adjusted Job Zone level were included at the outset as fixed components of the model.
2. Screening of Potential Predictors: All 43 O*NET descriptors defining activities [41], context [42], and styles [43] were evaluated for entry using a liberal threshold ($p \leq 0.25$) to avoid prematurely excluding relevant construction-specific factors.
3. Retention Based on Contribution: Predictors that did not provide meaningful explanatory value were removed, using a stricter significance criterion ($p \leq 0.05$).
4. Final Model Interpretation: Predictors that remained were classified as risk amplifiers (positive association) or risk mitigators (negative association), enabling ergonomic interpretation tailored to construction environments.

2.5. Model Performance

The final model retained 10 significant predictors and explained approximately 49% of the variation in MSD event frequency across construction occupations. This level of explanatory power is consistent with ergonomic research where injury outcomes are influenced by multiple physical and organizational factors.

3. Results

3.1. Predictor Screening and Sector-Specific Patterns

To balance model complexity with predictive power, a systematic stepwise selection procedure was employed. A liberal entry criterion of $p \leq 0.25$ ensured that potentially relevant construction-specific factors were considered, while a stringent retention threshold of $p \leq 0.05$ determined which variables remained in the final model. During each iteration, the model re-evaluated all variables to ensure only those contributing significantly to

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the explained variance were retained after controlling for fixed moderators. Ultimately, this procedure narrowed the 43 O*NET descriptors down to 10 significant predictors, removing 33 variables from further consideration. These non-significant predictors are shown in Table 1, alphabetized by variable name for easier reference. Many variables traditionally associated with MSD risk—such as bending or twisting (F = 0.03, p = 0.8533), kneeling/crouching (F = 1.44, p = 0.2308), repetitive motions (F = 0.81, p = 0.3703), and vibration exposure (F = 0.85, p = 0.3583)—did not meet the retention threshold in the construction-only model.

Table 1. MSD Non-Predictors Stepwise Regression Results (n = 33).

MSD Non-Predictor	Description	F-Value	Pr > F
accuracy_import	Importance of Being Exact or Accurate	1.70	0.1934
auto_degree	Degree of Automation	1.03	0.3110
balance	Spend Time Keeping or Regaining Balance	0.18	0.6690
bending	Spend Time Bending or Twisting Your Body	0.03	0.8533
climbing	Spend Time Climbing Ladders, Scaffolds, or Poles	1.79	0.1820
common_attire	Wear Common Protective or Safety Equipment such as Safety Shoes, Glasses, Gloves, Hearing Protection, Hard Hats, or Life Jackets	0.15	0.6977
competition	Level of Competition	3.45	0.0640
contaminants	Exposed to Contaminants	0.06	0.8058
crouching	Spend Time Kneeling, Crouching, Stooping, or Crawling	1.44	0.2308
enclosed_veh	In an Enclosed Vehicle or Operate Enclosed Equipment	2.07	0.1508
error_conseq	Consequence of Error	0.24	0.6253
freedom_dec	Freedom to Make Decisions	0.02	0.8903
freq_dec	Frequency of Decision Making	0.77	0.3801
hands	Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls	0.67	0.4154
haz_equip	Exposed to Hazardous Equipment	2.04	0.1546
high_places	Exposed to High Places	1.97	0.1619
impact_rslt	Impact of Decisions on Co-workers or Company Results	0.61	0.4349
indoors_envr_ctrl	Indoors, Environmentally Controlled	0.14	0.7057
indoors_nonenvr_ctrl	Indoors, Not Environmentally Controlled	0.00	0.9510
lights	Exposed to Extremely Bright or Inadequate Lighting Conditions	0.13	0.7194
open_veh	In an Open Vehicle or Operating Equipment	0.11	0.7418
out_exposed_weather	Outdoors, Exposed to All Weather Conditions	0.94	0.3325
out_under_cover	Outdoors, Under Cover	0.00	0.9809
pace_equip	Pace Determined by Speed of Equipment	0.12	0.7305
physical_prox	Physical Proximity	0.36	0.5467
repetitive	Spend Time Making Repetitive Motions	0.81	0.3703
running	Spend Time Walking or Running	0.25	0.6195
standing	Spend Time Standing	2.55	0.1110
structure_wk	Determine Tasks, Priorities and Goals (i.e., can regulate work/life balance)	2.35	0.1259
tasks_repeat	Importance of Repeating Same Tasks	3.75	0.0537
temperature	Exposed to Very Hot or Cold Temperatures	0.09	0.7643
vibration	Exposed to Whole Body Vibration	0.85	0.3583
work_schedule	Work Schedules	0.55	0.4582

This screening pattern aligns with the nature of construction work, where such biomechanical exposures are nearly universal across trades and therefore do not discriminate MSD risk between occupations. In other words, the absence of significance for these variables reflects their ubiquity rather than their irrelevance.

Environmental descriptors that are common across multiple construction roles, such as outdoor weather exposure (F = 0.94, p = 0.3325) and temperature extremes (F = 0.09, p = 0.7643), also failed to reach significance, suggesting that they do not meaningfully explain variation in MSD event counts within the sector.

3.2. Descriptive Characteristics of Predictors Retained in the Model

The 10 occupational descriptors that met significance thresholds are summarized in Table 2. These variables represent high-intensity exposures typical of construction trades.

Table 2. Descriptive Statistics: MSD Predictors (n = 10).

Ref.	MSD Predictor	Description	Mean	SD
a.	cramped	Exposed to Cramped Workspace, Awkward Positions	55.2	13.3
b.	disease	Exposed to Disease or Infections	7.5	7.2
c.	duration_wk	Duration of Typical Work Week	66.8	14.8
d.	haz_conditions	Exposed to Hazardous Conditions	50.4	17.3
e.	minor_bcbs	Exposed to Minor Burns, Cuts, Bites, or Stings	58.8	11.8
f.	noise	Exposed to Sounds, Noise Levels that are Distracting or Uncomfortable	79.7	11.5
g.	radiation	Exposed to Radiation	5.8	7.1
h.	sitting	Spend Time Sitting	27.6	19.2
i.	special_attire	Wear Specialized Protective or Safety Equipment such as Breathing Apparatus, Safety Harness, Full Protection Suits, or Radiation Protection	48.4	16.6
j.	time_pressure	Time Pressure	71.5	8.7

Notes: Letters a–j in the reference (Ref) column are used to identify predictors in narrative. SD = Standard Deviation.

Key examples include:

- Noise exposure: mean = 79.7, SD = 11.5, indicating that most construction occupations operate in consistently loud environments.
- Cramped workspace: mean = 55.2, SD = 13.3, consistent with framing, mechanical, and finishing tasks performed in enclosed areas.
- Special protective attire: mean = 48.4, SD = 16.6, characteristic of trades requiring respirators, harnesses, or heat-resistant gear.
- Time pressure: mean = 71.5, SD = 8.7, reflects production-driven task pacing typical in construction.

These descriptive statistics support the view that the retained predictors capture the most intense and variable exposures within SOC 47, enabling meaningful discrimination between occupations.

3.3. Final Regression Model: Risk Amplifiers and Mitigators

The final regression model identified seven risk amplifiers and three risk mitigators, all statistically significant at $p < 0.05$ (Table 3). Together, these variables explained 48.9% of the variance in MSD event counts across construction occupations.

Table 3. MSD Predictor Regression Model.

Ref.	Variable	Estimate (x)	SE	t Value	Pr > |t|	Exp (x)
			MSD Risk Amplifiers			
b.	disease	0.0633	0.0135	4.67	<0.0001	0.0653
f.	noise	0.0386	0.0103	3.77	<0.001	0.0394
h.	sitting	0.0306	0.0068	4.51	<0.0001	0.0311
i.	special_attire	0.0303	0.0066	4.57	<0.0001	0.0307
e.	minor_bcbs	0.0289	0.0089	3.26	<0.01	0.0293
j.	time_pressure	0.0249	0.0104	2.39	<0.05	0.0252
d.	haz_conditions	0.0220	0.0098	2.24	<0.05	0.0223
			MSD Risk Mitigators			
c.	duration_wk	−0.1151	0.0123	−9.33	<0.0001	−0.1087
a.	cramped	−0.0772	0.0107	−7.19	<0.0001	−0.0743
g.	radiation	−0.0595	0.0121	−4.91	<0.0001	−0.0577
			MSD Event Moderators			
Jobzone (Adjusted: 0–4)		0.9197	0.2366	3.89	<0.001	1.51
MSD_outcome		0.8420	0.1524	5.53	<0.0001	1.32
MSD_symptoms		0.3894	0.1524	2.56	<0.05	0.48
MSD_outcome + MSD_symptoms		1.2314				2.43
Intercept		6.8163	1.0324	6.60	<0.0001	912.62
Adjusted R-square		0.4894				

Note: Letters a–j in the reference (Ref) column are used to identify predictors in narrative.

3.3.1. Risk Amplifiers (Positive Predictors)

The following occupational descriptors were significantly and positively associated with MSD frequency, meaning that higher exposure corresponds to higher MSD counts. Several statistically significant predictors identified in this study likely function as contextual or proxy indicators of hazardous and complex construction work environments rather than direct causal agents of musculoskeletal injury. The variables are presented in descending order based on the magnitude of their estimated effect.

Exposure to Disease or Infections (Estimate = 0.0633, $p < 0.0001$): This was the strongest amplifier. It reflects occupations with extensive contact with wastewater, drainage lines, or contaminated materials (e.g., plumbers, pipefitters). Such environments can exacerbate fatigue, inflammation, or injury susceptibility.

Distracting/Uncomfortable Noise (Estimate = 0.0386, $p < 0.001$): High noise exposure often coincides with heavy machinery operation and power tool use. Noise can impair communication and situational awareness, heightening the chance of awkward or forceful movements that increase MSD risk.

Time Spent Sitting (Estimate = 0.0306, $p < 0.0001$): In construction, sitting primarily represents equipment and vehicle operation, not sedentary clerical work. Operators experience prolonged static loading and whole-body vibration, well-known contributors to low-back and trunk MSDs.

Special Protective Attire (Estimate = 0.0303, $p < 0.0001$): Full-body protective suits, respirators, fall-arrest harnesses, and arc-flash gear can restrict mobility, add weight, and alter postural mechanics—amplifying physical strain during task execution.

Exposure to Minor Burns, Cuts, Bites, or Stings (Estimate = 0.0289, $p < 0.01$): This variable does not imply that minor injuries directly cause musculoskeletal disorders. Rather, it likely reflects high-risk, multifaceted construction work environments characterized by frequent interaction with sharp tools, abrasive materials, or hazardous conditions. Its significance suggests that this descriptor may function as a proxy indicator of overall workplace hazard intensity, where complex task demands and cumulative physical strain increase MSD risk. Further research is warranted to clarify the direct and indirect mechanisms linking these environments to musculoskeletal outcomes.

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Time Pressure (Estimate = 0.0249, $p < 0.05$): Time pressure directly reflects production-driven schedules and compressed timelines—conditions that encourage workers to cut micro-breaks, lift more rapidly, or assume awkward positions to maintain workflow.
Exposure to Hazardous Conditions (Estimate = 0.0220, $p < 0.05$): This includes tasks near energized systems, moving vehicles, unstable surfaces, and confined excavation areas. Such high-hazard contexts require reactive, forceful movements that increase MSD risk.

3.3.2. Risk Mitigators (Negative Predictors)

The following occupational descriptors were significantly and negatively associated with MSD frequency, indicating potentially protective conditions or tasks with inherently lower biomechanical loading. The variables are presented in descending order based on the magnitude of their estimated negative effect.

Duration of Typical Work Week (Estimate = -0.1151, $p < 0.0001$): This variable showed the strongest protective association. In construction, longer work weeks often correspond to supervisory or technical positions rather than direct manual labor. These roles primarily involve planning, oversight, or inspection tasks with substantially lower biomechanical loading.
Cramped Workspace Exposure (Estimate = -0.0772, $p < 0.0001$): Although this finding appears counterintuitive, cramped-space tasks often occur in controlled environments like mechanical rooms or during interior builds. These contexts may impose a slower work pace and stable surfaces, encouraging workers to engage in more deliberate posture adjustment and controlled movements, thus mitigating MSD risk.
Radiation Exposure (Estimate = -0.0595, $p < 0.0001$): This variable typically applies to specialized inspection roles (e.g., non-destructive testing) that operate under strict procedural controls. These roles are often subject to mandated rest periods and highly regulated ergonomic environments designed to minimize exposure, which may inadvertently reduce overall physical strain.

3.3.3. Moderator Effects of MSD Outcome, Symptom Category, and Job Zone

The analysis revealed significant moderating effects based on how the MSD was classified (by outcome, symptom, or job preparation level), suggesting these factors influence the magnitude of the observed MSD counts.

Job Zone (Estimate = 0.9197, $p < 0.001$): This variable showed the strongest moderating effect. Higher preparation-level occupations (e.g., heavy equipment operators, inspectors) experienced significantly more MSD events than lower preparation-level roles. This finding is consistent with elevated exposure to specific risk factors in these roles, such as vibration, prolonged static postures, or precision-based tasks.
MSD Outcome (Estimate = 0.8420, $p < 0.0001$): MSD injuries resulting in days away from work were significantly more common than those leading to restricted duty. This effect reflects the limited availability of light-duty options in many construction trades, leading to less severe injuries resulting in full time off.
MSD Symptoms (Estimate = 0.3894, $p < 0.05$): Sprains, strains, and tears (representing 62.8% of all events) generated significantly more MSD counts than general soreness or pain. This pattern is consistent with the force-intensive and dynamic nature of typical construction tasks.

3.4. MSD Distribution by Job Zone and Injury Characteristics

Table 4 illustrates that:

- High school–level occupations accounted for 73.9% of all MSD events, consistent with their numerical dominance and higher physical demands.

- Sprains, strains, and tears represented 62.8% of all construction MSDs.
- These severe injuries resulted in:
    - 36.3% days away from work.
    - 26.5% restricted duty events.

Table 4. MSD Events by Outcome and Symptoms of per Occupation Job Zone.

MSD Outcome:	Job Transfer/Restrictions				Away from Work				Job Zone Totals (n = 86)	
MSD Symptom:	Sore or Pain		Sprains… or Tears		Sore or Pain		Sprains… or Tears			
Job Zone	*n*	%	*n*	%	*n*	%	*n*	%	*N*	%
No HS or GED	1990	2.5	5260	2.5	5610	2.6	5390	1.9	18,250	2.3
(n = 2)	10.9		28.8		30.7		29.5		100	
HS/GED	59,540	75.3	153,980	73.1	162,610	75.1	210,650	73.2	586,780	73.9
(n = 70)	10.1		26.2		27.7		35.9		100	
AA/AS	17,490	22.1	51,460	24.4	48,220	22.3	71,830	25.0	189,000	23.8
(n = 14)	9.3		27.2		25.5		38.0		100	
MSD Event	79,020	100	210,700	100	216,440	100	287,870	100	794,030	100
Totals (N)	10.0		26.5		27.2		36.3		100	

Note: HS/GED = High School/General Educational Development (High School Equivalent diploma); AA/AS: Associate of Arts/Associate of Science (2-year degree).

4. Discussion

The present study provides a focused examination of MSD determinants within U.S. construction-sector occupations, revealing a risk profile distinct from that observed in the broader workforce. Rather than traditional ergonomic predictors such as bending, kneeling, or repetitive motions—which did not discriminate MSD incidence among construction occupations—this analysis found that environmental hazards, constrained body postures associated with equipment operation, and production-driven organizational pressures were the primary factors elevating MSD events in SOC 47. These findings underscore the need to rethink MSD mitigation strategies in construction by extending attention from general biomechanical guidelines to the specific contextual and operational realities of construction worksites.

4.1. Environmental and Contextual Hazards as Key MSD Drivers

Environmental exposures—including noise, hazardous conditions, and potential disease contact—emerged as some of the most influential predictors of MSD frequency [7,44,45]. This contrasts with findings from national-level analyses, where physical repetition or sustained awkward postures often dominate MSD models. Construction workers frequently perform tasks amid high noise and mechanical vibration, in proximity to energized systems, unstable structures, partially enclosed spaces, or contaminated materials. These conditions not only create acute physical strain but also impair workers' ability to maintain safe posture or coordinate movement, amplifying the risk of sudden, forceful, or compensatory motions that contribute to sprains, strains, or tears.

From a practical standpoint, these findings highlight the need for integrated hazard management that goes beyond PPE and task protocols. Strategies such as early detection of environmental hazards, improved communication systems in noisy zones, and real-time field monitoring technologies (e.g., noise dosimeters or environmental sensors) could significantly reduce MSD risk by allowing supervisors and workers to adjust task methods before fatigue or distraction trigger injury events.

4.2. Equipment Operation, Seating Constraints, and Static Loading

Another strong amplifier—time spent sitting—provides valuable insight into MSD risk among heavy equipment operators, crane operators, and vehicle-based trades. Unlike sedentary office work, seated construction tasks involve vibration exposure, limited lumbar

movement, and constrained posture. These conditions create continuous loading on the lower back and hips, elevating MSD occurrence [7]. This suggests that MSD prevention in construction cannot rely solely on general lifting guidelines or stretching programs; ergonomic interventions must include equipment design improvements, vibration damping technology, and rotation schedules for seated operators.

4.3. Organizational Pressures and Musculoskeletal Risk

Time pressure, a significant positive predictor, reflects the deeply embedded production-driven nature of construction projects. Compressed timelines, interdependent trade sequencing, and contractual penalties often push workers to complete tasks faster, reduce micro-breaks, or lift and maneuver materials with less caution. These pressures can override even well-established safety protocols. This finding aligns with research documenting the impact of psychosocial stressors on injury risk across high-demand industries [46,47].

To address this, contractors and project managers may benefit from adopting capacity-based scheduling, improved task planning, and realistic productivity allowances that do not incentivize unsafe acceleration of physical tasks. Such organizational changes could generate meaningful reductions in MSD rates without requiring specialized equipment.

4.4. Why Some Common Biomechanical Predictors Were Not Significant

The absence of traditional ergonomic predictors (e.g., bending, kneeling, vibration) from the significant subset of variables should not be interpreted as suggesting that these exposures are safe or non-contributory. Instead, their non-significance likely reflects their uniformity across construction roles. Because nearly all construction occupations involve manual exertion, these variables do not distinguish high-risk from low-risk occupations. This is an important nuance for practitioners:

MSD prevention strategies cannot rely solely on reducing common biomechanical exposures—they must target differential exposures such as environmental hazards, constrained operator postures, and production speed.

4.5. Protective Factors and Their Practical Implications

The finding that cramped workspace exposure reduced MSD risk appears counterintuitive but likely reflects the nature of certain finishing or mechanical tasks performed in controlled environments with stable surfaces and slower task pace. These contexts inherently limit rapid or forceful movements. Similarly, radiation exposure—associated with highly regulated inspection tasks—predicts lower MSD frequency due to strict procedural oversight and mandatory recovery periods.

These mitigators suggest that task organization and procedural control, rather than job physicality alone, can play a meaningful protective role. Incorporating more regulated workflows, even for non-radiation tasks, could yield ergonomic benefits.

4.6. The Role of Job Preparation and Skill Level

The positive relationship between Job Zone and MSD events challenges assumptions that higher-skilled roles are safer. Instead, occupations requiring more technical training—such as equipment operation, inspection, or specialized installation—often involve static loading, constrained seating, or high concentration in awkward positions. These insights highlight the need to expand ergonomic surveillance beyond manual trades and recognize that skilled technical workers face their own unique ergonomic risks, which should be incorporated into training and safety planning.

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5. Implications for Construction Safety Management and Policy

This study provides actionable guidance for policymakers, safety engineers, and construction managers:

- Prioritize environmental hazard mitigation (noise control, hazard isolation) as much as biomechanical training.
- Redesign operator cabins and seating interfaces to reduce vibration and static loading.
- Adopt scheduling practices that minimize time pressure, especially during high-risk phases of a project.
- Enhance PPE procurement policies, ensuring protective attire reduces, rather than adds, ergonomic burden.
- Train supervisors to recognize high-risk combinations of environmental exposure and organizational stress.
- Introduce trade-specific task rotation systems—especially between equipment operation and manual tasks.
- Apply procedural rigor from regulated environments (e.g., radiation-handling tasks) to other high-risk activities.

From a policy standpoint, integrating O*NET descriptors with SOII outcomes—as demonstrated in this study—offers a scalable method for prioritizing ergonomic interventions across construction trades, supporting data-driven approaches to injury prevention.

6. Limitations

While this study provides important insights into MSD risk determinants within the construction sector, limitations should be acknowledged. The analysis relies on publicly available datasets (SOII and O*NET), which, although authoritative, are subject to inherent limitations. SOII data may underreport injuries due to industry reporting practices, and O*NET descriptors, while standardized, represent averaged occupational characteristics rather than task-specific exposures. This may introduce measurement imprecision when describing conditions at specific worksites. This study operates at the occupation level rather than the task or worker level. Construction tasks are highly variable, even within a single occupation. As a result, the model captures broad exposure patterns but cannot account for individual-level variation, daily work sequencing, crew practices, or unobserved psychosocial factors. Construction occupations span only three Job Zones (0–2), with no representation of bachelor's-level or graduate-level occupations. This limits the generalizability of Job Zone–related findings and may underestimate MSD risks in specialized supervisory or hybrid technical-management roles not captured in SOC 47. This study is cross-sectional and does not allow for causal inferences. The observed associations indicate relationships between job descriptors and MSD outcomes but cannot confirm whether specific exposures directly cause injuries. Longitudinal methods would be required to confirm causal pathways.

7. Conclusions

This study provides sector-specific evidence on the determinants of musculoskeletal disorders (MSDs) across U.S. construction occupations, revealing a risk profile shaped primarily by environmental hazards, equipment-induced posture constraints, and production-oriented work organization. Unlike broader occupational analyses, which often emphasize repetitive movements or static postures, the present findings demonstrate that MSD risk in construction is driven by a set of exposures that reflect the dynamic, high-variability nature of construction worksites. Predictors such as noise intensity, hazardous working conditions, specialized protective gear, and constrained operator seating were among

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the strongest risk amplifiers, while mitigators tended to reflect structured, controlled work environments.

These insights underscore the need for a multidimensional approach to injury prevention in construction that integrates ergonomic design, worksite hazard control, and organizational strategies. Interventions aimed at reducing noise exposure, minimizing equipment vibration, optimizing PPE design, and moderating time pressure could produce substantial reductions in MSD burden. Moreover, task planning and scheduling practices that allow for controlled pacing and rotation between high- and low-strain tasks may reduce the frequency of severe sprains, strains, and tears that dominate construction injury statistics.

Overall, this study contributes an occupation-centered, data-driven framework for understanding MSD risk in construction. By identifying specific job attributes that amplify or mitigate risk, the results offer a roadmap for contractors, safety managers, and policymakers seeking to design more targeted, effective ergonomic interventions. These findings reinforce the importance of tailoring safety strategies to the unique operational conditions of construction rather than relying on generalized ergonomic guidelines.

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Abbreviations

The following abbreviations are used in this manuscript:

BLS	U.S. Bureau of Labor Statistics
MSDs	Musculoskeletal disorders
NAICS	North American Industry Classification System
O*NET	Occupational Information Network
PPE	Personal Protective Equipment
SD	Standard Deviation
SOC	Standard Occupational Classification
SOII	Survey of Occupational Injuries and Illnesses
U.S.	United States

References

1. Dong, X.S.; Choi, S.D.; Borchardt, J.G.; Wang, X.; Largay, J.A. Fatal Falls from Roofs among U.S. Construction Workers. *J. Saf. Res.* **2013**, *44*, 17–24. [CrossRef]
2. U.S. Department of Labor. *National Census of Fatal Occupational Injuries in 2023*; News Resease Bureau of Labor Statistics: Washington, DC, USA, 2024.
3. Syed Basheer, S.; Jeeva, R. Avoiding Challenges in the Construction Industry. *Int. J. Res. Publ. Rev.* **2024**, *5*, 5587–5597. [CrossRef]

4. Rahman, M.S.; Sakamoto, J. The Risk Factors for the Prevalence of Work-Related Musculoskeletal Disorders among Construction Workers: A Review. *J. Appl. Res. Ind. Eng.* **2024**, *11*, 155–165. [CrossRef]
5. Valero, E.; Sivanathan, A.; Bosché, F.; Abdel-Wahab, M. Musculoskeletal Disorders in Construction: A Review and a Novel System for Activity Tracking with Body Area Network. *Appl. Ergon.* **2016**, *54*, 120–130. [CrossRef]
6. Odebiyi, D.O.; Okafor, U.A.C. Musculoskeletal Disorders, Workplace Ergonomics and Injury Prevention. In *Ergonomics—New Insights*; IntechOpen: London, UK, 2023; ISBN 978-1-80356-471-5.
7. Abdullah, A.R.; Susilowati, I.H. Risk Factor for Musculoskeletal Disorder in Construction Worker: Literature Review. *Media Publ. Promosi Kesehat. Indones. (MPPKI)* **2024**, *7*, 2458–2464. [CrossRef]
8. Inyang, N.; Al-Hussein, M.; El-Rich, M.; Al-Jibouri, S. Ergonomic Analysis and the Need for Its Integration for Planning and Assessing Construction Tasks. *J. Constr. Eng. Manag.* **2012**, *138*, 1370–1376. [CrossRef]
9. Dong, X.S.; Betit, E.; Dale, A.M.; Barlet, G.; Wei, Q. *Trends of Musculoskeletal Disorders and Interventions in the Construction Industry*; CPWR-The Center for COnstruction Research and Training: Silver Spring, MD, USA, 2019.
10. Umer, W.; Li, H.; Szeto, G.P.Y.; Wong, A.Y.L. Identification of Biomechanical Risk Factors for the Development of Lower-Back Disorders during Manual Rebar Tying. *J. Constr. Eng. Manag.* **2017**, *143*, 04016080. [CrossRef]
11. Dutta, A.; Breloff, S.P.; Dai, F.; Sinsel, E.W.; Warren, C.M.; Wu, J.Z. Identifying Potentially Risky Phases Leading to Knee Musculoskeletal Disorders during Shingle Installation Operations. *J. Constr. Eng. Manag.* **2020**, *146*, 04019118. [CrossRef]
12. Santos, W.; Lorente, A.; Rojas, C.; Isidoro, R.; Dias, A.; Mariscal, G.; Zabady, A.H.; Lorente, R. A Systematic Review and Meta-Analysis on the Prevalence and Demographic Risk Factors of Work-Related Musculoskeletal Disorders in Construction Workers. *Front. Public Health* **2025**, *13*, 1651921. [CrossRef]
13. Yuliani, E.N.S.; Prakoso, G.; Iridiastadi, H.; Adiatmika, I.P.G. Evaluation to Reduce Occupational Risk In Excavator Manufacturing. *J. Sustain. Glob. South* **2020**, *4*, 22. [CrossRef]
14. Choi, S.D.; Yuan, L.; Borchardt, J.G. Musculoskeletal Disorders in Construction: Practical Solutions From the Literature. *Prof. Saf.* **2016**, *61*, 26–32.
15. Kisi, K.P.; Kayastha, R. Analysis of Musculoskeletal Pains and Productivity Impacts among Hispanic Construction Workers. *Heliyon* **2024**, *10*, e24023. [CrossRef]
16. Fredericks, T.K.; Abudayyeh, O.; Choi, S.D.; Wiersma, M.; Charles, M. Occupational Injuries and Fatalities in the Roofing Contracting Industry. *J. Constr. Eng. Manag.* **2005**, *131*, 1233–1240. [CrossRef]
17. Welch, L.; Haile, E.; Boden, L.I.; Hunting, K.L. Musculoskeletal Disorders among Construction Roofers—Physical Function and Disability. *Scand. J. Work Environ. Health* **2009**, *35*, 56–63. [CrossRef]
18. Hong, X.; Lee, Y. Prevalence of Musculoskeletal Symptoms Among Construction Workers. In *Proceedings of the Man-Machine-Environment System Engineering*; Long, S., Dhillon, B.S., Eds.; Springer Nature: Singapore, 2023; pp. 140–145.
19. Guduru, R.K.R.; Domeika, A.; Obcarskas, L.; Ylaite, B. The Ergonomic Association between Shoulder, Neck/Head Disorders and Sedentary Activity: A Systematic Review. *J. Healthc. Eng.* **2022**, *2022*, 5178333. [CrossRef] [PubMed]
20. Assadi, S.N. Ergonomics and Prevention of Occupational Musculoskeletal Disorders. *East Afr. Sch. J. Med. Sci.* **2023**, *6*, 153–156. [CrossRef]
21. U.S. Bureau of Labor Statistics. Survey of Occupational Injuries and Illnesses Data. Available online: https://www.bls.gov/iif/nonfatal-injuries-and-illnesses-tables.htm (accessed on 6 December 2025).
22. Meyers, A.R.; Dale, A.M.; Yung, M.; Evanoff, B. *Effectiveness of New Guidelines to Prevent Workplace Hand-Wrist MSDs*; NIOSH Science Blog: Cincinnati, OH, USA, 2019.
23. Welch, L.S.; Haile, E.; Boden, L.I.; Hunting, K.L. Impact of Musculoskeletal and Medical Conditions on Disability Retirement—A Longitudinal Study among Construction Roofers. *Am. J. Ind. Med.* **2010**, *53*, 552–560. [CrossRef]
24. Bhattacharya, A. Costs of Occupational Musculoskeletal Disorders (MSDs) in the United States. *Int. J. Ind. Ergon.* **2014**, *44*, 448–454. [CrossRef]
25. Yelin, E.; Weinstein, S.; King, T. The Burden of Musculoskeletal Diseases in the United States. *Semin. Arthritis Rheum.* **2016**, *46*, 259–260. [CrossRef]
26. The US Burden of Disease Collaborators. The State of US Health, 1990–2016: Burden of Diseases, Injuries, and Risk Factors Among US States. *JAMA* **2018**, *319*, 1444–1472. [CrossRef]
27. National Safety Council. *Work Injury Costs and Time Lost*; National Safety Council: Itasca, IL, USA, 2023.
28. McGaha, J.; Miller, K.; Descatha, A.; Welch, L.; Buchholz, B.; Evanoff, B.; Dale, A.M. Exploring Physical Exposures and Identifying High-Risk Work Tasks within the Floor Layer Trade. *Appl. Ergon.* **2014**, *45*, 857–864. [CrossRef]
29. Gautam, S.R.; Acharya, S.; Kayastha, R.; Mahmud, T.; Kisi, K. Muscle Activation Patterns in Stooping Posture on Sloped Roofing Surfaces. *Proc. Assoc. Sch. Constr.* **2025**, *6*, 816–825.
30. Antwi-Afari, M.F.; Li, H.; Edwards, D.J.; Pärn, E.A.; Owusu-Manu, D.-G.; Seo, J.; Wong, A.Y.L. Identification of Potential Biomechanical Risk Factors for Low Back Disorders during Repetitive Rebar Lifting. *Constr. Innov. Inf. Process Manag.* **2018**, *18*, 206–226. [CrossRef]

31. Grzywiński, W.; Wandycz, A.; Tomczak, A.; Jelonek, T. The Prevalence of Self-Reported Musculoskeletal Symptoms among Loggers in Poland. *Int. J. Ind. Ergon.* **2016**, *52*, 12–17. [CrossRef]
32. Ouyang, Y.; Luo, X. Differences between Inexperienced and Experienced Safety Supervisors in Identifying Construction Hazards: Seeking Insights for Training the Inexperienced. *Adv. Eng. Inform.* **2022**, *52*, 101602. [CrossRef]
33. Acharya, S.; Kisi, K.; Gautam, S.R.; Mahmud, T.; Kayastha, R. A High-Performance Hybrid Transformer–LSTM–XGBoost Model for sEMG-Based Fatigue Detection in Simulated Roofing Postures. *Buildings* **2025**, *15*, 3005. [CrossRef]
34. Anwer, S.; Li, H.; Antwi-Afari, M.F.; Wong, A.Y.L. Associations between Physical or Psychosocial Risk Factors and Work-Related Musculoskeletal Disorders in Construction Workers Based on Literature in the Last 20 Years: A Systematic Review. *Int. J. Ind. Ergon.* **2021**, *83*, 103113. [CrossRef]
35. Paramasivam, S.K.; Mani, K.; Paneerselvam, B.; Paramasivam, S.K.; Mani, K.; Paneerselvam, B. Unveiling Gender-Based Musculoskeletal Disorders in the Construction Industry: A Comprehensive Analysis. *Buildings* **2024**, *14*, 1169. [CrossRef]
36. Zhou, X.; Liao, P.-C.; Xu, Q. Reinvestigation of the Psychological Mechanisms of Construction Experience on Hazard Recognition Performance. *Hum. Factors Ergon. Soc.* **2022**, *66*, 221–233. [CrossRef]
37. Wang, D.; Dai, F.; Ning, X. Risk Assessment of Work-Related Musculoskeletal Disorders in Construction: State-of-the-Art Review. *J. Constr. Eng. Manag.* **2015**, *141*, 04015008. [CrossRef]
38. National Safety Council Glossary 2025. Available online: https://injuryfacts.nsc.org/glossary (accessed on 8 December 2025).
39. National Center for O*NET Development. O*NET 28.1 Data Dictionary at O*NET Resource Center. Available online: https://www.onetcenter.org/dictionary/28.1/excel/ (accessed on 6 December 2025).
40. U.S. Bureau of Labor Statistics. Occupational Employment and Wage Statistics (OEWS) Tables. Available online: https://www.bls.gov/oes/tables.htm (accessed on 6 December 2025).
41. National Center for O*NET Development. Browse by Work Activities. Available online: https://www.onetonline.org/find/descriptor/browse/4.A/ (accessed on 6 December 2025).
42. National Center for O*NET Development. Browse by Work Context. Available online: https://www.onetonline.org/find/descriptor/browse/4.C (accessed on 6 December 2025).
43. National Center for O*NET Development. Browse by Work Styles. Available online: https://www.onetonline.org/find/descriptor/browse/1.D (accessed on 6 December 2025).
44. Gowtham, S.; Eshwar, A.; Thozhanenjan, I.; Vittal, P. Prevalence of Musculoskeletal Disorders and Associated Risk Factors Among Leather Factory Workers in Chengalpattu District, Tamil Nadu, India: A Cross-Sectional Study. *Cureus* **2025**, *17*, e95931. [CrossRef] [PubMed]
45. Gorce, P.; Jacquier-Bret, J. Is There an Effect of Anthropometric Data, Environmental Parameters and Temporal Trend on Prevalence? Worldwide Systematic Review and Meta-Analysis of Work-Related Musculoskeletal Disorders among Nurses. 2025. Available online: https://journals.sagepub.com/doi/10.1177/10519815251388969 (accessed on 8 December 2025).
46. Mabuting, R.E.; Dastas, D.F.; Rabe, S.J.Z.; Meneses, J.L.R.; Sinapilo, L.D. Correlational Analysis of Physical and Cognitive Workload Factors to Musculoskeletal Discomfort Experienced by Machine Operators in Semi-Automated Hollowblock Manufacturing Sites. In Proceedings of the International Conference on Industrial Engineering and Operations Management, Houston, TX, USA, 13–16 June 2023; IEOM Society International: Southfield, MI, USA, 2023.
47. Alex, K.J.; Abdullah, F.; Jaafar, M.H.; Zuknik, M.H.; Amil, N.; Ismail, Z.S.; Alex, K.J.; Abdullah, F.; Jaafar, M.H.; Zuknik, M.H.; et al. Multifactorial Causal Analysis of Workplace Musculoskeletal Disorders (WMSDs) and Psychological Stress Among Teaching Professionals for Adult Learners: A Narrative Review. *Healthcare* **2025**, *13*, 2897. [CrossRef] [PubMed]

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Hierarchical Modeling of Safety Factors in the Construction Industry Using Interpretive Structural Modeling (ISM) and Decision-Making Trial and Evaluation Laboratory (DEMATEL)

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Abstract

Understanding the causal relationships between safety factors is essential for successful intervention in industries with intrinsically high-risk environments such as the construction industry. Therefore, the aim of this study is to employ the Interpretive Structural Modeling (ISM) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) techniques to analyze and map the interdependencies among various safety-related elements affecting construction safety. According to the results, resource allocation was shown to be the highest-level, most independent element in the analysis, highlighting its function as the primary facilitator of safety initiatives. This strategic commitment directly drives Management Commitment and Competence, which form the core organizational support structure. Mid-level elements that translate management intent into site-level practice include workers' training, safety motivation, and communication structure. The frequency of safety observations, workers' involvement in safety decisions, and subcontractor and procurement management—the immediate procedural controls—are then used to assess operational efficacy. Crucially, the most dependent factor was found to be Workers' Compliance, indicating that frontline safety behavior is the result of efficient management at all higher levels. Therefore, in order to improve overall safety performance in construction, this research emphasizes the importance of improving resource provision and leadership commitment. The outputs of the current study provide an organized, evidence-based roadmap for selecting interventions.

Keywords: construction safety; safety hierarchy; interpretive structural modeling; cross-impact matrix multiplication applied to classification; decision-making trial and evaluation laboratory

1. Introduction

The construction industry serves as a foundational pillar of the local and global economy, responsible for developing the critical infrastructure and built environments that underpin modern society. Despite its indispensable role, the sector consistently ranks among the most hazardous worldwide [1]. Construction environments are inherently dynamic and complex, characterized by transient workspaces, the use of heavy machinery, and exposure to significant risk factors, including work at height, dropped objects, and complex lifting operations. The imperative to improve Occupational Health and Safety (OHS) in this sector is therefore threefold: it is an ethical obligation to safeguard human life, a legal necessity to ensure compliance with governmental regulations, and an economic mandate. High incident rates translate directly into catastrophic business impacts,

including soaring insurance and litigation costs, diminished workforce morale and productivity, project delays, and severe reputational damage [2,3]. It is critical to create and implement comprehensive, proactive strategies for upgrading safety performance above mere compliance in order to ensure the construction industry's long-term sustainability and societal value.

Occupational safety and health is affected by a complex interplay of numerous factors that can be classified as direct workplace risks, organizational/human factors, and external socioeconomic effects [4,5]. Direct factors include environmental hazards (noise, temperature), chemical hazards (fumes, dust), biological hazards (microorganisms), and ergonomic hazards (manual material handling). Beyond the direct factors, organizational and human factors have a key influence, such as, the degree of management commitment, the strength of the company's safety culture, the quality of training and education provided, and individual worker behavior. Finally, external factors such as government regulations and enforcement, overall economic situation, and technological shifts all have a significant impact on the resources allocated to OSH and the standards maintained in the workplace, making worker protection a continuous challenge. The enhanced focus on organizational and individual factors is crucial, because these elements represent the root causes of the majority of workplace incidents [6,7]. These incidents are typically not random but are symptoms of systemic failures, such as high production pressure, inadequate training, poor design, and weak safety culture. Furthermore, the organizational and individual factors determine the success of all other safety measures; for instance, a lack of management commitment will lead to non-compliance and misuse of safety equipment, rendering even the best engineering controls unreliable. Therefore, there is a need to study the complex relationship between these factors and the safety level.

Several studies investigated the factors affecting safety in the construction sector using different tools. For instance, a combination of multi-criteria decision making (MCDM) tools [8–10] statistical models [11–13], machine learning techniques [14], and structural equation modeling [15,16]. However, according to the literature, none of the previous research determined the hierarchal structure of influence of the driving factors and the dependent factors that affect the safety levels in the construction sector. Therefore, to study the hierarchy of these factors, interpretive structural modeling (ISM) integrated with Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique can be used. Interpretive Structural Modeling (ISM) is a highly effective tool for studying the factors affecting safety, particularly in complex domains like the construction sector, because it provides a systemic, hierarchical structure rather than just a simple list of factors. The primary strength of ISM is its ability to model complexity and interdependence (e.g., whether Factor A drives Factor B), thereby clarifying how a change in one factor propagates throughout the entire safety system. Furthermore, ISM is crucial for establishing a hierarchy of influence, as it distinguishes between the high-leverage driving factors (the root causes) and the dependent factors (the outcomes), which is vital for efficient strategic planning. Finally, Because ISM can efficiently manage qualitative and expert data, it is well-suited for safety research. By utilizing the combined expertise of experts, it can produce a rational, actionable, and theoretically grounded model that directs the development of safety policies as well as actions. Moreover, the DEMATEL technique was applied for several reasons. First, to verify the relationship obtained from the ISM tool. The DEMATEL analysis classifies factors into either causes or effects. Second, to measure the influence of each factor quantitative. Therefore, the objectives of the current study were:

- To determine and model the contextual interrelationships between the human and organizational elements that influence safety levels in the construction industry.

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- To create a hierarchical structure by classifying the factors into different levels using the ISM technique.
- To identify the most important, high-leverage driving factors that need to be addressed in order to effectively improve systemic safety.
- To quantify the influence of the casual factors affecting safety levels using the DEMATEL analysis.

This research contributes to the field of OSH by going beyond simple factor identification to develop a hierarchical, practical framework for construction safety management. Furthermore, it enables OSH specialists to strategically devote resources to the most crucial root drivers, boosting the efficiency and effectiveness of building safety interventions.

Background

As mentioned earlier, the safety level in the construction sector is affected by multiple factors. For instance, management commitment and safety rules have constantly been regarded as the most influential factors for site safety. For instance, management commitment has been consistently acknowledged as a critical driver of safety levels. According to research, when management prioritizes safety, establishes clear goals, and actively supports safety programs, workers' safety attitudes, compliance, and overall safety outcomes increase significantly [17–19].

Most studies show that adequate safety training decreases accidents, injuries, and fatalities in high-risk industries, such as construction, mining, and manufacturing [20]. Investing in safety training decreases safety dangers, worker injuries, and increases the likelihood of being chosen by procurement professionals [21]. For example, a 10% increase in safety training hours per capita led to a 6–10% decrease in safety hazards, and mandatory training requirements reduced injury rates by up to 19% [22].

Active worker participation in safety decision-making leads to a stronger safety levels, increased compliance, and lower accident rates. Employee participation in safety policies, procedures, and conversations promotes a sense of accountability, ownership, and teamwork, all of which directly lower workplace hazards and accidents [23]. Furthermore, organizational support and leadership enhance the advantages of employee involvement, particularly when paired with a culture of safety and open communication [24].

Increased safety incentive results in improved safety involvement, compliance, and fewer infractions or accidents. Workers who are driven to put safety first are more likely to adhere to safety protocols, take part in safety-related activities, and refrain from dangerous behaviors, all of which improve safety results [25,26]. The relationship between safety management and safety performance is frequently mediated by safety motivation. For example, transformational leadership and a positive safety level increase safety motivation, which in turn enhances safety behaviors and reduces incidents [27].

By enabling prompt hazard detection and proactive responses, safety monitoring is essential to preserving and raising safety standards across a range of sectors. In organizational settings, safety monitoring serves as a leading indicator that reflects the dynamic safety potential of the system, helping to motivate safety-related activities and improve overall safety performance [28].

Management and supervisor safety competence directly improves employee safety behaviors and reduces accidents. High proficiency in safety management is essential for preventing accidents in a variety of industries and enhances the connection between safe employee behavior and safety culture [29,30]. Competent managers build a good safety climate by emphasizing safety, communicating effectively, and taking timely remedial steps. These skills are consistently identified as the one of most influential factors in

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shaping organizational safety climates and outcomes [31]. Positive leadership and safety participation explained 22.8% and 33.6% of safety compliance behavior, respectively [32].

Higher worker competence leads to better safety performance and in turn fewer accidents. Studies in construction and industrial settings reveal that workers with more safety knowledge, abilities, and attitudes are more likely to comply with safety protocols and participate in safety activities, which directly reduces risky behaviors and occurrences [33,34].

Several studies revealed that the presence and quality of safety policies are highly related to greater safety performance and fewer workplace incidents. Corporations with comprehensive safety policies have much lower injury rates and better safety results than those without such policies [35]. Safety policies provide clear expectations, give guidance for safe behavior, and establish accountability, all of which are crucial for establishing a safe workplace.

Multiple studies showed that clear, open, and multi-directional communication structures—encompassing both formal (e.g., safety briefings, meetings) and informal (e.g., peer conversations) channels—are crucial for increasing safety in high-risk contexts. Effective communication ensures that safety information, expectations, and concerns are shared promptly, enabling collective awareness and rapid response to hazards [36]. Both top-down (management to workers) and bottom-up (workers to management) communication are necessary: top-down communication clarifies roles and procedures, while bottom-up channels empower employees to report hazards and suggest improvements [37].

Several approaches have been used to study the relationship between safety factors in different sectors. Table 1 summarizes these approaches in the OSH field. However, none of these approaches determined the hierarchy of the safety factors that contribute to the overall level of safety, especially in the construction sector.

Table 1. Summary of different approaches used in modeling safety factors.

Approach	Description and Application	References
Regression Analysis	Used to model relationships between safety outcomes (e.g., incidents) and potential predictors. Includes linear, logistic, and negative binomial regression for crash or incident data	[38,39]
Structural Equation Modeling (SEM)	Assesses direct and indirect effects of multiple factors (e.g., safety climate, rules, behavior) on safety performance, allowing for complex causal modeling	[40,41]
Factor Analysis	Identifies underlying factors that explain observed correlations among measured factors, often used in survey-based safety research	[42]
Machine Learning (ML) Models	Decision trees, random forests, neural networks, and boosting algorithms are used for prediction and to rank the importance of safety-related factors	[15,16]
Meta-Analysis	Aggregates data from multiple studies to estimate pooled effects of various factors on safety performance	[43]
Fuzzy Analytic Network Process (FANP)/FAHP	Weighs and ranks the influence of various safety factors, especially when data is uncertain or subjective.	[44,45]
DEMATEL	To determine the relationship between the factors that affect safety climate.	[46]

2. Methodology

2.1. Key Factors Affecting Safety Levels in the Construction Sector

As mentioned earlier, safety levels in the construction sector are affected by many factors. Table 2 shows the factors included in the current study. The 12 critical factors identified in this study were derived from the Nordic Occupational Safety Climate Questionnaire-50

(NOSACQ-50), a validated instrument widely recognized for measuring the safety climate across various industrial sectors, including construction [47].

Table 2. Factors affecting the level of safety in the construction sector.

Code	Factor	Definition
A1	Resource Allocation	The process of assigning adequate financial, material, and human resources necessary for effective safety implementation.
A2	Safety Observation Frequency	Formal and informal site inspections and observations conducted by supervisors or dedicated safety personnel.
A3	Workers' Training	Providing required safety knowledge and skills to workers through formal training sessions.
A4	Workers' Participation in Safety Decisions	The extent to which workers are actively involved in the development, decision-making, and execution of safety measures.
A5	Safety Motivation	The initiatives created by management to encourage employees to commit to safety, often through rewards/recognition.
A6	Management Commitment and Leadership	The role of senior management in setting the safety direction and personally demonstrating the importance of safety as a core value.
A7	Management Safety Competence	The knowledge, skills, and ability of managers and supervisors to effectively plan, organize, implement, monitor, and enforce safety.
A8	Workers' Safety Competence	The individual worker's capability to perform their assigned duties in a manner that adheres to safety requirements.
A9	Safety Policy and Goal Setting	The formal written document establishing the organization's overall safety objectives, principles, and rules.
A10	Procurement/Subcontractor Management	The method of selecting, pre-qualifying subcontractors and material to ensure they meet the required safety standards.
A11	Communication Structure	The channels used to ensure clear, timely, and accurate transmission of safety information between all organizational levels.
A12	Worker Safety Behavior/Compliance	The actual actions and adherence of workers to established safety rules.

2.2. Experts Selections

The methodology for data collection in ISM analysis uses a systematic way to obtain expert assessments on the relationship between factors. In the current study, a panel of 19 experts, each with adequate levels of expertise in OSH and construction domains, participated in the assessments, as delineated in Table 3 below. Moreover, the specialists were provided with a list that consists of 12 factors that are considered important to safety in the construction industry. Then, the experts received detailed instructions on how to interpret and use the evaluation matrix, to ensure consistency and accuracy in the assessment process. The experts were urged to perform the comparisons based on their professional experience and knowledge in OSH and construction. Each expert performed a pairwise comparison matrix to evaluate how each factor affected the others. Note, employing a purposive sampling strategy, this study deliberately selected experts based on their specialized knowledge and extensive experience within the occupational safety and health (OSH) domain, rather than relying on random selection. Experts were selected based on having sufficient years of hands-on experience in OSH or construction. Moreover, to ensure independence and minimize organizational bias, the panel was recruited from a minimum of five distinct organizations. All expert judgments were collected anonymously.

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Table 3. Profiles of the experts that participated in the research.

Expert #	Academic Level	Occupation	Scope	Years of Experience
1	Doctoral	OSH Learning Facility	Professor, and certified OSH trainer	20
2	Doctoral	Industrial Safety Engineering	Professor, and certified OSH trainer	14
3	Doctoral	Occupational Safety and Health	Associate Professor, and certified OSH trainer	8
4	Master's	OSH Specialist	Commercial Projects	23
5	Master's	Project Manager	Commercial Projects	17
6	Bachelor's	OSH Supervisor	Residential Housing Development	16
7	Bachelor's	OSH Supervisor	Industrial Construction	20
8	Bachelor's	OSH Supervisor	Construction Risk Management	9
9	Bachelor's	Safety Specialist	Commercial Projects	14
10	Bachelor's	Contractor	Mechanical, Electrical, and Plumbing (MEP) Trades	7
11	Bachelor's	Supervisor	Residential Housing Development	21
12	Bachelor's	Contractor	Temporary Works (Scaffolding)	10
13	Bachelor's	Contractor	Residential Housing Development	11
14	Bachelor's	Contractor	Mechanical, Electrical, and Plumbing (MEP) Trades	19
15	Bachelor's	OSH Supervisor	Residential Housing Development	9
16	Bachelor's	OSH Supervisor	Industrial Construction	18
17	Diploma	Supervisor	Residential Housing Development	16
18	Diploma	Supervisor	Residential Housing Development	14
19	Diploma	Safety Assistant	Temporary Works (Falsework)	18

2.3. Interpretive Structural Modeling (ISM)

Considering that safety in the construction sector is continuously affected by many factors, the reason for selecting the ISM is that it is a well-established methodology for identifying relationships among specific items. The steps of ISM development is described below:

Step 1: Development of the Structural Self-Interaction Matrix (SSIM): Experts used pairwise comparisons to establish the relationship between every pair of factors (i and j) based on the defined contextual relation. In the case of Conflicting SSIM Entries, the final accepted entry for all SSIM judgments was determined by the majority rule (the option selected by $\geq$50% of the experts). The relationships are encoded using four symbols:

- V: Factor i affects Factor j.
- A: Factor j affects Factor i.
- X: Factors i and j affect each other.
- O: Factors i and j are unrelated.

Step 2: The SSIM is converted into a binary matrix called the Initial Reachability Matrix (IRM) by replacing the symbols (V, A, X, O) with 1 s or 0 s.

- If the relationship is V, i $\rightarrow$ j is 1 and j $\rightarrow$i is 0.
- If the relationship is A, i $\rightarrow$ j is 0 and j $\rightarrow$ i is 1.
- If the relationship is X, i $\rightarrow$ j is 1 and j $\rightarrow$ i is 1.
- If the relationship is O, i $\rightarrow$ j is 0 and j $\rightarrow$ i is 0.

Step 3: Application of Transitivity and Generation of the Final Reachability Matrix (FRM): The transitivity rule of mathematics is applied to the IRM to determine and incorporate implicit (indirect) relationships. The rule states that if Factor i influences Factor j, and Factor j influences Factor k, then Factor i also implicitly influences Factor k (i.e., i $\rightarrow$ j and j $\rightarrow$ k, implies i $\rightarrow$ k). For example, in the current study Resource Allocation does not directly watch a worker on-site, it influences "Training," and "Training" influences "Compliance." This justifies the "indirect link" created by the math. The resulting matrix, which includes both direct and indirect influences, is the Final Reachability Matrix (FRM). The

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transitivity rule is mathematically represented by the equation for the Final Reachability Matrix, FRM:

$$R = (M + I)^n$$

where

M is the Initial Reachability Matrix (the binary form of the SSIM).
I is the Identity Matrix (a square matrix with ones on the main diagonal and zeros elsewhere)
+ represents the Boolean addition (OR operation: 1 + 1 = 1, 1 + 0 = 1, 0 + 0 = 0).
n is the power to which the matrix must be raised until no further changes occur (i.e., until $R = (M + I)^n = (M + I)^{n+1}$

Step 4: Internal consistency is one of the most often used methods to measure the reliability of a questionnaire. One of the techniques used to assess internal consistency is the item–total correlation method, which is defined as the correlation between an individual item and the total score without that particular item. The corrected item–total correlation test was performed to check if any item in the set of the questionnaire is inconsistent with the averaged behavior of the others. Formula (10) was used to find the corrected item–total correlation [48].

$$Coorected\ item - total\ corraltion = Corr\ (x_i^{(a)}, \sum_{i=1}^{N} X_j - x_i^{(a)})$$

where

$x_i^{(a)}$: The responses of expert a.
$\sum_{i=1}^{N} X_j$: The sum of the experts' responses to question i.

Step 5: Partitioning of the Final Reachability Matrix into Hierarchical Levels: The FRM is partitioned iteratively to assign a hierarchical level to each factor. For each factor, three sets are identified:

- Reachability Set (R(i)): Factors influenced by i.
- Antecedent Set (A(i)): Factors that influence i.
- Intersection Set (I(i)): The intersection of R(i) and A(i). Factors for which R(i) = I(i) are positioned at the topmost level of the hierarchy (the most dependent factors). These factors are then removed, and the process is repeated until levels have been assigned to all factors.

Step 6: Construction of the Diagraph and Final ISM Model: A directed graph (diagraph) was constructed based on the hierarchical levels and the relationships identified in the FRM. All redundant or transitive links were removed from the diagraph to create a simplified, and easily interpretable model of the system's structure.

2.4. MICMAC Analysis

The MICMAC analysis, which is an extension of the ISM process, is applied to the Final Reachability Matrix (FRM) to categorize the system factors based on their relative Driving Power and Dependence Power. The steps involved in the MICMAC analysis are as follows:

Step 1: Calculation of Driving and Dependence Power: The powers are derived directly from the FRM:

- Driving Power (Influence): Calculated as the sum of all '1 s' in the row corresponding to the factor, which represents the total number of other factors it affects.
- Dependence Power: Calculated as the sum of all '1 s' in the column corresponding to the factor, which represents the total number of other factors that affected it.

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Step 2: Driving-Dependence Power Plot is constructed. Dependence power (D) is plotted on the *x*-axis, and Driving power (R) is plotted on the *y*-axis. Each factor is mapped as a point in this plane. The chart's *x*-axis (Driving Power) ranges from the minimum D to the maximum D, and the *y*-axis (Dependence Power) ranges from the minimum R to the maximum R observed among the 12 factors. The standard practice in MICMAC analysis is to set the cut-off boundaries (the intersection point of the four quadrants) at the arithmetic mean (average) of the Driving Power sums and the arithmetic mean of the Dependence Power sums.

Step3: The plot is divided into four quartiles, allowing for the strategic classification of all factors:

Q1. Autonomous Factors: (Low Driving Power, Low Dependence Power) These factors have weak linkages to the other factors. They are usually stable and can be controlled independently.

Q2. Dependent Factors: (Low Driving Power, High Dependence Power) These factors are sensitive to change because they are heavily influenced by the primary drivers and connection factors while having little influence on the system itself. They represent the system's outcomes.

Q3. Linkage Factors: (High Driving Power, High Dependence Power) These factors are extremely unstable and active. Any change in these parameters has a significant impact on others. Due to the complicated feedback loops, strategic intervention in this case necessitates careful preparation.

Q4. Independent/Driver Factors: (High Driving Power, Low Dependence Power) These factors form the system's foundation. They are the most powerful influencers or root drivers, requiring little support from others. These factors represent key levers for systemic transformation.

2.5. Decision Making Trial and Evaluation Laboratory (DEMATEL) Analysis

The DEMATEL analysis is performed after an ISM analysis to complement the structure with quantitative relationship strength, thereby maximizing the advantages of both methods. The DEMATEL method is a structured approach used to analyze complex systems and visualize causal relationships among factors. The process involves several mathematical steps as follows:

Step 1: Establish the Direct Relation Matrix (A) using a numerical scale to perform the pairwise comparisons between the factors. Table 4 illustrates the evaluation criteria.

Table 4. Evaluation criteria used in the DEMATEL pairwise comparisons.

Verbal Judgment	Numerical Scale
No effect	0
Very low effect	1
Low effect	2
High effect	3
Very high effect	4

The responses for all experts are aggregated by taking the average to form the initial Direct Relation Matrix, A = $[a_{ij}]$ where a_{ij} is the averaged degree of direct influence of Factor i on Factor j.

Step 2: The Direct Relation Matrix A is normalized to obtain the Normalized Direct Relation Matrix, *D*. The normalization is typically performed by dividing A by the largest sum of a row in matrix A.

Step 3: Calculate the Total Influence Matrix (*T*) using the formula below:

$$T = D*(I - D)^{-1}$$

where I is the identity matrix.

Step 4: For each Factor i, two key metrics are calculated from the Total Influence Matrix T to Determine Influence Degrees:

- Driving Power (D_i): The sum of the rows in matrix T. This represents the total influence Factor i exerts on all other factors.
- Receiving Power (R_i): The sum of the columns in matrix T. This represents the total influence Factor i receives from all other factors.

Step 5. The calculated D_i and R_i are combined to determine the role of each factor in the system:

- Prominence: The sum of driving and receiving power (Di + Ri). This value shows the overall importance of the factor in the system. Factors with a high prominence are crucial, highly interconnected factors.
- Relation: The difference between driving and receiving power (Di − Ri). This value determines the factor's causal role. If (Di − Ri) > 0, the factor belongs to the Cause Group (net driver). If (Di − Ri) < 0, the factor belongs to the Effect Group (net dependent).

Step 6: Generate the Cause-and-Effect Relationship Diagram, in which the x-axis represents prominence (Di + Ri), and the y-axis represents relation (Di − Ri).

3. Results

3.1. Interpretive Structural Modeling (ISM)

Table 5 illustrates the pairwise relationship prevailing structural self-interaction matrix (SSIM) which shows the relation between the factors according to the experts' evaluations. Moreover, Table 6 represents the initial reachability matrix that was obtained after converting the SSIM to 0's or 1's based on their relationship types. Additionally, Table 7 shows the final reachability matrix after including the transitivity effect between the factors.

For evaluating the internal consistency of the questionnaire, a corrected item–total correlation was used, with the criterion of 0.30 considered an acceptable threshold [48].

The computed values of the corrected item–total correlation between the experts and the behaviors of others are shown in Table 8. Since all these values are significantly above the 0.30 criterion, this indicates a suitable consistency level.

Table 5. Structural self-interaction matrix (SSIM). The symbols ↓ and → indicate the direction of the relationship, where the row factor i influences the column factor j.

Factor i↓/j→	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
A1	_	V	V	V	V	V	V	V	O	V	V	V
A2		_	V	V	V	V	A	X	V	X	V	V
A3			_	V	X	O	A	V	A	O	V	V
A4				_	A	A	A	A	A	V	A	V
A5					_	O	A	V	A	O	A	V
A6						_	X	V	A	O	O	V
A7							_	V	V	V	V	V
A8								_	A	O	A	V
A9									_	V	X	V
A10										_	A	V
A11											_	V
A12												_

Table 6. Initial reachability matrix.

Factor	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
A1	1	1	1	1	1	1	1	1	0	1	1	1
A2	0	1	1	1	1	1	0	1	1	1	1	1
A3	0	0	1	1	1	0	0	1	0	0	1	1
A4	0	0	0	1	0	0	0	0	0	1	0	1
A5	0	0	1	1	1	0	0	1	0	0	0	1
A6	0	0	0	1	0	1	1	1	0	0	0	1
A7	0	1	1	1	1	1	1	1	1	1	1	1
A8	0	1	0	1	0	0	0	1	0	0	0	1
A9	0	0	1	1	1	1	0	1	1	1	1	1
A10	0	1	0	0	0	0	0	0	0	1	0	1
A11	0	0	0	1	1	0	0	1	1	1	1	1
A12	0	0	0	0	0	0	0	0	0	0	0	1

Table 7. Final reachability matrix.

Factor	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
A1	1	1	1	1	1	1	1	1	1 *	1	1	1
A2	0	1	1	1	1	1	1 *	1	1	1	1	1
A3	0	1 *	1	1	1	0	0	1	1 *	1 *	1	1
A4	0	1 *	0	1	0	0	0	0	0	1	0	1
A5	0	1 *	1	1	1	0	0	1	0	1 *	1 *	1
A6	0	1 *	1 *	1	1 *	1	1	1	1 *	1 *	1 *	1
A7	0	1	1	1	1	1	1	1	1	1	1	1
A8	0	1	1 *	1	1 *	1 *	0	1	1 *	1 *	1 *	1
A9	0	1 *	1	1	1	1	1 *	1	1	1	1	1
A10	0	1	1 *	1 *	1 *	1 *	0	1 *	1 *	1	1 *	1
A11	0	1 *	1 *	1	1	1 *	0	1	1	1	1	1
A12	0	0	0	0	0	0	0	0	0	0	0	1

* Asterisk implies that it was derived using the principle of transitivity.

Table 8. Corrected item—total correlation between experts' responses.

Between Expert i and the Remaining Experts	Corrected Item—Total Correlation
E1 and other	0.885
E2 and other	0.902
E3 and other	0.845
E4 and other	0.918
E5 and other	0.923
E6 and other	0.947
E7 and other	0.846
E8 and other	0.864
E9 and other	0.946
E10 and other	0.947
E11 and other	0.91
E12 and other	0.909
E13 and other	0.866
E14 and other	0.907
E15 and other	0.894
E16 and other	0.916
E17 and other	0.923

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Table 8. *Cont.*

Between Expert i and the Remaining Experts	Corrected Item—Total Correlation
E18 and other	0.86
E19 and other	0.879
E20 and other	0.887
E21 and other	0.909

Level partitioning are shown in Tables 9–12, depicting iterations 1–4, respectively. Moreover, Figure 1 shows the ISM diagraph that summarizes the hierarchy and the relationship between the factors affecting safety in the construction sector.

Table 9. Iteration 1 of level partitioning.

Factor	Reachability	Antecedents	Intersection	Level
A1	A1,A2,A3,A4,A5,A6,A7,A8,A9, A10,A11,A12	A1	A1	
A2	A2,A3,A4,A5,A6,A7,A8,A9,A10, A11,A12	A1,A2,A3,A4,A5,A6,A7,A8, A9,A10,A11,	,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,	
A3	A2,A3,A4,A5,A8,A9, A10,A11,A12	A1,A2,A3,A5,A6,A7,A8,A9,A10,A11,	A2,A3,A5,A8,A9,A10,A11	
A4	A2,A4,A10,A12	A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11,	A2,A4,A10	
A5	A2,A3,A4,A5,A8,A10, A11,A12	A1,A2,A3,A5,A6,A7,A8,A9,A10,A11	A2,A3,A5,A8,A10,A11	
A6	A2,A3,A4,A5,A6,A7,A8,A9,A10, A11,A12	A1,A2,A6,A7,A8,A9,A10,A11	A2,A6,A7,A8,A9,A10,A11,	
A7	A2,A3,A4,A5,A6,A7,A8,A9,A10, A11,A12	A1,A2,A6,A7,A9	A2,A6,A7,A9	
A8	A2,A3,A4,A5,A6,A8,A9,A10, A11,A12	A1,A2,A3,A5,A6,A7,A8,A9,A10,A11	A2,A3,A5,A6,A8,A9,A10,A11	
A9	A2,A3,A4,A5,A6,A7,A8,A9,A10, A11,A12	A1,A2,A3,A6,A7,A8,A9, A10,A11	A2,A3,A6,A7,A8,A9,A10,A11	
A10	A2,A3,A4,A5,A6,A8,A9,A10, A11,A12	A1,A2,A3,A4,A5,A6,A7,A8,A9, A10,A11	,A2,A3,A4,A5,A6,A8,A9,A10,A11,	
A11	A2,A3,A4,A5,A6,A8,A9,A10, A11,A12	A1,A2,A3,A5,A6,A7,A8, A9,A10,A11	A2,A3,A5,A6,A8,A9,A10,A11,	
A12	A12	A1,A2,A3,A4,A5,A6,A7,A8,A9, A10,A11,A12	A12	1

Table 10. Iteration 2.

Factor	Reachability	Antecedents	Intersection	Level
A1	A1,A2,A3,A4,A5,A6,A7,A8,A9, A10,A11,	A1	A1	
A2	A2,A3,A4,A5,A6,A7,A8,A9, A10,A11,	A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11	A2,A3,A4,A5,A6,A7,A8, A9,A10,A11	2
A3	A2,A3,A4,A5,A8,A9,A10,A11	A1,A2,A3,A5,A6,A7,A8,A9,A10,A11	A2,A3,A5,A8,A9,A10,A11	
A4	A2,A4, A10	A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11	A2,A4, A10	2
A5	A2,A3,A4,A5,A8,A10,A11,	A1,A2,A3,A5,A6,A7,A8,A9,A10,A11	A2,A3,A5,A8,A10,A11	
A6	A2,A3,A4,A5,A6,A7,A8,A9,A10,A11	A1,A2, A6,A7,A8,A9,A10,A11	A2,A6,A7,A8,A9,A10,A11	
A7	A2,A3,A4,A5,A6,A7,A8,A9,A10,A11	A1,A2,A6,A7,A9	A2,A6,A7,A9	
A8	A2,A3,A4,A5,A6,A8,A9,A10,A11	A1,A2,A3,A5,A6,A7,A8,A9,A10,A11	A2,A3,A5,A6,A8,A9,A10,A11	
A9	A2,A3,A4,A5,A6,A7,A8,A9,A10,A11	A1,A2,A3,A6,A7,A8,A9,A10,A11	A2,A3,A6,A7,A8,A9,A10,A11	
A10	A2,A3,A4,A5,A6,A8,A9,A10,A11	A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,A11	A2,A3,A4,A5,A6,A8,A9,A10,A11	2
A11	A2,A3,A4,A5,A6,A8,A9,A10,A11	A1,A2,A3,A5,A6,A7,A8,A9,A10,A11	A2,A3,A5,A6,A8,A9,A10,A11	

Table 11. Iteration 3.

Factor	Reachability	Antecedents	Intersection	Level
A1	A1,A3,A5,A6,A7,A8,A9,A11,	A1	A1	
A3	A3,A5,A8,A9,A11	A1,A3,A5,A6,A7,A8,A9,A11	A3,A5,A8,A9,A11	3
A5	A3,A5,A8,A11	A1,A3,A5,A6,A7,A8,A9,A11	A3,A5,A8,A11	3
A6	A3,A5,A6,A7,A8,A9,A11	A1,A6,A7,A8,A9,A11	A6,A7,A8,A9,A11	
A7	A3,A5,A6,A7,A8,A9,A11	A1,A6,A7,A9	A6,A7,A9	
A8	A3,A5,A6,A8,A9,A11	A1,A3,A5,A6,A7,A8,A9,A11	A3,A5,A6,A8,A9,A11	3
A9	A3,A5,A6,A7,A8,A9,A11	A1,A3,A6,A7,A8,A9,A11	A3,A6,A7,A8,A9,A11	
A11	A3,A5,A6,A8,A9,A11	A1,A3,A5,A6,A7,A8,A9,A11	A3,A5,A6,A8,A9,A11	3

Table 12. Iteration 4.

Factor	Reachability	Antecedents	Intersection	Level
A1	A1,A6,A7,A9	A1	A1	5
A6	A6,A7,A	A1,A6,A7,A9	A6,A7,A9	4
A7	A6,A7,A9	A1,A6,A7,A9	A6,A7,A9	4
A9	A6,A7,A9	A1,A6,A7,A9	A6,A7,A9	4

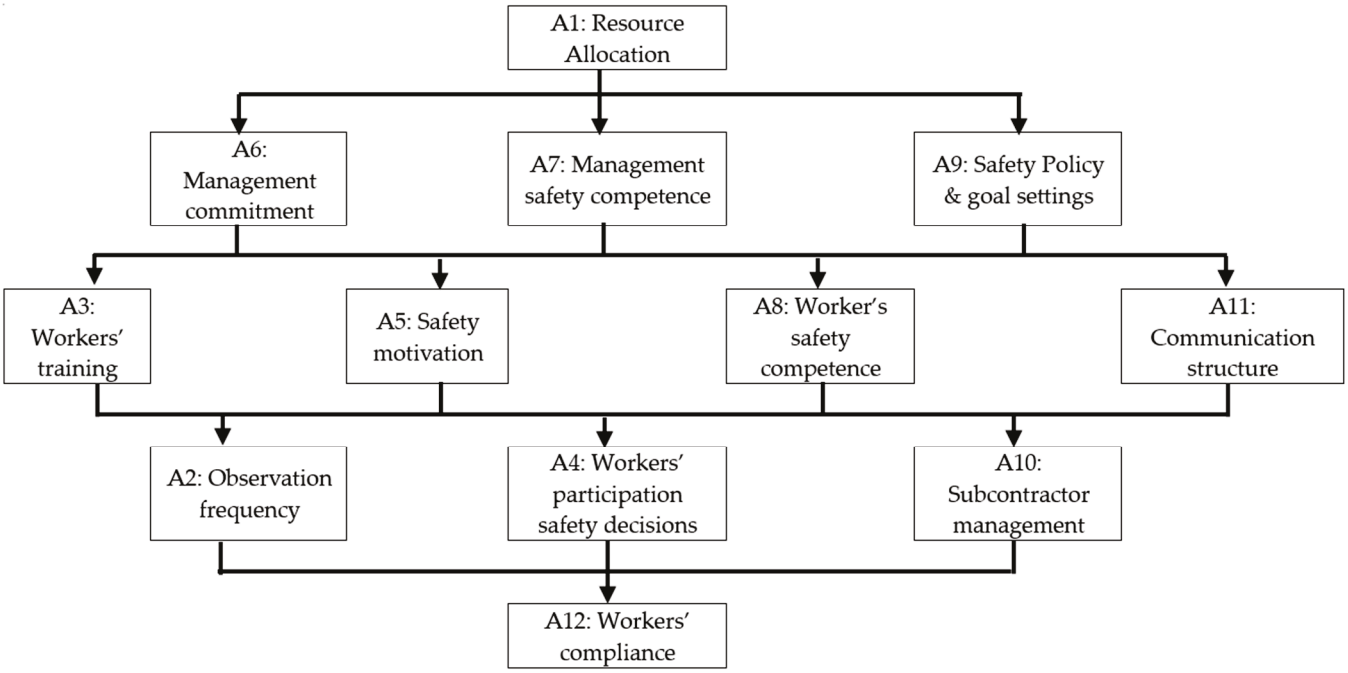

Figure 1. The ISM diagraph.

In order to conduct the MICMAC analysis, the values of the dependence and the driving power of the factors were determined as shown in Table 13. These values are then used to plot the MICMAC chart, which classifies the factors as shown in Figure 2. It is worth noting that none of the selected factors fell under the "autonomous" quartile. The absence of any factor in Quadrant 1 (Autonomous Factors—low driving power, low dependence power) is not an artifact of arbitrary cut-off parameters, but rather a logical consequence of the selection and nature of the factors chosen for the analysis. Autonomous factors are typically disconnected from the rest of the system, and they have few links to other factors and are generally not influenced by them. The twelve factors selected are all fundamental Human and Organizational Performance (HOP) elements in the construction domain. By definition, these factors were specifically chosen because they are believed to be

highly interconnected within the organizational safety system. Therefore, the finding that no factor falls into Q1 confirms that, according to the expert panel, all twelve factors play an active, integral, and necessary role in the influence structure. There are no "isolated" factors that can be ignored. This result strengthens the conclusion that safety in construction is a tightly coupled system.

Table 13. Dependence and driving powers of factors.

Factor	A12	A2	A4	A10	A3	A5	A8	A11	A6	A7	A9	A1
Dependence	12	11	11	11	10	10	10	12	8	5	9	1
Driving	1	11	4	10	9	8	10	10	11	11	11	12
Level	1	2	2	2	3	3	3	3	4	4	4	5

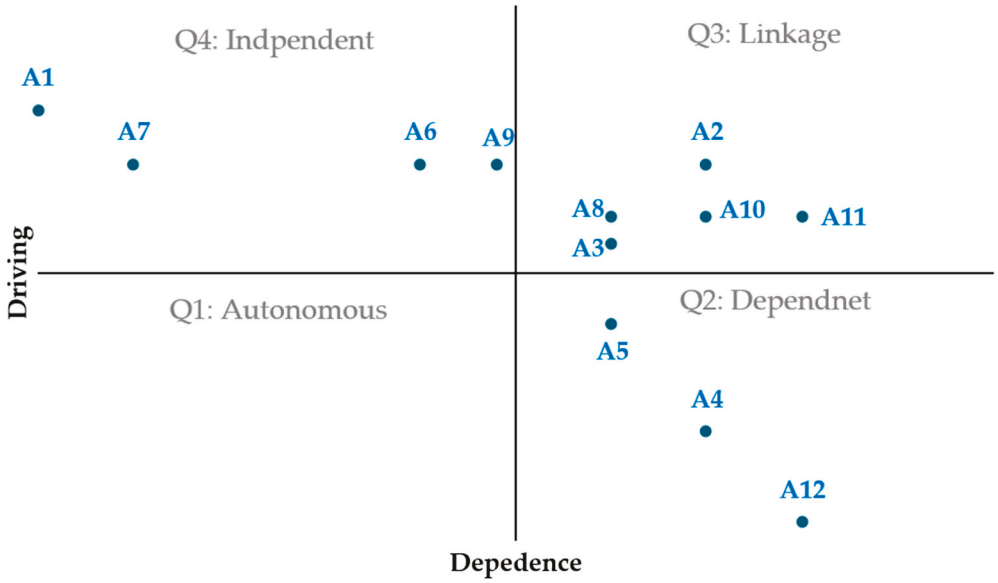

Figure 2. Driving power and dependence diagram.

3.2. DEMATEL

The goal of using the DEMATEL analysis in the current study is to verify the results obtained from the ISM model, and to measure the effect of casual Factors. According to the calculations, A1: Resource Allocation, A6: Management Commitment and Leadership, A7: Management Safety Competence, and A9: Safety Policy and Goal Setting were identified as the most influential causal factors. On the other hand, Factor A12: Worker Safety Behavior/Compliance was the factor that affected by the main causes. These results are consistent with the results obtained from the ISM analysis. Table 14 shows the computations of prominence, relation, and factor type. Similarly, Figure 3 depicts the mapping of cause and effects relationships.

Table 14. Calculation of prominence, relation, and factor type.

Dimension	Prominence	Relation	Factor Types
A1: Resource Allocation	0.850	0.001	Cause
A2: Safety Observation Frequency	0.214	0.302	Effect
A3: Workers' Training	0.163	0.236	Effect
A4: Workers' Participation in Safety Decisions	0.030	0.618	Effect
A5:Safety Motivation	0.123	0.349	Effect
A6: Management Commitment and Leadership	0.240	0.197	Cause

Table 14. *Cont.*

Dimension	Prominence	Relation	Factor Types
A7: Management Safety Competence	0.556	0.183	Cause
A8: Workers' Safety Competence	0.094	0.385	Effect
A9: Safety Policy and Goal Setting	0.427	0.120	Cause
A10: Procurement/Subcontractor Management	0.036	0.334	Effect
A11: Communication Structure	0.151	0.268	Effect
A12: Worker Safety Behavior/Compliance	0.009	0.675	Effect

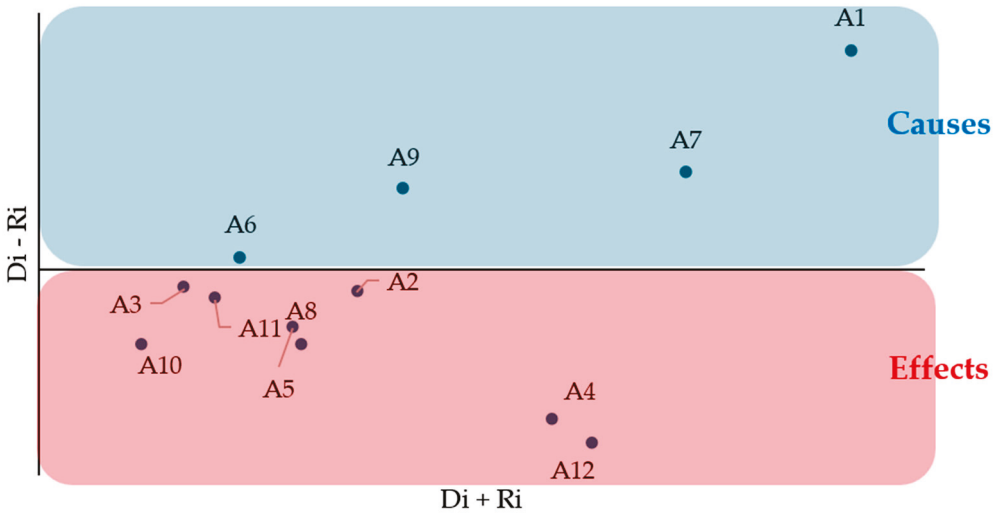

Figure 3. Mapping causes and effects of factors affecting safety levels in the construction industry.

3.3. Sensitivity Analysis

Sensitivity analysis in ISM and MICMAC is crucial primarily to validate the model's robustness and structural stability, as the entire framework is built upon subjective expert judgments in the SSIM. By intentionally altering a few key relationships, analysts can determine if the resulting hierarchical structure (ISM) or factor categorization (MICMAC) is stable; a high degree of sensitivity indicates that the initial consensus requires further investigation to confirm the critical relationships. This process effectively identifies critical leverage points by highlighting factors whose classification (e.g., driver vs. outcome) is vulnerable to input variations, ultimately allowing practitioners to refine strategic intervention plans and increase the credibility and scientific rigor of the final model. In the current study, sensitivity analysis was performed by randomly excluding the assessments of two and three experts, respectively, to test the ISM model's robustness and stability against variations in expert judgment. The sensitivity analysis reveals one shift in the system's structure. Only one factor out of the twelve has been changed. For instance, Factor A8 has moved down from Level 3 to Level 2 and changed from a volatile Linkage Factor to a simple Dependent Factor, signifying that it could be a result driven by higher-level factors. Some experts might view Workers' Safety Competence is positioned as a Dependent Factor because it functions as an outcome or resulting state, driven by higher-level organizational inputs. It could be driven by Workers' Training (which imparts the necessary knowledge and skills), Safety Motivation (which determines the willingness and consistency of application), and the Communication Structure. The finding that only one out of twelve factors experienced minor, single-level positional change in the sensitivity analysis is a strong indicator of the high robustness and structural stability of the ISM model. This minimal movement confirms that the strategic hierarchy—particularly the identification of the top-level drivers and bottom-level outcomes—is reliable and not highly

sensitive to potential subjective variations in the expert judgments (SSIM). Consequently, the core strategic recommendations derived from the original ISM structure are validated, demonstrating that the model accurately captures the fundamental relationships in the system. Table 15 summarizes the sensitivity analysis of the ISM and MICMAC models.

Table 15. Summary of sensitivity analysis.

	Factor Level			Factor Classification		
Factor	**Original**	**2 Experts Excluded**	**3 Experts Excluded**	**Original**	**2 Experts Excluded**	**3 Experts Excluded**
A1	Level 5	Level 5	Level 5	Independent	Independent	Independent
A2	Level 2	Level 2	Level 2	Linkage	Linkage	Linkage
A3	Level 3	Level 3	Level 3	Linkage	Linkage	Linkage
A4	Level 2	Level 2	Level 2	Dependent	Dependent	Dependent
A5	Level 3	Level 3	Level 3	Dependent	Dependent	Dependent
A6	Level 4	Level 4	Level 4	Independent	Independent	Independent
A7	Level 4	Level 4	Level 4	Independent	Independent	Independent
A8 *	Level 3	Level 2	Level 2	Linkage	Dependent	Dependent
A9	Level 4	Level 4	Level 4	Independent	Independent	Independent
A10	Level 2	Level 2	Level 2	Linkage	Linkage	Linkage
A11	Level 3	Level 3	Level 3	Linkage	Linkage	Linkage
A12	Level 1	Level 1	Level 1	Dependent	Dependent	Dependent

* Asterisk Indicates a change in the factor level and type.

4. Discussion

4.1. The Integration of ISM and DEMATEL Models

The main objective of the current study is to determine the relations, hierarchy, and the strength of influence of the factors affecting safety level in the construction sector. Therefore, the ISM analysis was used to determine the relationship between the factors and the DEMATEL analysis was applied to quantify the influence of the casual factors affecting safety levels. The ISM analysis reveals a clear, tiered hierarchy of factors affecting safety in the construction sector. At the foundational and strategic level (Levels 4 and 5) they are the Independent Drivers, which possess the highest driving power and lowest dependence. The absolute most critical factor is A1: Resource Allocation (Level 5), which acts as the root cause influencing the success of nearly every other safety measure. In the field of OSH, resource allocation is the fundamental strategic decision-making process by which an organization dedicates its finite assets toward achieving its health and safety goals [49]. Without adequate resources (funding, personnel, equipment), the quality of policies, management commitment, training programs, and safety observations will all be compromised. Firstly, financial resources (budget) are essential, covering the costs for purchasing high-quality control measures like proper Personal Protective Equipment (PPE) and engineering controls, funding for OSH training, certification programs, and the maintenance of management systems and facilities [50]. This result is in line with previous studies that concluded that recognize that without earmarked funds, safety measures are under-implemented and accident risk rises [51,52]. Secondly, human resources (personnel and expertise) are critical, requiring the allocation of sufficient, qualified safety professionals (such as OSH managers and industrial hygienists) and, crucially, the dedicated, paid time for all employees—from management to frontline workers—to actively participate in safety activities, including training, inspections, and safety committee meetings [53]. A recent study found that recruitment, selection, and training-oriented HR practices significantly improve workers' knowledge and awareness of OHS programs, leading to safer behavior in manufacturing and other industries [54]. Third, the provision and upkeep of essential safety infrastructure, such as emergency communication systems, first-aid stations, and efficient information systems for documenting and evaluating incident data to support ongoing

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improvement, requires the allocation of physical and technical resources. Altogether, the allocation of these three resource types determines the true strength and effectiveness of an organization's OSH management system. Moreover, A1: resource allocation sits at the absolute top of the hierarchy (Level 5). Therefore, improving resource allocation will immediately create a chain reaction, strengthening the other top-tier drivers. The DEMATEL results provide a clear picture of how different organizational factors interact to shape the overall safety level. The prominence values indicate that some factors occupy a more central position in the safety system, whereas the relation values distinguish between those that act primarily as drivers ("cause" factors) and those that function mainly as outcomes ("effect" factors). Resource Allocation (A1) emerges as the most central factor in the network, with the highest prominence (0.850) and a relation value close to zero, and it is classified as a cause factor. This suggests that decisions regarding financial, human, and material resources devoted to safety are foundational and exert influence across the entire system, while being only minimally shaped by other factors. In other words, resourcing appears to be an upstream strategic decision rather than a reactive response to other safety dimensions. This finding supports the view that sustained investment in safety is a precondition for building effective training, observation, and communication practices, rather than a consequence of them.

Key management factors are as follows: A6: Management Leadership and Commitment, A7: Management Safety Proficiency, and A9: Safety Policy and Goal Setting (all level 4). Management must give these fundamental components top priority and make significant investments in order to bring about systemic transformation. Factor A6: Management commitment is crucial because it establishes the organization's safety culture and values and guarantees that management clearly puts safety ahead of budget and schedule. For instance, in an Asian construction company, management commitment was one of only two factors significantly predicting workers' safe behavior [55]. Additionally, in Chinese mining enterprises, safety management commitment increased workers' safety compliance and participation, partly through better training and safety policies [56]. The technical capacity for effective implementation is provided by Factor A7: Management Safety Competence, which enables managers to make well-informed decisions, accurately identify hazards, choose suitable controls, and carry out the required supervision and quality training that directly affect A12: Worker Safety Behavior/Compliance. For example, construction research from Malaysia identified safety management competence (planning, budgeting, training, monitoring) as the top core competency of safety managers, directly tied to lower accident rates on sites [57]. Lastly, Factor A9: Safety Policy acts as the official roadmap and guidance, converting the dedication and proficiency into precise, documented guidelines, protocols, and quantifiable goals that set clear expectations and form the basis for all A3: Workers' Training and compliance initiatives throughout the site [58]. In China, stricter, broader, and more technically detailed safety policies show a strong long-term negative correlation with work-related mortality; increasing stringent policies significantly improved production safety [59]. Without this top-level direction, capability, and commitment, all operational safety initiatives will lack the support, clarity, and resources needed to be sustained which affect the overall safety level [60]. These results are in line with the DEMATEL results, which stated that management-related attributes also figure prominently among the cause factors. Management Safety Competence (A7) shows a relatively high prominence (0.556), indicating that competent managers who understand safety principles and regulatory requirements influence multiple downstream elements. Similarly, Safety Policy and Goal Setting (A9), with a prominence of 0.427, is another influential driver, implying that clearly articulated safety objectives and formalized policies shape how safety is operationalized in daily activities. Management Commitment and Leadership (A6), though having moderate

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prominence (0.240), is also categorized as a cause factor; this suggests that visible leadership support acts as a catalyst that channels resources, reinforces policies, and legitimizes safety initiatives. Together, these results indicate that safety performance is strongly conditioned by the way top and middle management frame, resource, and operationalize safety.

Immediately below these are the Linkage Factors (Level 3), characterized by high driving and high dependence. These include A3: Workers' Training, A8: Workers' Safety Competence, and the essential A11: Communication Structure. These elements are both strong drivers of the factors at the operational level and results of the strategic level (e.g., training depends on resource allocation). A5: Safety Motivation is another factor at this intermediate level. Although it is very dependent, it is essential for creating an engaged safety culture. The function of element A3: Workers' Training in creating A8: competence is a crucial Linkage Factor (Level 3) that converts management's strategic intent into concrete operational capability. A recent study found that construction workers who received safety and health training showed higher safety knowledge, safer behavior, and greater safety awareness than untrained workers [61]. Workers' safety competence is a direct and essential factor in improving workers' compliance [62]. Training enhances the knowledge required to understand specific construction hazards, legal compliance, and the consequences of unsafe acts. Simultaneously, it develops the necessary practical skills, providing instruction and practice in safe operating procedures (SOPs), correct equipment use (including PPE), and emergency response. Thus, training is the essential vehicle that converts management's commitment and allocated resources into an empowered and competent workforce, directly enabling the desired outcome of A12: Worker Safety Behavior/Compliance. Factor A11: Communication Structure is considered a Linkage Factor in the construction site safety model because its defining characteristic is having both high driving power and high dependence, making it a critical intermediary between strategy and execution. Several studies found that clear top-down communication of rules, hazards, and expectations improves workers' understanding of procedures, roles, and safe behavior, boosting performance and motivation [63,64]. Additionally, strong bottom-up paths (easy reporting of hazards, near misses, concerns) support awareness, learning from incidents, and a more supportive climate, reducing accidents and disasters. Its high dependence means the quality of communication is highly sensitive to and determined by factors higher up, specifically the formal establishment from A9: Safety Policy and Goal Setting and the time and resources provided by A1: Resource Allocation and A6: Management Commitment and Leadership [65]. Conversely, its high driving power ensures it is a powerful force for change, acting as the essential channel that transmits safety content for A3: Workers' Training, thereby building A8: Workers' Safety Competence, and serving as the primary feedback loop that encourages A4: Workers' Participation in Safety Decisions [66]. Thus, the communication structure links the strategic will of management to the operational compliance and behavior of the workers, meaning any issue with communication will immediately disrupt the flow of safety information throughout the entire system.

The factors at Level 2 of the safety hierarchy—Safety Observation Frequency, Workers' Participation in Safety Decisions, and Subcontractor and Procurement Management—serve as the critical operational bridge between the high-level management commitment and resources (Levels 3, 4, 5) and the lowest level of on-site behavior, Workers' Compliance (Level 1). Regular observation of site operations offers data and quick feedback for ongoing development [67]. A case study showed safety performance increasing from 86% to 92.9% over 6 weeks after observation-based feedback, goal-setting, and recognition [68]. By actively including the workers in danger identification and process creation, Workers' Participation in Safety Decisions promotes ownership and increases Safety Motivation

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(Level 3) [69]. For example, in Malaysian institutions, employee involvement in formulating safety policies, procedures, and decisions was identified as the most important factor for cultivating a strong safety culture and moving toward zero-accident workplaces [70]. Last but not least, Subcontractor and Procurement Management extends the principal contractor's control over the entire project ecosystem by ensuring that other parties and acquired materials follow project safety standards. Because subcontractors are so prevalent and have such a big impact on construction sites, it is crucial to manage them well. Subcontractors, particularly smaller businesses, sometimes have varied degrees of safety resources and compliance, which, if improperly managed, can result in inconsistent safety procedures and increased accident rates [71,72]. Subcontractors can make up to 90% of the construction workforce and are often small firms with limited safety staff and poorer working conditions, which increases vulnerability to accidents [73]. Moreover, accident rates for subcontractor employees are frequently higher than for principal contractor staff, linked to economic pressure, long hours, weaker training, and fragmented communication. Together, these Level 2 factors represent the practical, action-oriented mechanisms that translate strategic safety goals into tangible, daily safety performance.

Finally, Factor A12: Worker Safety Behavior/Compliance is categorized in the Dependent Quartile (Level 1) in the ISM analysis. This factor exhibits the highest dependence score and the lowest driving power score. This categorization indicates that rather than being the main forces behind change, compliance and behavior are essentially the results of the whole safety management system, for instance, a worker's ability to comply is dictated by whether A1: Resource Allocation provides safe equipment and time, whether A6: Management Commitment enforces rules consistently, and whether A3: Workers' Training has built the necessary A8: Workers' Safety Competence. Multiple studies show that what workers do (compliance and participation) largely reflects the broader safety management system (SMS) and leadership. Across industries, management commitment, training, rules/procedures, communication, promotion policies, and worker involvement influence safety compliance, often via mediators like safety participation, safety knowledge, or motivation [74]. The strategic conclusion is obvious: businesses should prioritize addressing the higher-level Independent Drivers and Linkage Factors that regulate and facilitate safe conduct, rather than concentrating on treating the symptoms (worker behavior). In the DEMATEL analysis, Worker Safety Behavior/Compliance (A12) has the lowest prominence (0.009) but the highest relation value (0.675), positioning it as the most downstream element in the network. This implies that worker behavior is largely a product of upstream conditions rather than an autonomous driver of safety outcomes.

4.2. STAMP Analysis of Construction Safety Control Structure

To strengthen the complexity argument and demonstrate how the ISM-identified hierarchical dependencies operate in practice, this section presents a small case-model using the Systems-Theoretic Accident Model and Processes (STAMP) framework [75]. This case-model illustrates how organizational, management, and frontline safety factors interact through control structures, and feedback loops mechanisms. The STAMP framework conceptualizes safety as an emergent property of a complex socio-technical system where safety is maintained through feedback and control. Figure 4 presents the hierarchical control structure for the construction safety system, mapping the ISM-identified factors A1 to A12 into three distinct control levels.

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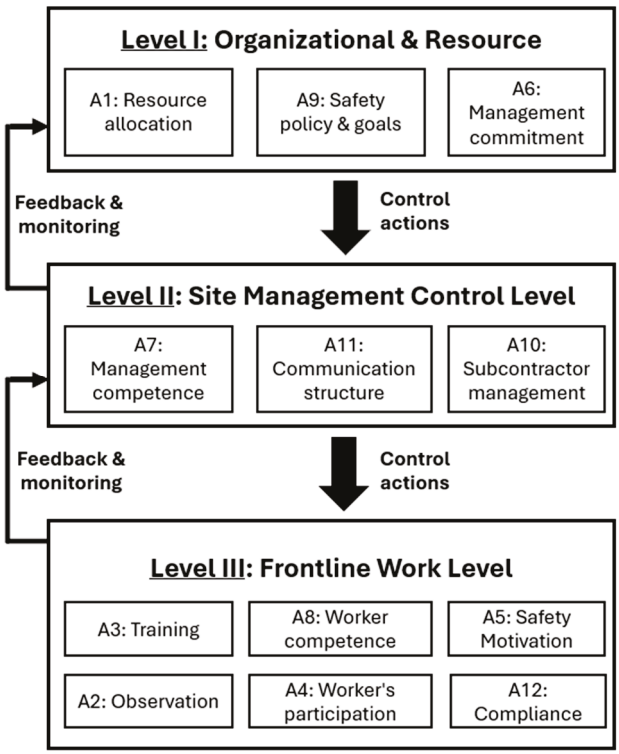

Figure 4. STAMP Control Structure for Construction Safety: Multi-level hierarchy with control and feedback loops.

The hierarchical levels and control actions:

Level I: Organization and Resource Level: These factors generate control actions that cascade downward, determining how much investment and priority are given to safety initiatives at the site level.

Level II: Site Management Control Level: Site managers translate organizational directives into operational safety management. Site managers receive control actions from Level 1 (e.g., resource availability, policy directives) and issue their own control actions downward regarding task planning, work procedures, and resource deployment. They also receive feedback from the frontline through observations, incident reports, and worker communications.

Level III: Frontline Work Level: At the frontline, workers and their immediate supervisors execute safety practices. Frontline factors are influenced by control actions from Level 2 (training programs, supervision schedules, participation opportunities) and generate feedback upward through observations, near-miss reports, and worker suggestions.

Feedback Loops:

The control structure includes critical feedback paths. First, monitoring feedback from Level 3 to Level 2: Safety observations (A2) and workers' participation (A4) provide real-time data on work conditions and compliance (A12). Second, escalation feedback from Level 2 to Level 1: Site managers report safety performance, incident trends, and resource constraints through communication structures (A11), informing higher-level decisions on resource allocation (A1) and policy refinement (A9). These feedback loops are essential for adaptive safety management; without them, the system cannot detect and correct deviations from safe performance.

4.3. Research Limitations

It is worth mentioning the research limitations and future research. ISM is a structural modeling technique; it determines "what affects what" but did not investigate the

measurable effect that occurs in the overall safety level. The model provides a clear structure but lacks empirical evidence regarding the statistical impact of each factor on overall safety performance. Therefore, future studies could investigate the effect of change on the overall system (e.g., how much a 10% increase in Resource Allocation impacts accident rates). Moreover, in the current study, only internal factors were included. However, future research could incorporate external factors, such as regulatory and legal environment, economic conditions, and technological advancement.

5. Conclusions

The current study produced a rigorous, five-level hierarchical structure that maps the dependency and driving power of safety factors within the construction sector, confirming that effective safety management requires strategic intervention at the highest levels of the organization. The model defines Resource Allocation (Level 5) as the most important independent driver, generating the financial and infrastructural capability that directly enables Management Commitment and Competence (Level 4), the fundamental factors influencing safety culture and leadership. These drivers subsequently translate intent into operational effectiveness through Workers Training, Safety Motivation, and Communication Structure (Level 3), alongside critical procedural controls: Safety Observation Frequency, Workers' Participation in Safety Decisions, and Subcontractor and Procurement Management (Level 2). Importantly, the analysis places Workers' Compliance (Level 1) as the most dependent factor, indicating that safety behavior on the job site is an effect rather than a cause of safety outcomes and stating that proactive strengthening of the resource and leadership commitments that come before operational execution is the ultimate control of construction hazards. Additionally, the DEMATEL results suggest that meaningful improvements in safety levels are more likely to be achieved by targeting upstream structural and managerial drivers than by focusing exclusively on downstream behaviors. Enhancing resource allocation for safety (A1), building management safety competence (A7), and strengthening safety policy, goal setting (A9), and leadership commitment (A6) should create favorable conditions that subsequently improve training, communication, motivation, and oversight practices. These changes, in turn, are expected to foster better worker participation, competence, and compliance. From a practical standpoint, the analysis thus argues for a strategic shift from behavior-centric interventions toward system-level managerial and resource reforms as the primary route to sustainable safety enhancement. To summarize, the strategy should be to achieve the appropriate budget and staff allocation for safety, as this single step is the prerequisite for all effective following interventions. If resources are constrained, every lower-level factor—like worker training or providing high-quality PPE—becomes an uphill struggle.

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Conflicts of Interest: The author declares no conflicts of interest.

References

1. Bilim, A. Demographic Analysis of Occupational Safety in the Construction Sector: Strategies and Insights for Risk Reduction. *Buildings* **2025**, *15*, 528. [CrossRef]
2. Juhari, M.L.; Rasli, F.N.; Rahman, A.H.A.; Yusoff, S.; Khalid, M.S. A Review of Occupational Safety and Health in the Construction Sector: Negative Impacts of Workplace Accidents. *Int. J. Acad. Res. Bus. Soc. Sci.* **2023**, *13*, 2682–2691. [CrossRef]
3. Aziz, N.A.A.; Nordin, R.M.; Ismail, Z.; Yunus, J.; Hashim, N. Occupational Safety and Health (OSH) Concept Towards Project Performance. *Built Environ. J.* **2019**, *16*, 55. [CrossRef]

4. El Kholti, R.; Soltani, S.; Durand, P.; El Kholti, A. P-405 Understanding the Role of Determinants in Improving Occupational Health and Safety. *Occup. Med.* **2024**, *74*, 405. [CrossRef]
5. Milošević, I.; Stojanović, A.; Nikolić, Đ.; Mihajlović, I.; Brkić, A.; Perišić, M.; Spasojević-Brkić, V. Occupational health and safety performance in a changing mining environment: Identification of critical factors. *Saf. Sci.* **2025**, *184*, 106745. [CrossRef]
6. Bouraima, M.B.; Gore, A.; Ayyildiz, E.; Yalcin, S.; Badi, I.; Kiptum, C.K.; Qiu, Y. Assessing of causes of accidents based on a novel integrated interval-valued Fermatean fuzzy methodology: Towards a sustainable construction site. *Neural Comput. Appl.* **2023**, *35*, 21725–21750. [CrossRef]
7. Chan, D.W.M.; Baghbaderani, A.B.; Sarvari, H. An Empirical Study of the Human Error-Related Factors Leading to Site Accidents in the Iranian Urban Construction Industry. *Buildings* **2022**, *12*, 1858. [CrossRef]
8. Gul, M.; Ak, M.F. Assessment of occupational risks from human health and environmental perspectives: A new integrated approach and its application using fuzzy BWM and fuzzy MAIRCA. *Stoch. Environ. Res. Risk Assess.* **2020**, *34*, 1231–1262. [CrossRef]
9. Demir, G.; Bouraima, M.B.; Badi, I.; Stević, Ž.; Das, D.K. Identification of Industrial Occupational Safety Risks and Selection of Optimum Intervention Strategies: Fuzzy MCDM Approach. *Mathematics* **2025**, *13*, 301. [CrossRef]
10. Ak, M.F.; Yucesan, M.; Gul, M. Occupational health, safety and environmental risk assessment in textile production industry through a Bayesian BWM-VIKOR approach. *Stoch. Environ. Res. Risk Assess.* **2022**, *36*, 629–642. [CrossRef]
11. Seo, H.J.; Rhee, S.-Y.; Kim, N.K. A Study on the Factors Affecting Safety Behaviors and Safety Performance in the Manufacturing Sector: Job Demands-Resources Approach. *Safety* **2025**, *11*, 29. [CrossRef]
12. Ghahramani, A.; Ebrahimi, M.; Hajaghazadeh, M. Development and psychometric evaluation of an occupational health and safety performance tool for manufacturing companies. *Heliyon* **2023**, *9*, e17343. [CrossRef]
13. Hoła, B.; Nowobilski, T. Analysis of the Influence of Socio-Economic Factors on Occupational Safety in the Construction Industry. *Sustainability* **2019**, *11*, 4469. [CrossRef]
14. Kumar, L.S.; Burns, G.N. Determinants of safety outcomes in organizations: Exploring O*NET data to predict occupational accident rates. *Pers. Psychol.* **2024**, *77*, 555–594. [CrossRef]
15. Omidi, L.; Zakerian, S.A.; Hadavandi, E.; Saraji, J.N. Boosted neural network modeling of psychological and social factors of work affecting safety performance and job satisfaction in the process industry. *BMC Psychol.* **2025**, *13*, 866. [CrossRef]
16. Abbasianjahromi, H.; Aghakarimi, M. Safety performance prediction and modification strategies for construction projects via machine learning techniques. *Eng. Constr. Archit. Manag.* **2023**, *30*, 1146–1164. [CrossRef]
17. Moda, H.M.; Ofodile, N.; Zailani, B.M.; Abubakar, M.; Ibrahim, Y.M. Management support as a critical success factor (CSF) for changing worker's safety attitude: A case of the Nigerian construction industry. *Int. J. Constr. Manag.* **2023**, *23*, 2551–2557. [CrossRef]
18. Jameel, M.; Khan, F. Factors Effecting Safety Culture in the Construction Industry. *Soc. Sci. Rev. Arch.* **2024**, *2*, 928–939. [CrossRef]
19. Him, N.F.; Ismail, W.N.T.; Abdullah, T.N.T. Assessment of safety management attitude practices toward the safety culture of the construction sector. *Plan. Malays.* **2023**, *21*, 12–23. [CrossRef]
20. Anireddy, A.R. Construction Safety Management: Analyzing the Effectiveness of Safety Training Programs on Job Sites. *Int. J. Sci. Res. Eng. Manag.* **2024**, *8*, 1–7. [CrossRef]
21. Chen, Y.; Sridhar, S.; Han, K.; Singh, S.; Mittal, V.; Im, T. The Value of Safety Training for Business-to-Business Firms. *J. Mark. Res.* **2024**, *61*, 742–759. [CrossRef]
22. Senouci, A.; Jedinia, A.; Eldin, N. Safety Performance in Industrial Construction: A Case Study. *J. Civ. Eng. Constr.* **2021**, *10*, 237–244. [CrossRef]
23. Wang, J.-M.; Liao, P.-C.; Yu, G.-B. The Mediating Role of Job Competence between Safety Participation and Behavioral Compliance. *Int. J. Environ. Res. Public Health* **2021**, *18*, 5783. [CrossRef]
24. Zhao, L.; Yang, D.; Liu, S.; Nkrumah, E.N.K. The Effect of Safety Leadership on Safety Participation of Employee: A Meta-Analysis. *Front. Psychol.* **2022**, *13*, 827694. [CrossRef]
25. Basahel, A.M. Safety Leadership, Safety Attitudes, Safety Knowledge and Motivation toward Safety-Related Behaviors in Electrical Substation Construction Projects. *Int. J. Environ. Res. Public Health* **2021**, *18*, 4196. [CrossRef]
26. Syed-Yahya, S.N.; Idris, M.A.; Shimazu, A. Support for safety in the fire service: A test of reciprocal causality for safety motivation. *Ind. Health* **2023**, *61*, 419–431. [CrossRef]
27. Peker, M.; Doğru, O.C.; Meşe, G. Role of Supervisor Behavioral Integrity for Safety in the Relationship Between Top-Management Safety Climate, Safety Motivation, and Safety Performance. *Saf. Health Work* **2022**, *13*, 192–200. [CrossRef] [PubMed]
28. Reiman, T.; Pietikäinen, E. Leading indicators of system safety—Monitoring and driving the organizational safety potential. *Saf. Sci.* **2012**, *50*, 1993–2000. [CrossRef]
29. Zhang, S.; Hua, X.; Huang, G.; Shi, X. How Does Leadership in Safety Management Affect Employees' Safety Performance? A Case Study from Mining Enterprises in China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6187. [CrossRef]

30. Tappura, S.; Kivistö-Rahnasto, J. Assessing and developing safety management competences. *Int. J. Occup. Environ. Saf.* **2018**, *2*, 9–17. [CrossRef]
31. Bafail, O.; Alamoudi, M. Investigation and Analysis of Interrelationships Among Safety Managerial Aspects Affecting Safety Climate Using Decision-Making Trial and Evaluation Laboratory Approach. *Sustainability* **2024**, *16*, 10924. [CrossRef]
32. Tang, Z. Safety Culture in The Construction Industry: A Proposed Enhanced Safety Management Program. *J. Bus. Manag. Stud.* **2025**, *7*, 98–125. [CrossRef]
33. Wijayanto, P. The Effect of OHS Procedures and Worker Competence on Occupational Safety and Health with Worker Communication as a Mediator at Public Company (PERUM) Jasa Tirta II. *Return Study Manag. Econ. Bussines* **2025**, *4*, 269–283. [CrossRef]
34. Pourmazaherian, M.; Musonda, I. Worker competence and safety performance the mediation role of safety orientation in construction industry. *Cogent Public Health* **2022**, *9*, 2145702. [CrossRef]
35. Bautista-Bernal, I.; Quintana-García, C.; Marchante-Lara, M. Safety culture, safety performance and financial performance. A longitudinal study. *Saf. Sci.* **2024**, *172*, 106409. [CrossRef]
36. Zara, J.; Nordin, S.M.; Isha, A.S.N. Influence of communication determinants on safety commitment in a high-risk workplace: A systematic literature review of four communication dimensions. *Front. Public Health* **2023**, *11*, 1225995. [CrossRef]
37. Andelia, N.; Silaban, G.; Syahri, I.M. The Impact of Leadership and Communication on Safety Culture Maturity Level. *Contag. Sci. Period. J. Public Health Coast. Health* **2023**, *4*, 1056. [CrossRef]
38. Pernetti, M.; Antoniazzi, A.; Ketabdari, M.; Crispino, M.; Toraldo, E. Determining the Safety Level of State Roads: An Italian Case Study. *Appl. Sci.* **2024**, *14*, 6663. [CrossRef]
39. Oah, S.; Na, R.; Moon, K. The Influence of Safety Climate, Safety Leadership, Workload, and Accident Experiences on Risk Perception: A Study of Korean Manufacturing Workers. *Saf. Health Work* **2018**, *9*, 427–433. [CrossRef]
40. Bae, J.-H.; Park, J.-W. Research into Individual Factors Affecting Safety within Airport Subsidiaries. *Sustainability* **2021**, *13*, 5219. [CrossRef]
41. Stefanović, V.; Milijić, N.; Urošević, S.; Mladenović-Ranisavljević, I.; Završnik, B. New approach of modeling influential factors of safety climate in industrial companies with a predominantly female labor force. *Serbian J. Manag.* **2025**, *20*, 137–156. [CrossRef]
42. Abikenova, S.; Aitimova, S.; Daumova, G.; Koval, A.; Sarybayeva, I. Statistical Monitoring of OSH: Analysis of Deviations and Recommendations for Optimization. *Int. J. Saf. Secur. Eng.* **2023**, *13*, 1049–1059. [CrossRef]
43. Prihatiningsih, S.; Martiana, T.; Widajati, N.; Fajar, J.K. Determinants of safety performance in healthcare settings: A meta-analysis. *Narra J.* **2025**, *5*, e1654. [CrossRef]
44. Eskandari, D.; Gharabagh, M.J.; Barkhordari, A.; Gharari, N.; Panahi, D.; Gholami, A.; Teimori-Boghsani, G. Development of a scale for assessing the organization's safety performance based fuzzy ANP. *J. Loss Prev. Process Ind.* **2021**, *69*, 104342. [CrossRef]
45. Soltanzadeh, A.; Zarei, E.; Mahdinia, M.; Sadeghi-Yarandi, M. An integrated approach to assess safety and security risks in chemical process industries. *J. Loss Prev. Process Ind.* **2024**, *90*, 105344. [CrossRef]
46. Bafail, O.; Alamoudi, M. Prioritizing Worker-Related Factors of Safety Climate Using Fuzzy DEMATEL Analysis. *Systems* **2025**, *13*, 383. [CrossRef]
47. Kines, P.; Lappalainen, J.; Mikkelsen, K.L.; Olsen, E.; Pousette, A.; Tharaldsen, J.; Tómasson, K.; Törner, M. Nordic Safety Climate Questionnaire (NOSACQ-50): A new tool for diagnosing occupational safety climate. *Int. J. Ind. Ergon.* **2011**, *41*, 634–646. [CrossRef]
48. Javali, S.B.; Gudaganavar, N.V.; Raj, S.M. Effect of Varying Sample Size in Estimation of Coefficients of Internal Consistency Effect of Varying Sample Size in Estimation of Coefficients of Internal Consistency. *WEbmed Cent. Biostat.* **2011**, *2*, 1–8.
49. Peng, J.; Zhang, Q.; Feng, Y.; Liu, X. Optimization of construction safety resource allocation based on evolutionary game and genetic algorithm. *Sci. Rep.* **2023**, *13*, 17097. [CrossRef]
50. Yang, K.; Kim, K.; Go, S. Towards Effective Safety Cost Budgeting for Apartment Construction: A Case Study of Occupational Safety and Health Expenses in South Korea. *Sustainability* **2021**, *13*, 1335. [CrossRef]
51. Sitanggang, A.P.; Manurung, E.H.; Purwanto, D. Occupational Safety and Health (K3) Budget for Construction in Accordance with the Omnibus Law. *SENTRI J. Ris. Ilm.* **2024**, *3*, 823–827. [CrossRef]
52. Seo, H.J.; Rhee, S.-Y.; Yoon, Y.-G. Enhancing Worker Safety Behaviors Through the Job Demands–Resources Approach: Insights from the Korean Construction Sector. *Buildings* **2025**, *15*, 486. [CrossRef]
53. Obeidat, M.S.; Sarhan, L.O.; Qasim, T.Q. The influence of human resource management practices on occupational health and safety in the manufacturing industry. *Int. J. Occup. Saf. Ergon.* **2023**, *29*, 1279–1293. [CrossRef] [PubMed]
54. Ajmal, M.; Isha, A.S.N.; Nordin, S.M.; Al-Mekhlafi, A.-B.A. Safety-Management Practices and the Occurrence of Occupational Accidents: Assessing the Mediating Role of Safety Compliance. *Sustainability* **2022**, *14*, 4569. [CrossRef]
55. Badriyah, L.; Widajati, N.; Haqi, D.N.; Ernawati, M. The Effect of Occupational Health and Safety (OHS) Management on Safety Behavior of Workers at Construction Service Company in Surabaya. *J. Vocat. Health Stud.* **2022**, *6*, 134–141. [CrossRef]

56. Lu, Y.; Taksa, L.; Jia, H. Influence of management practices on safety performance: The case of mining sector in China. *Saf. Sci.* **2020**, *132*, 104947. [CrossRef]
57. Adnan, H.; Yussof, F.N.M.; Jaafar, F.W.; Rashid, Z.Z.A.; Abidin, Z.Z.; Bakhary, N.A. Safety Manager Competencies in Managing Construction Projects in Malaysia. *IOP Conf. Ser. Earth Environ. Sci.* **2019**, *385*, 012057. [CrossRef]
58. Nykänen, M.; Puro, V.; Tiikkaja, M.; Kannisto, H.; Lantto, E.; Simpura, F.; Uusitalo, J.; Lukander, K.; Räsänen, T.; Heikkilä, T.; et al. Implementing and evaluating novel safety training methods for construction sector workers: Results of a randomized controlled trial. *J. Saf. Res.* **2020**, *75*, 205–221. [CrossRef]
59. Wang, X.; Wei, C.; He, Y.; Zhang, H.; Wang, Q. Research on the Correlation between Work Accidents and Safety Policies in China. *Processes* **2021**, *9*, 805. [CrossRef]
60. Bundalevski, S.; Gjorgjiev, M. The influence of occupational safety training management on the perception of safety among construction workers. *Ekonomika* **2025**, *71*, 13–22. [CrossRef]
61. Bęś, P.; Strzałkowski, P. Analysis of the Effectiveness of Safety Training Methods. *Sustainability* **2024**, *16*, 2732. [CrossRef]
62. Jamil, Z.; Nordin, S.M.; Miraj, M.; Alqahtani, M.; Shaik, R.A.; Akhtar, S.; Isha, A.S.N. Sustainable safety practices and hazard management in the oil and gas industry: An HSE perspective. *Front. Public Health* **2025**, *13*, 1611106. [CrossRef]
63. Nordin, S.M.; Rizal, A.R.A.; Rashid, R.A.; Omar, R.C.; Priyadi, U. Incidents and Disaster Avoidance: The Role of Communication Management and the Organizational Communication Climate in High-Risk Environments. *Sustainability* **2021**, *13*, 10138. [CrossRef]
64. Cigularov, K.P.; Chen, P.Y.; Rosecrance, J. The effects of error management climate and safety communication on safety: A multi-level study. *Accid. Anal. Prev.* **2010**, *42*, 1498–1506. [CrossRef]
65. Acheampong, A.; Adjei, E.K.; Adade-Boateng, A.; Acheamfour, V.K.; Afful, A.E.; Boateng, E. Impact of construction workers informal safety communication (CWISC) on safety performance on construction sites. *Eng. Constr. Archit. Manag.* **2025**, *32*, 4338–4356. [CrossRef]
66. Mutlu, N.G.; Altuntas, S. Developing an integrated conceptual framework for monitoring and controlling risks related to occupational health and safety. *J. Eng. Res.* **2021**, *9*, 262–278. [CrossRef]
67. Varma, P.; Dash, M.; Sagar, V.J.; Purohit, S. Examining the Effect of Occupational Health and Safety Practices on Improving Workplace Safety Outcomes. *Health Leadersh. Qual. Life* **2022**, *1*, 143. [CrossRef]
68. Choudhry, R.M. Behavior-based safety on construction sites: A case study. *Accid. Anal. Prev.* **2014**, *70*, 14–23. [CrossRef] [PubMed]
69. Kim, M.-J.; Ahn, S.-P.; Shin, S.-H.; Kang, M.-G.; Won, J.-H. Comparison of Influencing Factors on Safety Behavior and Perception Between Contractor Managers and Subcontractor Workers at Korean Construction Sites. *Buildings* **2025**, *15*, 963. [CrossRef]
70. Ahmad, S.; Zain, A.Z.M.; Rahman, I.A.; Fadzil, S.M.; Zulkifly, S.S. The Relationship Impact of Employee Participation in the Safety Culture of TVET Institutions in Malaysia. *PaperASIA* **2025**, *41*, 322–329. [CrossRef]
71. Dale, A.M.; Colvin, R.; Barrera, M.; Strickland, J.R.; Evanoff, B.A. The association between subcontractor safety management programs and worker perceived safety climate in commercial construction projects. *J. Saf. Res.* **2020**, *74*, 279–288. [CrossRef]
72. Liu, K.; Luo, X.; Feng, J.; Li, H.; Liu, B.; Jian, Y. Research on the Impact of Managers' Safety Perception on Construction Workers' Safety Behaviors. *Buildings* **2024**, *14*, 3467. [CrossRef]
73. Çeküç, S.; Gürcanlı, G.E.; Akın, F.D.; Kale, Ö.A. Determination of Subcontractor Selection Criteria from the View of Occupational Health and Safety in the Construction Industry. *Int. J. Adv. Eng. Pure Sci.* **2024**, *36*, 23–32. [CrossRef]
74. Valluru, C.T.; Dekker, S.; Rae, A. How and why do subcontractors experience different safety on high-risk work sites? *Cogn. Technol. Work.* **2017**, *19*, 785–794. [CrossRef]
75. Leveson, N.G. A systems-theoretic approach to safety in software-intensive systems. *IEEE Trans. Dependable Secur. Comput.* **2004**, *1*, 66–86. [CrossRef]

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Transnational Construction Project Risk Factors and Their Impact Pathways

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Abstract

This paper investigates risk factors and their propagation pathways in multinational building projects. An initial set of 30 key risk variables associated with transnational engineering projects was identified. Using Interpretive Structural Modeling (ISM), we constructed a hierarchical framework to elucidate the interrelationships and transmission dynamics among risk factors. The Cross-Impact Matrix Multiplication Applied to Classification (MICMAC) method was then employed to categorize these factors into three distinct layers: root causes, intermediaries, and surface-level outcomes. Our analysis revealed 16 risk transmission pathways. Among the 30 variables, four were identified as root drivers, 22 as propagation factors, and four as surface triggers. Risk typically migrates from the root layer to the surface within three to four steps. Notably, ten factors—most prominently stakeholder demand mismatch, sociocultural conflict, and inefficient information exchange—collectively account for 55% of the total causal influence, forming the "risk core" of the system. This study enhances the theoretical understanding of risk evolution in international construction projects and offers practical guidance for effective risk management.

Keywords: transnational construction projects; risk management; ISM; MICMAC

1. Introduction

In the context of the accelerating pace of globalization, transnational construction projects have emerged as a vital force in driving international economic cooperation and infrastructure development. However, these large-scale projects are fraught with complex and interrelated risks, leading to frequent project failures, significant economic losses, and far-reaching socio-economic impacts. Although existing research has made progress in identifying risk factors, it remains largely fragmented—often focusing on a single isolated dimension of project vulnerability and lacking a systematic or empirical classification of their interrelationships. This fragmented approach fails to capture the overall risk structure of transnational projects, leaving managers and policymakers without a clear roadmap for predicting, mitigating, or responding to cascading failures. As the scale and geographical scope of such projects continue to expand, the urgency of establishing a holistic and hierarchical understanding of their risk mechanisms has become increasingly apparent.

This study offers novel insights into the mechanisms underlying the impact of risk factors in transnational construction projects. By virtue of this study, engineering managers can clarify the hierarchy of risks and the transmission pathways of risks in transnational construction projects, thereby facilitating the development of risk control measures by managers of such projects.

2. Literature Review

2.1. Risk Classification

Researchers have classified risk concerns in multinational engineering projects from multiple viewpoints. Initial studies often classified these risk factors into two main categories: external risks and internal risks. External risks pertain to uncertainties in the project's external environment and mainly consist of natural environment risks (such as earthquakes, floods, and extreme weather conditions) [1], political risks (such as policy changes, wars, and expropriation) [2], economic risks (such as exchange rate fluctuations, inflation, and changes in market demand) [3], and socio-cultural risks (such as labor conflicts, religious customs, and community resistance) [4]. Internal risks, on the other hand, refer to uncertainties within the organization during project implementation and primarily include technical risks (such as design flaws and immature construction techniques) [3], management risks (such as decision-making errors and improper resource allocation), and contractual risks (such as ambiguous terms and claim disputes). Additionally, some scholars [5] have classified risks from the perspective of the entire project life cycle, dividing them into pre-project risks (such as deviations in feasibility studies and errors in bidding strategies), design phase risks (such as conflicts in standards and design changes), construction phase risks (such as supply chain disruptions and safety accidents), and operation phase risks (such as overruns in maintenance costs and insufficient market demand).

Recent research has increasingly utilised more thorough classification frameworks for risks in multinational engineering projects. These frameworks generally include target risks (such as conflicts among stakeholders' objectives and compliance failures) [6], environmental risks (including geopolitical issues, market volatility, and natural disasters) [7], technical risks (involving differences in technical standards and insufficient maturity of innovative technologies), organizational risks (such as barriers in cross-cultural management and inefficient team collaboration) [8], information risks (arising from delays in data transmission and the presence of information silos) [9], and management risks (including lengthy decision-making processes and reliance on single financing channels) [10]. This classification approach provides a more systematic coverage of the diverse uncertainties faced by transnational engineering projects, thereby offering clearer guidance for risk management.

Current taxonomies of risk are overly broad, lacking the detailed specificity required for the unique context of transnational engineering projects. A significant portion of the literature [5,11] continues to depend on simplistic dichotomies such as "internal vs. external risks" or "political–economic–technological" classifications, thereby failing to differentiate risk types according to the project-specific contingencies inherent in transnational endeavors—specifically, the EPC (Engineering-Procurement-Construction) turnkey contracting model, consortium governance complexities, and conflicts among diverse technical standards.

2.2. Methods for Risk Identification

The evolution of the methodology for risk analysis in transnational engineering projects reflects the synergistic development of risk management theory and engineering practice. Early research primarily relied on qualitative analysis methods. Expert interviews, for instance, demonstrated unique value in identifying latent risks such as political risks, yet they were subject to significant subjectivity [12]. Case analysis, through systematic examination of failure cases, established a framework for risk pattern recognition, but its generalizability was constrained by the specificity of the cases studied [13]. The Delphi method, by conducting multiple rounds of expert surveys, effectively converged risk lists, but it was limited by its time-consuming nature and dependence on experts [14].

In recent years, risk analysis methods have shown a trend of integrating qualitative and quantitative approaches. Pitchaimuthu et al. [15] combined Interpretive Structural Modeling (ISM) with System Dynamics (SD), using ISM to identify key risk factors and then employing SD to simulate the dynamic evolution process. This approach was successfully applied to risk analysis in Belt and Road projects. Chen et al. [16] innovatively introduced Social Network Analysis (SNA), using centrality analysis to identify key nodes in the risk network and uncovering risk aggregation phenomena that were difficult to detect with traditional methods. Machine learning methods, such as the XGBoost (eXtreme Gradient Boosting) algorithm [17], have achieved an accuracy rate of 89% in risk early warning, while Long Short-Term Memory (LSTM) neural networks have shown excellent performance in time-series risk prediction, although they face the issue of being a "black box." Digital twin technology [18] has enabled real dynamic risk assessment by establishing real-time interaction between physical projects and virtual models, but it requires a robust Internet of Things (IoT) infrastructure to support its implementation.

The methodological literature [19] indicates that ideal research on engineering risk management should achieve "triangulation": the theoretical dimension (literature review), the expert dimension (Sheffield method), and the practice dimension (questionnaire survey). This study strictly follows this paradigm by first establishing an initial framework through a literature review, then refining it iteratively with expert input, and finally validating it with questionnaire data, thus forming a complete methodological chain. Particularly in addressing unique issues of transnational engineering projects, such as cultural risks and conflicts in technical standards, this mixed-method approach identifies 23% more key risk factors than a single method [20].

Nevertheless, prevailing approaches to risk-factor identification have yet to embrace triangulated validation, thereby undermining the credibility of their findings. Most studies rely on a single method—such as expert elicitation or machine-learning algorithms—without addressing the absence of theory-expert-practice triangulation [21]. For instance, although Yang et al. [22] report an 89% accuracy for their XGBoost model, the training data remain undisclosed and thus non-replicable, and the model offers no theoretical or empirical account of how latent risks such as "technical-standard conflicts" are identified.

2.3. Contributions of This Study

Question 1: Existing risk frameworks for transnational construction projects suffer from coarse contextual granularity and limited practical applicability. Can a more fine-grained and systemically comprehensive risk taxonomy be developed?

To address this question, we propose a six-dimensional risk taxonomy that decomposes into 30 specific risk factors. The schema furnishes an operationally detailed, systemic theoretical lens for mapping the full risk profile of transnational construction endeavors.

Question 2: Existing research offers insufficient specification of the mechanisms by which risks propagate across factors, thereby depriving managers of the means to pinpoint root causes and disrupt propagation routes. Can an empirically validated, multi-layer causal hierarchy and set of propagation channels be uncovered?

In response, we integrate Interpretative Structural Modeling (ISM) with MICMAC analysis to construct a four-level causal hierarchy and identify sixteen empirically grounded risk-propagation pathways. This transforms an otherwise unordered risk set into a stratified, relationally transparent decision model, supplements the literature with evidence-based risk-transmission mechanisms, and equips practitioners with concrete levers for locating root causes and severing propagation routes.

3. Risk Factor Identification

3.1. Preliminary Identification of Risk Factors

To comprehensively identify the risk factors of transnational engineering projects, this paper integrates the characteristics of transnational construction projects with relevant literature to preliminarily identify various types of risks associated with transnational construction projects. External risks mainly include natural risks, geological risks, political risks, economic risks, social risks, and cultural risks; internal risks are primarily composed of technical risks, project execution risks, organizational management risks, and contract risks.

Based on the screening of the aforementioned risk factors and in combination with the characteristics of transnational engineering projects, we have categorized the risk factors of overseas construction projects into six dimensions, namely objectives, environment, technology, organization, information, and management. Drawing on existing research, we have compiled the risk factors of transnational engineering projects across these six dimensions and developed a survey questionnaire. The questionnaire was distributed to experts in this field. This study employed a two-round Delphi approach, inviting domain experts who had participated in transnational construction projects to assess the reasonableness of the risk factors and to propose revisions to the draft questionnaire based on their feedback. Table 1 summarizes their profiles.

Table 1. Profiles of the Experts.

No.	Professional Title	Affiliation
1	Professional	Liaocheng University
2	Associate Professor	Liaocheng University
3	Associate Professor	Liaoning Technical University
4	Associate Professor	Liaoning Institute of Science and Engineering
5	Lecturer	Fuyang Normal University
6	Senior Engineer	China State Construction Engineering Corporation
7	Senior Engineer	China State Construction Engineering Corporation
8	Engineer	China State Construction Engineering Corporation

In Round 1 of the Delphi survey, risk factors for overseas construction projects were discussed with the experts. Based on their responses, the risk factors initially extracted from the literature were supplemented and refined as follows.

① The scope of "project complexity" is too broad; it can cover objectives, organization, technology, environment, management, and more. Therefore, this paper replaces "project complexity" with "technical complexity."

② The term "organizational risk" is inappropriate and is rephrased as "risk of dynamic adaptation of organizational structure."

③ The expression "BIM technology risk" is also unsuitable and is revised to "risk of digital collaboration technology failure."

In the second-round Delphi interview, experts were asked to evaluate the risk factors revised in Round 1. The results showed that the experts essentially reached a consensus on the revisions.

After two rounds of Delphi interviews, a consolidated set of 34 risk factors specific to transnational construction projects was established across six dimensions: objectives, environment, technology, organization, information and management, as detailed below.

Objectives dimension: Inconsistency in Project Objectives at Various Stages (V1); Compliance Objectives Failure Risk (V2); Conflict of Sustainable Development Goals (V3); Stakeholder Coordination Failure Risk (V4); Inconsistent Needs of Stakeholders (V5); Project Milestone Breach Risk (V6).

Technology dimension: Dynamic Adaptation Risk of Technical Standards (V7); Engineering Design Integrity Risk (V8); Process Change Chain Risk (V9); Innovation Technology Maturity Risk (V10); Digital Collaboration Technology Failure Risk (V11); Technical Complexity Risk (V12).

Organization dimension: Cross-Cultural Governance Efficiency Risk (V13); Dynamic Adaptation Risk of Organizational Structure (V14); Team Collaboration Efficiency Decline Risk (V15); Improper Allocation of Project Management Resources Risk (V16); EPC Collaboration Failure Risk (V17).

Environment dimension: Consortium Strategic Deviation Risk (V18); Localization of Resource Integration Risk (V19); Geopolitical Extreme Risk (V20); Market Environment Perception Bias Risk (V21); Supply Chain Resilience Insufficiency Risk (V22); Socio-Cultural Conflict Risk (V23); Natural Disasters and Climate Risk (V24).

Information dimension: Information Uncertainty (V25); Inefficient Information Communication (V26).

Project Information Collaboration Barrier Risk (V27); Information Acquisition Capability and Extent (V28).

Management dimension: Improper Project Management Decision-Making Process (V29); Uncertainty in Project Management Methods and Tools (V30); Insufficiently Diversified Financing Channels (V31); Project Contract Relationship (V32); Technology Transfer Compliance Risk (V33); Improper Allocation of Project Management Resources Risk (V34).

3.2. Design and Distribution of the Questionnaire

This study developed questionnaire items and used a 5-point Likert scale to evaluate the 34 risk variables across the six dimensions, based on the six risk dimensions and 34 risk factors listed in Table 2. The following is how the scale was adjusted based on how significant each risk element was thought to be in relation to international building projects: 3 = "Moderate," 4 = "Important," and 5 = "Very Important," Two is "Unimportant," and one is "Very Unimportant."

Table 2. Further Reliability Analysis of Measurement Data for Risk Factors in Multinational Construction Projects.

Risk Factor	Item-Test Correlation	Cronbach's α After Item Deletion	Overall Cronbach's α
V1	0.3629	0.9087	
V2	0.3258	0.9091	
V3	0.3599	0.9090	
V4	0.7554	0.9055	
V5	0.3569	0.9100	
V6	0.5530	0.9062	
V7	0.6210	0.9049	

Table 2. *Cont.*

Risk Factor	Item-Test Correlation	Cronbach's α After Item Deletion	Overall Cronbach's α
V8	0.3527	0.9088	
V9	0.8827	0.8982	
V10	0.5568	0.9065	
V11	0.3729	0.9087	
V12	0.3227	0.9008	
V13	0.5635	0.9077	
V14	0.8749	0.9042	
V15	0.4635	0.9077	
V18	0.8110	0.9026	
V19	0.5837	0.9056	
V20	0.8869	0.9008	
V21	0.7310	0.9024	
V22	0.5115	0.9086	
V23	0.5645	0.9059	
V24	0.7081	0.9051	
V25	0.5377	0.9066	
V26	0.7659	0.9027	
V27	0.6466	0.9049	
V28	0.3493	0.9088	
V29	0.5412	0.9118	
V30	0.3987	0.9083	
V31	0.8169	0.9010	
V33	0.4156	0.9005	
			0.9094

In addition to academic specialists, university teachers, and doctoral and master's degree students involved in engineering research, the poll also targeted practitioners with experience in international construction projects. 246 people answered the survey, which was sent out between April and May of 2025. A final sample of 211 valid responses, with an effective response rate of 86.1%, was obtained after 35 invalid questionnaires were eliminated throughout the screening process. Incomplete or missing responses, duplicate responses within the same project, and responses that were uniform or systematic, suggesting a lack of effort, were among the criteria used to weed out surveys that were deemed invalid. A total of 53.6% of the respondents had at least four years of work experience in international construction projects, and 79.6% of the valid questionnaires were filled out by people with a bachelor's degree or above. The respondents' extensive work experience and high level of education guaranteed both the efficacy of the survey and the calibre of the questionnaire responses. Stata 15 software was used to analyse the data.

3.3. Multivariate Data Analysis of the Sample

3.3.1. Reliability Analysis

Cronbach's α coefficient, Cronbach's α values after item deletion, and corrected item–total correlation (CITC) were used in this study to assess the data's reliability. Better internal consistency and reliability of the questionnaire are indicated by higher Cronbach's α values, which range from 0 to 1. Generally speaking, an α score less than 0.7 indicates poor consistency, which may call for the addition or removal of pertinent items. The CITC value is used to assess the consistency of individual items with the rest of the items. A CITC value of no less than 0.3 is considered acceptable for the consistency of the item with other items.

The Cronbach's α value after item deletion reflects the change in the internal consistency coefficient of the subscale composed of the remaining items after removing a particular item. Generally, if the Cronbach's α value after deleting a specific item is lower than the overall Cronbach's α value, it indicates that the item has a positive effect on the internal consistency of the entire questionnaire, suggesting better internal consistency of the questionnaire.

For 34 risk factors, we performed a reliability analysis on the survey data. The total measuring scale has a high degree of reliability, as indicated by the overall Cronbach's α coefficient of 0.8825, which is higher than 0.7. However, V16, V17, V32, and V34 did not fulfil the criterion since their Corrected Item-Total Correlation (CITC) values were all less than 0.3. Consequently, it is necessary to eliminate V16, V17, V32, and V34 from the analysis.

Table 2 provides additional examination of the measurement data's dependability following item deletion. When V16, V17, V32, and V34 are eliminated, the total Cronbach's α is 0.9094, which is higher than 0.7. Following the deletion of each item, the Cronbach's α values are all less than the total Cronbach's α value. Thus, after removing V16, V17, V32, and V34, the measurement data's overall reliability satisfies the criteria.

3.3.2. Exploratory Factor Analysis

Considering that there may be relatively strong correlations among the risk factors of overseas construction projects, it is necessary to employ exploratory factor analysis (EFA) to classify the 30 risk factors analyzed above. Prior to conducting the EFA, the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity should be performed to determine whether the variables are suitable for factor analysis. The KMO value ranges from 0 to 1. Higher values indicate stronger correlations among variables and greater suitability for factor analysis. The KMO value for the measurement data of risk factors in multinational construction projects is 0.806 (greater than 0.7), and the significance level of Bartlett's test of sphericity is 0.000 (less than 0.001), indicating that there are correlations among the risk factors of overseas construction projects, and exploratory factor analysis can be conducted.

Since the risk factors in Section 3.1 are not consecutively numbered, we have renumbered the risk factors. The renumbered risk factors for multinational construction projects are shown in Table 3.

The rotated factor loading matrix of risk factors for multinational construction projects is shown in Table 4. The 30 risk factors of multinational construction projects are classified into six principal components, each of which includes several sub-factors. The cumulative variance explained is 69.857% (greater than 60%), and the loadings of the 30 factors are all greater than 0.5, indicating that the classification of the six principal components is appropriate. The six principal factors are named as follows: Objective Risk, Environmental Risk, Technical Risk, Organizational Risk, Information Risk, and Management Risk.

Table 3. List of Risk Factors for Multinational Construction Projects.

Dimension	Risk Factor	Dimension	Risk Factor
Objectives	Inconsistency in Project Objectives at Various Stages (V1)	Environment	Consortium Strategic Deviation Risk (V16)
	Compliance Objectives Failure Risk (V2)		Localization of Resource Integration Risk (V17)
	Stakeholder Coordination Failure Risk (V3)		Geopolitical Extreme Risk (V18)
	Conflict of Sustainable Development Goals (V4)		Market Environment Perception Bias Risk (V19)
	Inconsistent Needs of Stakeholders (V5)		Supply Chain Resilience Insufficiency Risk (V20)
	Project Milestone Breach Risk (V6)		Socio-Cultural Conflict Risk (V21)
Technology	Dynamic Adaptation Risk of Technical Standards (V7)		Natural Disasters and Climate Risk (V22)
	Engineering Design Integrity Risk (V8)	Information	Information Acquisition Capability and Extent (V23)
	Process Change Chain Risk (V9)		Inefficient Information Communication (V24)
	Innovation Technology Maturity Risk (V10)		Project Information Collaboration Barrier Risk (V25)
	Digital Collaboration Technology Failure Risk (V11)		Information Uncertainty Risk (V26)
	Technical Complexity Risk (V12)	Management	Improper Project Management Decision-Making Process (V27)
Organization	Cross-Cultural Governance Efficiency Risk (V13)		Management Team Decision Lag Risk (V28)
	Dynamic Adaptation Risk of Organizational Structure (V14)		Insufficiently Diversified Financing Channels (V29)
	Team Collaboration Efficiency Decline Risk (V15)		Project Contract Relationship (V30)

Table 4. Rotated Factor Loading Matrix of Risk Factors for Multinational Construction Projects.

Risk Factor	Principal Component					
	F1	F2	F3	F4	F5	F6
V1	0.7966					
V2	0.8956					
V3	0.7213					
V4	0.8985					
V5	0.8069					
V6	0.7986					
V7		0.7523				
V8		0.6985				
V9		0.7012				

Table 4. *Cont.*

Risk Factor	Principal Component					
	F1	**F2**	**F3**	**F4**	**F5**	**F6**
V10		0.7632				
V11		0.6895				
V12		0.7651				
V13			0.6532			
V14			0.7523			
V15			0.7652			
V16				0.7523		
V17				0.6985		
V18				0.7013		
V19				0.7965		
V20				0.8698		
V21				0.6423		
V22				0.6428		
V23					0.8023	
V24					0.7596	
V25					0.6985	
V26						0.6985
V27						0.7562
V28						0.6456
V29						0.7025
V30						0.8123
Cumulative Variance Explained				69.857%		

3.3.3. Confirmatory Factor Analysis

In the confirmatory factor analysis, we employed multiple indices to evaluate the fit of the confirmatory factor analysis model for the six dimensions of risk in overseas construction projects. The criteria for judgment are detailed in Table 5.

Table 5. Fit Indices and Criteria for Confirmatory Factor Analysis Model.

Test Index	Name	Criteria
KMO Test	-	>0.6
Bartlett's Test of Sphericity	-	*p*-value is significant
FL	Factor Loadings	Greater than 0.4, and *p*-value is significant
Chi square/df	Chi-square to Degrees of Freedom Ratio	<3
RMSEA	Root Mean Square Error of Approximation	<0.08
AGFI	Adjusted Goodness of Fit Index	>0.8
GFI	Goodness of Fit Index	>0.9
IFI	Incremental Fit Index	>0.9
TLI	Tucker–Lewis Index	>0.9
CFI	Comparative Fit Index	>0.9

The fit indices statistics for the confirmatory factor analysis 6 models of the risk factors in multinational construction projects are shown in Table 6. Table 6 indicates that the model has a good fit, suggesting that objective risk can be measured as a single dimension.

Table 6. Fit Indices Statistics for Risk Factor Models.

	χ^2/df	RMSEA	AGFI	GFI	IFI	TLI	CFI
Model of Objective Risk Factor	2.956	0.069	0.912	0.925	0.996	0.941	0.926
	<3	<0.08	>0.8	>0.9	>0.9	>0.9	>0.9
Model of Technical Risk Factors	2.001	0.031	0.882	0.905	0.943	0.909	0.973
	<3	<0.08	>0.8	>0.9	>0.9	>0.9	>0.9
Model of Technical Risk Factors	1.964	0.067	0.821	0.913	0.933	0.928	0.951
	<3	<0.08	>0.8	>0.9	>0.9	>0.9	>0.9
Model of Organizational Risk Factors	2.364	0.037	0.991	0.987	0.993	0.967	0.989
	<3	<0.08	>0.8	>0.9	>0.9	>0.9	>0.9
Model of Information Risk Factors	1.778	0.068	0.983	0.997	0.969	0.987	0.909
	<3	<0.08	>0.8	>0.9	>0.9	>0.9	>0.9
Model of Environmental Risk Factors	2.578	0.048	0.883	0.946	0.956	0.978	0.912
	<3	<0.08	>0.8	>0.9	>0.9	>0.9	>0.9

4. Analysis of the Relationships and Pathways of Risk Factors

4.1. Principle of the ISM-MICMAC Method

4.1.1. Principle of ISM

ISM integrates expert experience, practical knowledge, and computer technology to decompose a complex system into subsystems, analyzes the relationships among elements with logical operations, and finally builds a hierarchical multilevel structural model. The ISM workflow comprises four sequential steps:

Definition of the factor set S: Identify and select all elements S that are pertinent to the problem or system under investigation.

$$S = \{s_i | i = 1, 2, 3, \cdots n\} \tag{1}$$

(1) Construction of the adjacency matrix $\boldsymbol{A}$: Systematically compare each pair of factors to determine the presence or absence of a direct causal relationship, and encode these pairwise judgments in the binary adjacency matrix $\boldsymbol{A}$.

$$A = \begin{array}{c} \\ s_1 \\ s_2 \\ \vdots \\ s_n \end{array} \begin{array}{c} \begin{array}{cccc} s_1 & s_2 & \cdots & s_n \end{array} \\ \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \end{array} \tag{2}$$

where a_{ij} denotes whether factor s_i exerts a direct influence on factor s_j ($a_i = 1$ if the influence exists, and $a_{ij} = 0$ otherwise).

(2) Computation of the reachability matrix $\boldsymbol{M}$ is performed using the following formula:

$$M = (A + I)^{n+1} = (A + I)^n \neq \cdots \neq (A + I)^2 = (A + I) \tag{3}$$

where $\boldsymbol{I}$ denotes the identity matrix, and n represents the maximum path length (i.e., the largest number of transitive steps in the absence of feedback loops) required to achieve the reachability matrix.

(3) Partition the factors into distinct regions and hierarchical levels to construct the interpretive structural model.

The hierarchical levels and directional influences among factors are then derived from the adjacency matrix. By integrating these levels and directed links, a structured model is generated that explicitly depicts the causal relationships among the influencing factors.

4.1.2. Principle of MICMAC

In the analysis of complex systems, ISM alone is not sufficient to fully assess the dynamic roles of various factors within the system. To address this limitation, the present study incorporates the Cross-Impact Matrix Multiplication Applied to Classification (MICMAC) method to further dissect the influence of each factor. MICMAC quantifies two key attributes for every factor—driving power and dependence—thereby offering a critical complement to system analysis. Specifically, driving power denotes the extent to which a factor influences others (i.e., the number of factors it can affect), whereas dependence measures the degree to which a factor is influenced by others (i.e., the number of factors that affect it). The MICMAC procedure comprises four sequential steps:

(1) Compute the driving power and dependence for each influencing factor.
(2) Construct a four-quadrant matrix.
(3) Classify the influencing factors accordingly.
(4) Generate the MICMAC diagram.

4.2. ISM Model for Risk Factors in Transnational Construction Projects

4.2.1. Adjacency Matrix Based on Interrelationships Among Factors

This study identifies 30 critical risk factors in transnational construction projects, confirming their interdependence and formation of a complex risk network. Using ISM and MICMAC methods, it transforms fragmented risks into a hierarchical model, clarifying each factor's position and role. This provides a systematic framework for risk management. Semi-structured interviews with eight experts (details in Table 1) across three iterative rounds refined assessments and identified direct causal linkages among the factors.

Round 1: Each expert received a 30×30 matrix and independently indicated whether factor i "directly influences" factor j (yes/no). A preliminary adjacency matrix was constructed using a 5-out-of-8 majority rule (yes $\geq 5 \rightarrow 1$; yes $\leq 2 \rightarrow 0$).

Round 2: Factor pairs that fell in the "intermediate zone" ($3 \leq$ yes ≤ 5) were resubmitted to the panel together with Round 1 frequency distributions and brief justifications. Experts could revise their earlier answers; the revised scores were aggregated using the same threshold.

Round 3: The third-round interviews validated the accuracy and reliability of the findings from the first two rounds. The same eight experts reviewed the consolidated results to ensure the derived relationships matched real-world conditions and accurately reflected the direct influences among risk factors.

Based on the inventory of risk factors in transnational construction projects presented in Table 6 and following deliberation by the expert panel, the pairwise direct-influence relationships were determined. These relationships were encoded to construct the adjacency matrix, as depicted in Figure 1.

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	V_{13}	V_{14}	V_{15}	V_{16}	V_{17}	V_{18}	V_{19}	V_{20}	V_{21}	V_{22}	V_{23}	V_{24}	V_{25}	V_{26}	V_{27}	V_{28}	V_{29}	V_{30}
V_1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
V_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
V_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_4	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
V_6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
V_7	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
V_9	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{10}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
V_{11}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
V_{12}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{13}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{14}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
V_{15}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{16}	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
V_{17}	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{18}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
V_{19}	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0
V_{20}	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{21}	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{22}	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{23}	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{24}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{25}	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
V_{26}	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{27}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
V_{28}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
V_{29}	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{30}	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 1. Adjacency Matrix.

4.2.2. Reachability Matrix and Hierarchical Representation of Risk Influencing Factors

The reachability matrix can be derived from the adjacency matrix by applying the transitive-closure principle: if factor a can directly or indirectly influence factor b, and factor b can directly or indirectly influence factor c, then factor a must be able to influence factor c. Given the large number of risk factors considered in this study, the computational formula is expressed as $\boldsymbol{M} = (\boldsymbol{A} + \boldsymbol{I})$ n + 1 = $(\boldsymbol{A} + \boldsymbol{I})$ n $\neq \ldots (\boldsymbol{A} + \boldsymbol{I})$ 2 $\neq (\boldsymbol{A} + \boldsymbol{I})$, where I denotes the identity matrix, and n represents the maximum number of transitive steps (i.e., the longest acyclic path length) required to achieve the reachability closure. Consequently, the computation was implemented in MATLAB (2018a). Iterative analysis reveals that the adjacency matrix converges to the reachability matrix after six iterations, indicating that the 30 factors are stratified into six hierarchical levels. The resulting reachability matrix is presented in Figure 2.

Based on the reachability matrix, the reachability set, antecedent set, and their intersection were computed for each factor. For instance, the reachability set of V1 comprises factors (V1, V5, V23, V29), its antecedent set is (V1, V19, V25, V26, V27, V28, V29), and their intersection is (V1, V19, V29). A factor is retained at the current hierarchy level if and only if its reachability set is identical to this intersection. Factors V3, V12, V15, and V23 satisfy this criterion and are therefore assigned to Level 1.

After removing the Level 1 risk factors V3, V12, V15, and V22, a new reachability matrix is generated. Repeating the computations for the reachability set, antecedent set, and their intersection identifies the Level 2 risk factors as V8, V9, V13, V16, V24, and V25. Finally, the risk factors of multinational construction projects are divided into six levels: Level 1 (V3, V12, V15, V23); Level 2 (V8, V9, V13, V16, V24, V25); Level 3 (V2, V4, V10, V11,

V17, V29, V30); Level 4 (V6, V7, V14, V20); Level 5 (V18, V19, V21, V27, V28); Level 6 (V1, V5, V22, V26).

	V_1	V_2	V_3	V_4	V_5	V_6	V_7	V_8	V_9	V_{10}	V_{11}	V_{12}	V_{13}	V_{14}	V_{15}	V_{16}	V_{17}	V_{18}	V_{19}	V_{20}	V_{21}	V_{22}	V_{23}	V_{24}	V_{25}	V_{26}	V_{27}	V_{28}	V_{29}	V_{30}
V_1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0
V_2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	1
V_3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_4	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0
V_5	0	0	0	0	1	0	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	1	1	0
V_6	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	1	0
V_7	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	1	0
V_8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	1	0	0	1	1	0
V_9	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	1	1	0
V_{10}	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	1	1	0
V_{11}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	1	0
V_{12}	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
V_{13}	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
V_{14}	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
V_{15}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	1	0	1	0	0	0	1	0
V_{16}	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0	1	1	0	0	1	0
V_{17}	0	0	1	0	0	1	1	1	1	1	0	0	0	0	0	0	1	1	1	0	0	0	1	0	1	1	0	1	1	0
V_{18}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
V_{19}	1	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	1	1	0
V_{20}	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	1	0	1	0	0	1	1	0
V_{21}	0	0	1	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1	0	0	1	1	0
V_{22}	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
V_{23}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0
V_{24}	0	0	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	1	1	1	0	0	1	1	0
V_{25}	1	0	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	0	0	1	1	0
V_{26}	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	1	0	1	1	0
V_{27}	1	0	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	1	0	0	0
V_{28}	1	0	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	1	0	0
V_{29}	1	0	0	0	1	1	1	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	1	1	0	1	1	0
V_{30}	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Figure 2. Reachability Matrix.

4.2.3. Hierarchy of Transnational Construction Project Risks

Based on the hierarchical partitioning derived from the reachability matrix and the direct mutual-influence relationships between any two distinct factors recorded in the adjacency matrix, the ISM model of risk-inducing factors was constructed and is presented in Figure 3.

Six different levels are created by stratifying the elements according to the direction in which risk influences propagate. At the bottom of the interpretive structural model are goal-related and environmental variables, which dominate levels L4, L5, and L6. On the other hand, the elements in L2 and L3 mostly consist of management and organisational aspects. These dimensions are located in the levels in between the fundamental and surface-level elements. These intermediary elements directly impact and limit the items in L1. Even though their effects are not as obvious as those in L1, they are nevertheless important factors that should not be disregarded when determining whether international building projects succeed or fail.

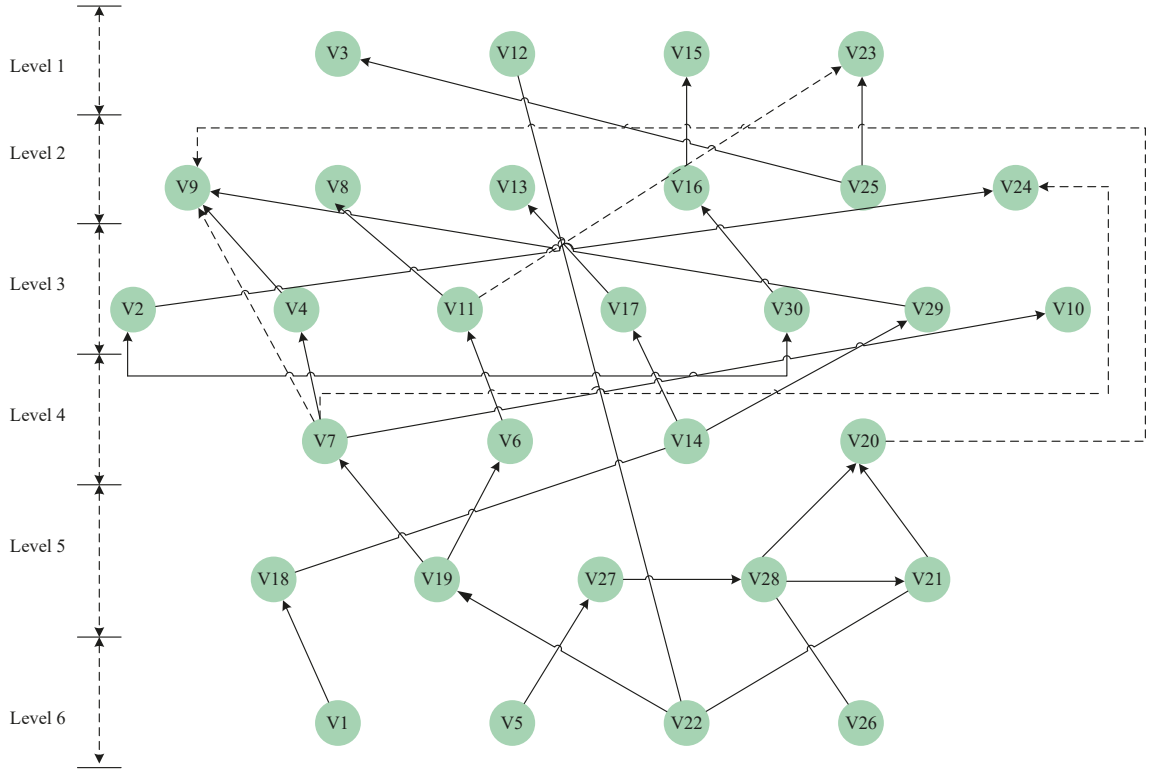

Figure 3. ISM of Risk Factors in Transnational Construction Projects.

4.3. MICMAC Model of Risk Factors in Transnational Construction Projects

4.3.1. Dependence–Driving Power of Risk Factors

Using the reachability matrix shown in Figure 2, we calculated the driving power (D) and dependence (De) of each risk-inducing factor within the transnational construction project system. Specifically, the driving power of a factor is obtained by summing the "1"s in its corresponding row, whereas the dependence is determined by summing the "1"s in its corresponding column. To quantify the relative relationship between driving power and dependence, we introduce the ratio λ = D/De. Table 7 presents the computed λ values for all risk-inducing factors.

Table 7. Dependence and Driving Power of Each Risk Factor.

Factor	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
Dependence	7	2	5	2	10	11	15	15	5	15
Driving Power	4	6	1	7	10	9	7	8	6	6
λ	7/4	3	1/5	7/2	1	9/11	7/15	8/15	6/5	6/15
Factor	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20
Dependence	1	2	1	1	6	3	5	10	7	5
Driving Power	5	1	2	3	1	8	14	1	12	9
λ	5	1/2	2	3	1/6	8/3	14/5	1/10	12/7	9/5
Factor	V21	V22	V23	V24	V25	V26	V27	V28	V29	V30
Dependence	1	1	21	1	21	5	1	18	22	2
Driving Power	12	2	3	12	12	12	10	10	11	6
λ	12	2	1/7	12	4/7	12/5	10	5/9	1/2	3

4.3.2. MICMAC Classification

Utilizing the dependence and driving-power values reported in Table 7, a MICMAC diagram was constructed to delineate the relational clusters among the risk-inducing factors. Four distinct groups—labeled Quadrants I, II, III, and IV—were identified and termed the Autonomous, Dependent, Linkage, and Independent (Driver) groups, respectively (Figure 4).

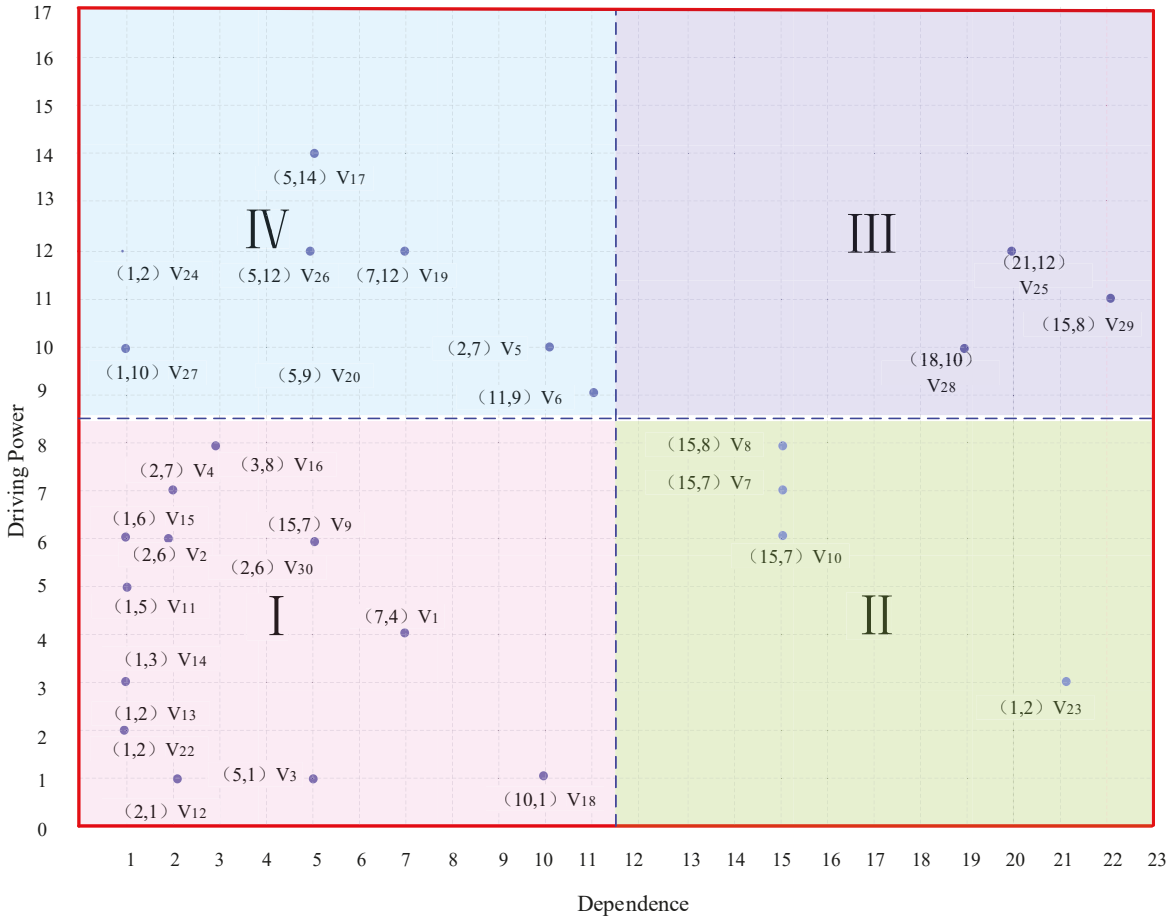

Figure 4. Classification of transnational construction-project risk factors by dependence and driving power.

Quadrant I—Autonomous factors: These factors exhibit comparatively low dependence and low driving power. Their interconnections with other elements are relatively weak; nevertheless, they are not entirely isolated, as they both exert limited influence on, and are marginally affected by, the remaining factors.

Quadrant II—Dependent factors: Characterized by high dependence and low driving power, these factors are markedly susceptible to the influence of Linkage and Driver factors, yet they exert minimal influence themselves. Elevated dependence signifies dense systemic linkages and high malleability.

Quadrant III—Linkage factors: Simultaneously possessing high driving power and high dependence, these factors are intrinsically sensitive. Any managerial action directed at them will propagate throughout the system and simultaneously induce feedback effects on themselves. Only a small subset of risks resides in Quadrant III, indicating that while inter-factor influences exist, the overall systemic connectivity remains moderate; consequently, controlling a limited number of Linkage factors is insufficient to achieve comprehensive risk governance.

Quadrant IV—Independent (Driver) factors: With strong driving power and low dependence, these factors are capable of exerting pronounced influence on the remainder of the system. Therefore, managerial attention should be disproportionately concentrated on Driver factors during the risk-management process.

4.4. Hierarchical Analysis of Risk Factors in Transnational Construction Engineering Projects

4.4.1. Root-Level Causal Risk Determinants

The drivers in quadrant IV of the MICMAC categorisation diagram have significant driving power but weak dependence, which causes them to have a disproportionate amount of impact over the other elements. These root-level determinants comprise: (V5) misaligned stakeholder requirements, (V6) milestone slippage risk, (V17) localized resource-integration risk, (V19) market-environment misperception risk, (V20) insufficient supply chain resilience, (V24) information-transfer impediments, (V26) information uncertainty, and (V27) flawed project-management decision workflows.

Concurrently, the following latent variables display elevated λ values and thus warrant designation as root-level risks: (V4) sustainable-development goal conflicts (λ = 7/2), (V11) digital collaboration technology failure (λ = 5), (V14) dynamic organizational-structure misalignment (λ = 3), (V16) consortium strategic divergence (λ = 2), and (V22) socio-cultural conflict (λ = 12). Additionally, the risk of inconsistent project objectives across life-cycle phases (V1), positioned at level 6, should likewise be treated as a root-level causal determinant.

4.4.2. Outcome-Level Risk Determinants

The risk factors of level L1 are exclusively influenced by other factors. They exert no causal influence on any other element. Hence, they are classified as outcome-level determinants. These factors include: (V3) stakeholder-coordination failure risk, (V12) technological-complexity risk, (V15) team-collaboration performance decay, and (V23) information-acquisition capacity inadequacy. Although each is situated in quadrant I (autonomous cluster) of the MICMAC diagram, their λ values—1/5, 1/2, 1/6, and 1/7, respectively—indicate a markedly higher dependence than driving power, given that λ is defined as the ratio of driving power to dependence. Consequently, the four aforementioned factors are confirmed as outcome-level risks residing at L1 of the ISM hierarchy.

4.4.3. Transmission-Level Risk Determinants

Excluding the 17 factors classified as root-level (drivers) and outcome-level (dependents), the remaining 13 risk variables constitute the transmission stratum. These are: (V1) misaligned objectives across project phases, (V2) compliance-target failure, (V7) dynamic adaptation of technical standards, (V8) engineering-design integrity deficit, (V10) immaturity of innovative technologies, (V13) cross-cultural governance inefficacy, (V22) natural-hazard and climatic risks, (V25) information-integration barriers, (V28) managerial decision-making inertia, (V29) insufficient financing-channel diversification, and (V30) contractual disputes.

4.5. Pathway Analysis of Risk Factors in Transnational Construction Projects

4.5.1. Modes of Risk Elicitation

Systemic risk elicitation can be classified into two archetypes: primary (direct) elicitation and secondary (propagated) elicitation. Primary elicitation is the direct impact of endogenous and exogenous risk factors on the system, generating perturbation events that affect the normal operation of the system. Secondary elicitation, however, is triggered by the chain reaction of perturbation events, leading to additional perturbation events and the

disruption of other subsystems. In transnational construction projects, these two elicitation modes frequently coexist.

However, this self-regulation breaks down and risk is triggered when the accumulated systemic risk load exceeds the adaptive threshold. Systemic risk is dynamic by nature, changing in reaction to changing influencing variables and interference sources. An increase in the quantity or severity of these sources increases the likelihood of system flaws and vulnerabilities, which in turn increases the departure from the desired goals. Figure 5 depicts the risk evolution trajectories for transnational construction projects under both primary and secondary elicitation scenarios.

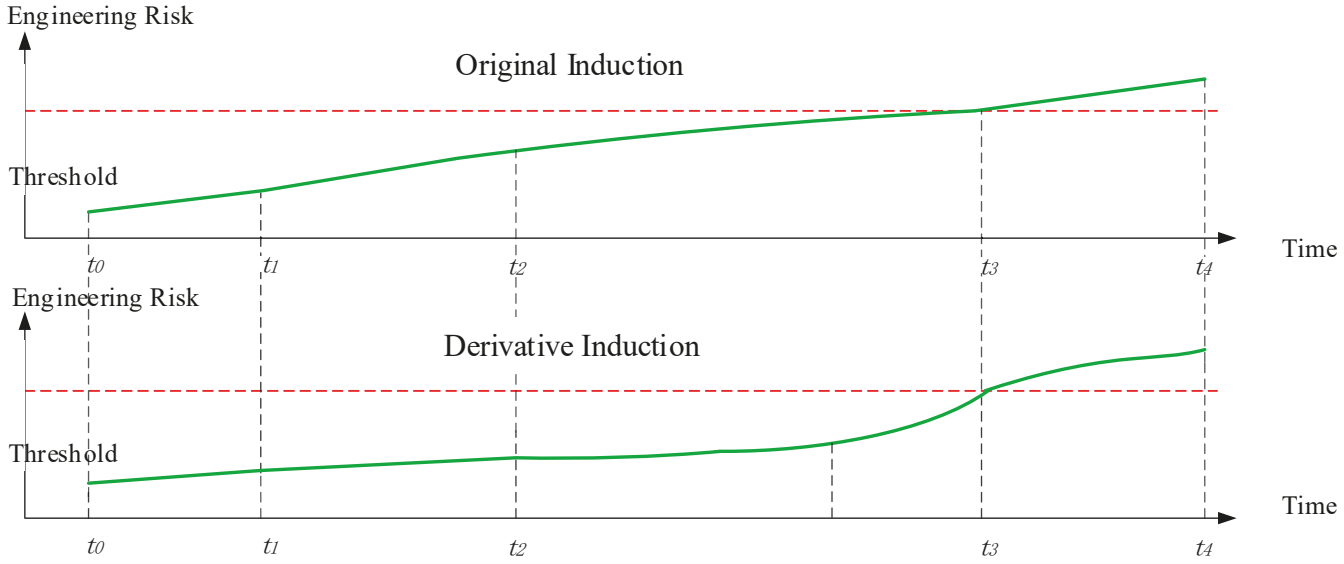

Figure 5. Risk evolution trajectories in transnational construction projects.

4.5.2. Risk Propagation Pathways

The 16 propagation paths are derived from Figure 3: starting from the root-level risk factors, there are 16 main routes leading to the surface-level outcomes.

Path 1 Inconsistent objectives across project phases → consortium strategic divergence → dynamic misalignment of organizational structure → insufficient financing-channel diversification → cascading engineering-change risk.

Path 2 Inconsistent objectives across project phases → consortium strategic divergence → dynamic misalignment of organizational structure → localized resource-integration risk → cross-cultural governance inefficacy.

Path 3 Stakeholder requirement misalignment → inappropriate project-management decision workflow → managerial decision-making inertia → inadequate supply chain resilience → cascading engineering-change risk.

Path 4 Stakeholder requirement misalignment → inappropriate project-management decision workflow → managerial decision-making inertia → socio-cultural conflict → inadequate supply chain resilience → cascading engineering-change risk.

Path 5 Natural-hazard and climatic risks → market-environment misperception → dynamic misalignment of technical standards → cascading engineering-change risk.

Path 6 Natural-hazard and climatic risks → market-environment misperception → dynamic misalignment of technical standards → sustainable-development goal conflicts → cascading engineering-change risk.

Path 7 Natural-hazard and climatic risks → market-environment misperception → milestone slippage risk → inconsistent objectives across project phases → information-acquisition capacity inadequacy.

Path 8 Natural-hazard and climatic risks → technological complexity risk.

Path 9 Natural-hazard and climatic risks → socio-cultural conflict → inadequate supply chain resilience → cascading engineering-change risk.

Path 10 Information uncertainty → managerial decision-making inertia → inadequate supply chain resilience → cascading engineering-change risk.

Path 11 Dynamic misalignment of technical standards → contractual disputes → consortium strategic divergence → team-collaboration performance decay.

Path 12 Compliance-target failure → contractual disputes → consortium strategic divergence → team-collaboration performance decay.

Path 13 Contractual disputes → compliance-target failure → information-transfer impediments.

Path 14 Project information-integration barriers → stakeholder-coordination failure.

Path 15 Project information-integration barriers → information-acquisition capacity inadequacy.

Path 16 Dynamic misalignment of technical standards → information-transfer impediments.

To ensure that the 16 risk-transmission pathways derived from the ISM model are not merely logical constructs but also reflect real-world project situations, we conducted an empirical validation. Eight experts who participated in constructing the adjacency matrix (Table 1) rated the realism of each pathway on a five-point Likert scale. A pathway was considered validated if its mean score was ≥ 4.0 and the agreement rate (proportion of scores ≥ 4) was $\geq$75%. All pathways met these criteria, with an overall mean of 4.34, demonstrating that they capture actual project conditions. In addition, we assessed inter-rater consistency using Kendall's coefficient of concordance; Kendall's W was 0.77, indicating significant and strong agreement among the experts [23]. Therefore, the 16 risk-transmission pathways are empirically valid.

5. Implications for Engineering Managers

(1) Management Implications for Addressing Root-Level Risks

The ISM model shows that inconsistent project phase goals (V1) and misaligned stakeholder needs (V5) are at the bottom level (Level 6) and act as the original driving force for higher-level risks. Engineering managers should focus on managing project goals. For example, they can use an "Objective-Requirement Coupling Matrix" at the project start to measure how well project goals (V1) match stakeholder needs (V5).

Natural disasters and climate risk (V22), which are external driving factors that internal project management cannot directly control, are likewise at the bottom level (Level 6). It is yet another unique factor that propels higher-level hazards. Project governance should first adopt a "resilience-oriented" approach at the strategy level, taking into account the probability distribution of extreme events while making decisions about the project life cycle. Second, engineering insurance and regionally distributed redundant supply chains can be used at the operations level to convert possible catastrophic losses into measurable financial expenses. Third, establishing a climate emergency response strategy at the organisational level helps guarantee that the project is stable even in the event of natural disasters.

One of the main causes of project risks is poor information flow (V26), which is also at the bottom level (Level 6). To enhance horizontal departmental coordination and vertical decision-making, a cross-functional information governance committee comprising representatives from project management, IT, legal, and local areas should be established. Operationally, to minimise the spread and amplification of uncertainty risks, an information

synchronisation system should be put in place to promptly detect, escalate, and resolve information flow problems on the job site.

(2) Management Implications for Addressing Transmission-Level Risk Factors

Engineering managers should regard the transmission layers (ISM Levels 3–5) as "amplifiers" for risk cascades. The primary concern is that interactions across different dimensions, such as those between technology and management or between organization and environment, can exacerbate risks. To address this issue, project managers can develop a three-step risk management model, namely "foresee, block, and immunize."

Foresee: Use the risk transmission network to spot key points where risks can spread (like conflicts between tech standards and supply chain disruptions). Analyze how these risks might grow using coupling coefficients.

Block: Set up cross-functional buffers for sensitive points (like adding extra design capacity or backup plans) to stop risks from getting bigger early on.

Immunize: Keep some extra time in the schedule, build a flexible org structure, and spread out resources to make the project stronger against risks and better at bouncing back.

(3) Management Implications for Addressing Outcome-Level Risk Factors

Risks in international construction projects can be readily triggered by outcome-level risk variables. Therefore, it is critical to eliminate or reduce these dangers as soon as possible. Use the risk transmission network as a roadmap to manage hazards in international building projects more effectively. In addition to managing the risks directly, pay attention to important transmission routes and parent node control. This can prevent the issue from spreading further and reduce the likelihood that it will occur. For instance, lessen the influence and probability of its parent nodes, such as "consortium strategic deviation risk" (V16), "project contract relationship" (V30), and "technical standards adaptation risk" (V7), while addressing "team collaboration decline risk" (V15).

6. Discussion

The Interpretive Structural Modeling (ISM) reveals a clearly defined six-level hierarchy, positioning fundamental elements including inconsistent project objectives (V1), misaligned stakeholder requirements (V5), and natural disaster and climate risks (V22) at the foundational level (Level 6). These factors function as deep-level drivers, exerting substantial influence throughout the entire system. This hierarchical structure underscores a critical management reality: addressing superficial symptoms without managing their root causes is likely to constitute an ineffective strategy.

In contrast to earlier frameworks that relied on broad classifications such as "internal vs. external" risks, this study contributes a structured and granular risk taxonomy specifically tailored to the context of transnational construction projects. Furthermore, by mapping 16 distinct risk propagation pathways, this research addresses a gap in the literature concerning how risks transmit across project subsystems.

The ISM-MICMAC analysis indicates that key risk factors (V5, V17, V19, V21, V24, V25, V26, V27, V28, V29) collectively contribute 55% of the total risk driving power. This finding validates the "risk kernel" principle suggested by loose coupling theory, wherein a very small number of latent variables can account for over half of the causal influence. Moreover, the sixteen identified transmission pathways provide a "roadmap" of risk propagation, clearly illustrating the process through which localized events can trigger project failure. This enables managers to monitor critical nodes and implement timely interventions to disrupt risk transmission.

While the ISM-MICMAC method excels at delineating structural relationships, it does not quantify the probability or intensity of these relationships. The model demonstrates

that risks can propagate but does not indicate the likelihood of propagation or the scale of potential impacts. Future work should integrate quantitative techniques such as Bayesian Networks or Structural Equation Modeling to calibrate the strength and probability of the identified pathways, thereby enabling predictive risk analysis.

7. Conclusions

The main conclusions of this paper are as follows:

Inconsistency in Project Objectives at Various Stages (V1), Inconsistent Needs of Stakeholders (V5), Natural Disasters and Climate Risk (V22), and Information Uncertainty Risk (V26) function as the deep-seated "root drivers" of risk in transnational construction projects, whereas Stakeholder Coordination Failure Risk (V3), Information Acquisition Capability and Extent (V23), Technical Complexity Risk (V12), and Team Collaboration Efficiency Decline Risk (V15) operate as surface-level triggers.

Localization of Resource Integration Risk (V17), Market Environment Perception Bias Risk (V19), Inconsistent Needs of Stakeholders (V5), Socio-Cultural Conflict Risk (V21), Inefficient Information Communication (V24), Project Information Collaboration Barrier Risk (V25), Information Uncertainty Risk (V26), Improper Project Management Decision-Making Process (V27), Management Team Decision Lag Risk (V28), and Insufficiently Diversified Financing Channels (V29)—ten factors in total—collectively account for 55% of the total causal influence, constituting the system's "risk kernel."

Once a transnational project risk is triggered, it typically converges on one of two collapse endpoints, cascading engineering change or team collaboration decline within an average of three to four steps, with the contract, organization, and supply chain serving as the critical transmission channels.

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References

1. Ebekozien, A.; Aigbavboa, C.; Ramotshela, M. A qualitative approach to investigate stakeholders' engagement in construction projects. *Benchmark. Int. J.* **2024**, *31*, 866–883. [CrossRef]
2. Gupta, R.; Das, B.; Jain, K. Risk management of oil refinery construction project: An Indian case study. *Int. J. Proj. Organ. Manag.* **2021**, *13*, 218–244. [CrossRef]
3. Nguyen, T.; Nguyen, L.H.; Chileshe, N.; Hallo, L. Investigating critical risk factors of selecting joint venture contractors for infrastructure projects implementation in Vietnam. *Int. J. Constr. Manag.* **2023**, *23*, 2438–2451. [CrossRef]
4. Larrondo-Ureta, A.; Ferreras-Rodríguez, E.-M. The potential of investigative data journalism to reshape professional culture and values. A study of bellwether transnational projects. *Commun. Soc.* **2021**, *34*, 41–56. [CrossRef]

5. Afzal, F.; Yunfei, S.; Nazir, M.; Bhatti, S.M. A review of artificial intelligence based risk assessment methods for capturing complexity-risk interdependencies: Cost overrun in construction projects. *Int. J. Manag. Proj. Bus.* **2021**, *14*, 300–328. [CrossRef]
6. Sang, S.; Lu, Z. Optimal Strategies for the Green Supply Chain with Reference Price Effect. *Eng. Lett.* **2025**, *33*, 3410–3419.
7. Xiang, P.; Yang, S.; Yuan, Y.; Li, R. Integrated measurement of public safety risks in international construction projects in the belt and road initiative. *Eng. Constr. Archit. Manag.* **2024**, *32*, 4673–4699. [CrossRef]
8. Jung, S.; Kim, S.-C.; Kim, D.-C. Analysis of the Impact of Enterprise Risk Management (ERM) on the Project Success through PRM Process: Focused on the Overseas Construction Projects. *J. Korean Soc. Ind. Syst. Eng.* **2024**, *47*, 93–106. [CrossRef]
9. Chen, H.; Wan, A.; Peng, B. Configuration path identification of investment risk in China's overseas energy projects: An exploration based on LDA and fsQCA. *Environ. Prog. Sustain. Energy* **2025**, *44*, e14549. [CrossRef]
10. Yao, Q.; Shao, L. Selection of Low-Carbon Contractors in a Fuzzy Multi-Objective Environment. *Eng. Manag. J.* **2025**, 1–19. [CrossRef]
11. Faber, M.H.; Stewart, M.G. Risk assessment for civil engineering facilities: Critical overview and discussion. *Reliab. Eng. Syst. Saf.* **2003**, *80*, 173–184. [CrossRef]
12. Wang, R.; Yang, K.; Guo, J.; Ma, C.; Chu, E.; Zhu, Y. Research on Design and Ideal Variable Transmission Ratio Control of Distributed Steering-By-Wire System. *Eng. Lett.* **2025**, *33*, 3345–3362.
13. Tadayon, M.; Jaafar, M.; Nasri, E. An assessment of risk identification in large construction projects in Iran. *J. Constr. Dev. Ctries.* **2012**, *17*, 57–69.
14. Ameyaw, E.E.; Hu, Y.; Shan, M.; Chan, A.P.; Le, Y. Application of Delphi method in construction engineering and management research: A quantitative perspective. *J. Civ. Eng. Manag.* **2016**, *22*, 991–1000. [CrossRef]
15. Pitchaimuthu, S.; Thakkar, J.J.; Gopal, P. Modelling of risk factors for defence aircraft industry using interpretive structural modelling, interpretive ranking process and system dynamics. *Meas. Bus. Excell.* **2019**, *23*, 217–239. [CrossRef]
16. Chen, W.; Deng, J.; Niu, L. Identification of core risk factors and risk diffusion effect of urban underground engineering in China: A social network analysis. *Saf. Sci.* **2022**, *147*, 105591. [CrossRef]
17. Wei, Z.; Chen, Y.; Guo, K.; Liu, B.; Liu, Y.; Li, Y. Efficient Beam Search For Satellite Communications On The Move Systems. *Eng. Lett.* **2025**, *33*, 3311–3317.
18. Luo, Q.; Sun, C.; Li, Y.; Qi, Z.; Zhang, G. Applications of digital twin technology in construction safety risk management: A literature review. *Eng. Constr. Archit. Manag.* **2025**, *32*, 3587–3607. [CrossRef]
19. Dzwigol, H. Research methodology in management science: Triangulation. *Virtual Econ.* **2022**, *5*, 78–93. [CrossRef]
20. Renz, S.M.; Carrington, J.M.; Badger, T.A. Two strategies for qualitative content analysis: An intramethod approach to triangulation. *Qual. Health Res.* **2018**, *28*, 824–831. [CrossRef]
21. Fetters, M.D.; Curry, L.A.; Creswell, J.W. Achieving integration in mixed methods designs—Principles and practices. *Health Serv. Res.* **2013**, *48*, 2134–2156. [PubMed]
22. Yang, J.; Li, Y.; Harper, D.; Clarke, I.; Li, J. Macro Financial Prediction of Cross Border Real Estate Returns Using XGBoost LSTM Models. *J. Artif. Intell. Inf.* **2025**, *2*, 113–118.
23. Gadedjisso-Tossou, A.; Adjegan, K.I.; Kablan, A.K.M. Rainfall and temperature trend analysis by Mann–Kendall test and significance for Rainfed Cereal Yields in Northern Togo. *Sci* **2021**, *3*, 17. [CrossRef]

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LOINSH Information Structure for the Assessment of Occupational Risks in the Execution of Roads Based on the LOIN Standard

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Abstract

Despite regulatory advances, there continues to be a high accident rate on construction sites, especially on road projects, mainly due to the lack of organization of safety information. Although there is research demonstrating the benefits of the BIM methodology for improving occupational safety, its scope is still limited. This study addresses the integration of occupational health and safety in road projects using the BIM methodology, in line with ISO 19650-1, proposing a standardization framework based on ISO 7817-1:2024. The concept of Level of Information for Safety and Health (LOINSH) is introduced, structured into four categories (100, 200, 300, and 350), which allows risks to be managed progressively throughout the project's life cycle. The framework defines graphical and alphanumeric requirements for BIM objects, establishing sets of parameters recognized by the open IFC format to ensure interoperability and traceability. It also proposes a system for assessing risks associated with activities and disciplines, facilitating preventive decisions from the design stage onwards. The results indicate that this standardization improves communication and collaboration between agents, reduces workplace accidents, and can be applied to other types of construction works.

Keywords: BIM; health and safety; information standardisation; LOINSH; risk assessment

1. Introduction

In recent years, the construction sector continues to be affected by high accident rates [1]. Thus, in the last decade, fatal accidents in construction have exceeded between three and six times those in other sectors [2,3]. In 2023, U.S. construction recorded the highest number of fatalities among industrial sectors (1075), the highest in the sector since 2011 [4]. In 2024 in the European Union, 22.9% of fatal occupational accidents in 2022 occurred in construction [5].

The particularities of construction activities contribute to the existence of many risks that are difficult to classify and predict, giving rise to a more complex risk identification process than in other industries [6]. In this sense, research to improve occupational risk prevention contributes to the achievement of the United Nations Sustainable Development Goals (SDGs) 2030, in particular, SDG3 "Good Health and Well-being" and SDG8 "Decent Work and Economic Growth" [7].

The research by Liu et al. [8] about patterns in construction accidents in China found that the key factors that cause most incidents are the implementation of an inadequate

occupational health management system or its ineffective implementation, the omission or lack of safety information that is not assimilated by workers, as well as psychological and physiological factors, such as absent-mindedness or disobedience to safety regulations, which are usually fatal. Buniya et al. [9] find other major barriers to the implementation of construction safety programmes in Iraq, such as a lack of commitment, inefficient safety training, a non-conductive work environment with a clear lack of collaboration among workers, and a lack of awareness of the dangers of construction site work.

Thus, some of the factors highlighted in recent years that reduce safety are the problems of coordination of safety technicians [10], the lack of technological innovation, and the scarce use of digital technologies to improve safety [11,12], the lack of standardization and resistance to change by the agents involved in the project [13], the lack of innovative strategies for the application of safety by institutions [14], the availability of contradictory, confusing, and disorganized information and security protocols [15], technological limitations that prevent the application of new digital tools [16], and a low level of awareness from workers about safety [17], with a consequent lack of commitment, motivation, and responsibility to apply risk prevention protocols [18].

Based on these factors, Sarvari et al. [19] conclude that the construction sector needs to adopt a more integrated approach to risk management that emphasizes cooperation between actors and the improvement of information and safety flows through the development and implementation of protocols employing digital technologies. This change can facilitate better coordination between all parties involved, as well as better information traceability, enabling a more cohesive and proactive security management strategy that addresses industry-specific risks.

Within this sector, road construction, due to its linear nature, presents particularities that require a differentiated analysis of the construction of buildings and other infrastructures. For example, they are at risk of fatal or serious injury when working near motorists, construction vehicles, and heavy equipment or machinery [20]. In particular, unfavourable working area conditions, atmospheric agents, and a lack of organized risk and safety information, as well as poor prevention training act as key risk factors in road construction [21]. Carelessness and the carefree attitude of workers, as well as habituation to safety and warning signs, also make up other conditioning factors that result in an increase in accident rates in this field of work [22].

In addition, in road projects, the possible presence of vehicle and pedestrian traffic and the vehicles used in construction in the vicinity of the works are critical external factors that aggravate the risks inherent in the construction of these infrastructures [23]. The complex interaction of these internal and external factors creates situations that are difficult to manage and often culminate in accidents [24], the consequences of which are suffered by workers, especially affecting machinery operators and construction labourers [25].

In addition, the presence of special risks requires a specific safety analysis [26,27]. Despite the recent literature on proposals for improving safety in road construction [21,23,28,29], accident statistics require further research. Moreover, the prevention of accidents at work on construction sites requires a high degree of specificity, both because of the nature of the risks involved and because of the temporary nature of the work [30].

During the road design phase, the health and safety of the life cycle of the asset must be taken into account following the principle of prevention through design (PtD, hereinafter), which includes the analysis of safety conditions, the identification of risks, and the provision of preventive measures and signage [31], resulting in a reduction in the accident rate during the subsequent phases [32]. Therefore, all the information on the construction process must be available from this initial phase of the project in a standardized and correctly organized way [33]. Despite its benefits, construction faces challenges when it comes to effectively

applying PtD, such as ignorance and a lack of confidence in the results obtained, fear of a considerable increase in cost and time, and a lack of standardization of methodologies and application cases where this technique is used [34].

On the other hand, the construction sector is immersed in a digitalization process known as Construction 4.0, through which several technologies are integrated into production processes [35]. This represents a paradigm shift in all disciplines involved in construction projects, including health and safety management, which will require new methods of evaluation and analysis of this information [36]. In this sense, the enabling tool of Construction 4.0 is the BIM methodology (Building Information Modelling), considered to be the technology with the greatest potential to improve current health and safety results, allowing the interconnection of other digital technologies [37].

BIM already has an increasing application in road projects [38], which has led the European Union to allow member states to require this methodology in public tenders [39]. This is due to its proven benefits for the design and construction of infrastructures, especially roads, and the improvement of coordination between the agents involved through streamlined communication, allowing for the traceability of information [40]. In addition, through BIM, the final conditions of the project can be anticipated accurately, such as being able to apply a preventive strategy from the design, which is more economical and technically feasible than applying corrective measures in situ later [41].

Thus, the evaluation of the health and safety of construction projects is included within the eighth dimension of BIM [42]. In this sense, construction professionals recognize the benefits of BIM for improving risk detection and task planning through 3D visualization [43], resulting in higher quality proactive prevention [44]. Other strengths are also highlighted, such as the identification of high-risk tasks [31]; the detection of potentially dangerous areas [45]; the automated generation of protocols for the identification and action against risk scenarios [43]; and the improvement of the flow of communication between agents through the traceability of safety information [46], along with benefits for the awareness and training of workers in risk prevention [47]. The BIM methodology also enables the automated assessment of risk levels on site for the provision of preventive measures from the design phase [48,49], as well as the preventive management of safety data during the operation of infrastructures [50,51]. These benefits of BIM have already been proven in little research where this technology is applied for safety management in road projects, which today is still a field of very limited extension. The advantages of BIM have been verified both to analyze the risk due to contact between power lines and machinery used during the construction of road works [52] and to carry out automated risk assessments on these infrastructures during their different phases of construction [28].

However, these investigations cover specific cases and conditions, so it is essential to establish a well-organized structure of safety information covering the potential risks in road projects, which can be incorporated into BIM models and managed in an open format using the Industry Foundation Classes (IFC) [53]. Its development has been slower in the case of infrastructures than buildings. Thus, the IFC2x3 standard (ISO 16739-1:2024) [54] covered only buildings (architecture, structure, MEP, and planning and management of facilities), and it is not until IFC4.3 (ISO 16739-1:2024) [54] that it covers both buildings and infrastructures.

Given the need to establish a structure for this information in BIM, the ISO 19650-1 [55], introduces the concept of the Level of Necessary Information, or LOIN, considered as an essential concept for the successful implementation of BIM [56]. This LOIN is established as a methodological framework to define the quality, quantity, and granularity of the information required at any point in the life cycle of an asset in order to ensure the uniqueness of the data and the availability of the information required and that is indispensable for

its management [57]. This directive defines LOIN as the result of the interaction of three components: Geometric Information (LOG), of a visual nature and represented on the model itself; Alphanumeric Information (LOI), of a parametric nature and embedded as intrinsic information within each of the BIM objects; and Associated Documentation (DOC), such as links to documentation that is outside the BIM environment database. In this way, this regulation defines the framework of the LOIN under four requirements that must be met: (1) the purpose, the reason for the data; (2) the delivery milestone, when; (3) the agent responsible for this information; and (4) the object to which it applies. With the response to these criteria, the agents involved in the project are responsible for justifying the existence of each piece of information, thus avoiding the overrepresentation of information and problems of duplication [58].

Given the complexity of the LOIN concept, the ISO 7817-1 (July 2024) [57] was developed. It re-codes the concepts and principles; therefore, it is very general to be valid for the information of any element of a construction, from a door to a tunnel. Part 2: ISO/AWI TS 7817-2 [59], which will define how to break down the information requirements according to the LOIN concept based on the purpose of use and the life cycle phase (design, construction, operation, and maintenance), is in early development. This standard will focus on the definition, structuring and validation of the information requirements within the BIM process, and the relationship between the level of information needed and the IFC. This highlights an important gap in this field.

Therefore, the supervision of the quality of project information through the management of LOIN is a dynamic, progressive, and adaptive activity to the changes that occur in the life cycle, so those responsible must enrich the LOIN of the BIM objects as the project phases progress, ensuring that only the necessary information is available at each stage [60]. However, the information from the different elements of the model will not evolve in the same way, since the LOIN is intrinsically linked to the purpose of the information [57].

Thus, to supervise compliance with these LOIN requirements, there is a process of reviewing deliverables, which is currently carried out manually, requiring excessive consumption of time and energy [61]. Consequently, the verification of information quality using automatic validation using machine-readable requirements is essential [62].

Due to the recent publication of the LOIN regulation, there is hardly any literature in which an organized LOIN structure is established to be integrated into BIM models. From a search in WoS, with the terms LOIN (Topic) and BIM (Topic), ten results appear. Only two of them mention the need to establish a LOIN structure for safety information in construction projects. Salzano et al. [63] define, as one of their objectives, the LOIN structure for the management of safety in the different phases of a building's project, which involves determining the specific data necessary to manage and mitigate risks in each phase. However, they do not present any LOIN information proposal or any parameter structure. On the other hand, Pham et al. [64] establish the LOIN for a BIM-based digital twin solely for contamination risk management during building renovation. Thus, these investigations focus on buildings, leaving aside the rest of the infrastructures, in addition to not addressing any proposal to establish a general LOIN structure to manage all the risks generated during the construction of these infrastructures.

Thus, construction has very high accident rates despite regulatory efforts. It has been shown that the lack of organization of information, deficiencies in its traceability, or difficulties in collaboration and communication between those involved are factors that increase the accident rate in road construction works.

The BIM methodology has been shown to have benefits for the accident rate of workers, the nature of which makes it suitable for the application of PtD. However, despite the

increasing number of road projects carried out in BIM, there are few projects where the integration of safety in BIM is realized.

For the successful implementation of the BIM methodology, the correct implementation of the LOIN is essential. For this purpose, there are two basic international standards: ISO 19650-1 [55] and ISO 7817-1:2024 [57]. However, the latter includes principles and concepts that make its application really complex, which is why the development of Part 2 of the standard is being initiated. On the other hand, the normative development of BIM standardization shows that it will take many years to develop the infrastructure-related aspects. In addition, the standardization of safety and health in BIM is scarce and insufficient.

Thus, it is demonstrated that there is a significant gap in the standardization of the level of health and safety information required in road projects carried out in BIM, depending on the nature of the activities, aligning with the need for specificity in the prevention of occupational risks in the construction sector. It is therefore considered to be a key factor impeding the adoption of BIM for health and safety and to be able to achieve its benefits.

Therefore, the aim of this research is to propose the level of information necessary for health and safety in road works which, based on the ISO 7817-1:2024 [57] standard, guarantees the quality and granularity of the information for the assessment of the usual risks in these projects in their design phase, for the usual agents and equipment, and which allows its relation with the IFC.

2. Materials and Methods

2.1. Occupational Risk Assessment Methodology

The proposed standardization is based on the risk assessment methodology [27], whose application in BIM has already been validated [28,49]. It assigns values to the probability of occurrence (Prob_R0i) and the severity of the consequence (Sev_R0i) of the risk. This score can be 1, 2, or 3, from lowest to highest as the probability or severity increases. The level of risk is the result of multiplying the probability by the severity (Val_R0i = Prob_R0i $\times$ Sev_R0i). The risk reassessment shall be carried out after applying the following preventive measures, which is the same procedure depending on these factors: reassessed probability (Re_Prob_0i), reassessed severity (Re_Sev_0i), and reassessed risk assessment (Re_Val_0i). The colour coding of the risk levels in the BIM model is the one established by the Spanish Institute for Occupational Safety and Health (SIOSH) [27].

To carry out the above process graphically in the model, each BIM object will represent one or more work units: excavation, embankment, pavement, etc., depending on the risk analysis to be carried out. In addition, each work unit needs a series of activities to carry it out: stakeout, compaction, spreading the primer irrigation, etc., which will have associated risks: cuts, falls at the same level, noise, etc.

Consequently, each BIM object of a work unit must incorporate as non-graphic information (parameters) all the information of the risk assessment process of the activities necessary to execute it. If any of the risks exist in more than one activity, the one with the highest assessment will be taken to be on the side of safety (Figure 1).

This parameterisation is automated by means of two codes created in Dynamo. The first one creates the parameters of Table 1 and associates them to the BIM objects starting from an Excel sheet in which the necessary information is defined according to the coding of the (SIOSH) [27]. The second shows the preliminary values of risks according to [65], structured in another Excel sheet, and enters them into the BIM objects according to the corresponding work unit. From this point, within the BIM model, the health and safety technician carries out the specific risk assessment according to the context of each activity and the area using tables or 3D views of the model.

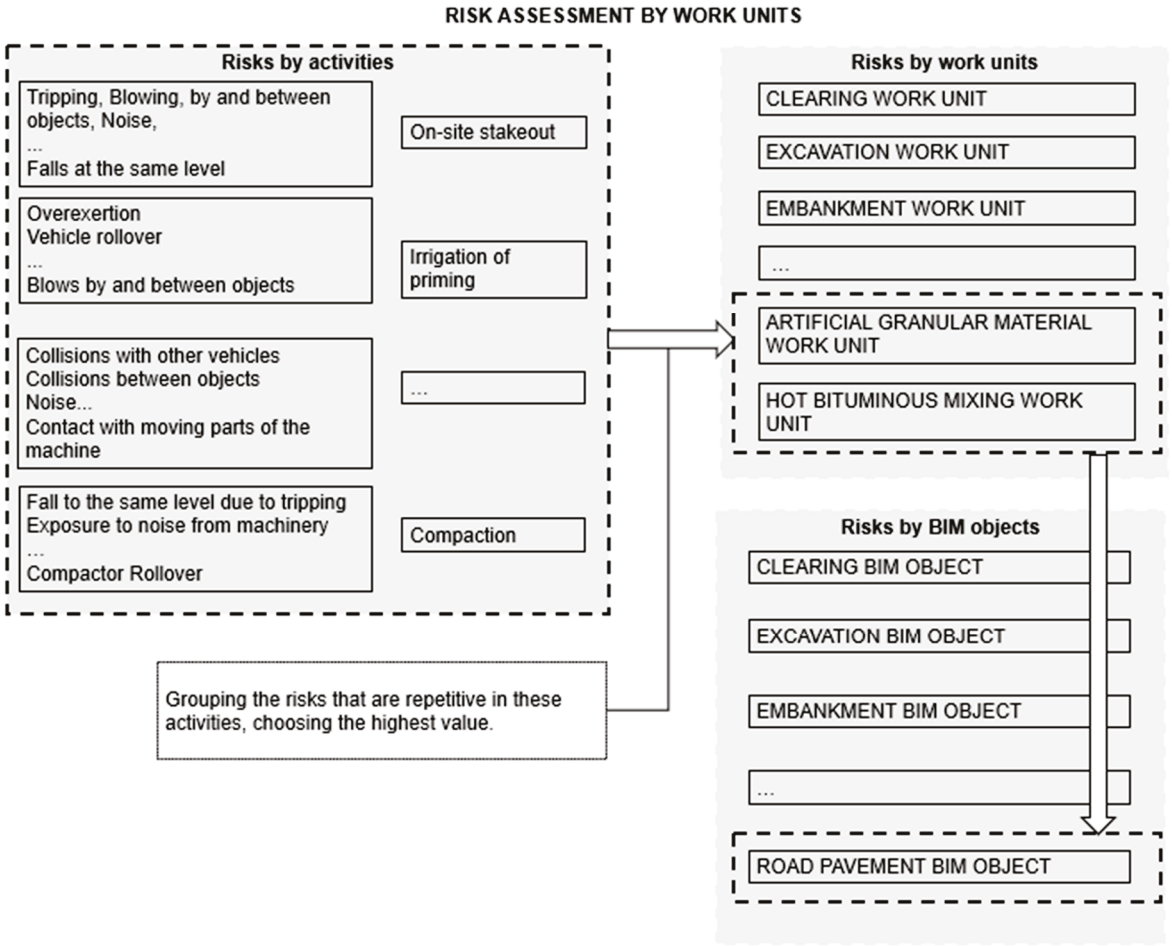


Figure 1. Example diagram of association of the risks of the activities grouped by work units [65], with the elements of the project represented by BIM object.

Table 1. Level of alphanumeric and documentary information associated with the LOINSH 100, 200, 300 and 350. Summary of the Pset established for this research.

Pset	Property	LOINSH	Type of Data	Description
1_IDENTIFICACION	01_01_PROYECTO	100/200/300/350	TEXT	Project code
1_IDENTIFICACION	01_02_FASE	100/200/300/350	TEXT	Identification of the phase in which the model element is within the project life cycle
1_IDENTIFICACION	01_03_DISCIPLINA	100/200/300/350	TEXT	Project discipline
1_IDENTIFICACION	01_04_ELEMENTO	200/300/350	TEXT	Element type
1_IDENTIFICACION	01_05_CLASIFICACION	200/300/350	TEXT	Classification code
1_IDENTIFICACION	01_06_NOMBRE	200/300/350	TEXT	Short name of the element
1_IDENTIFICACION	01_07_MATERIAL	200/300/350	TEXT	Reference to the material of the element
2_PROYECTO	02_01_CAPITULO	300 only for HS discipline/350	TEXT	Chapter of the budget for the work unit to which the element refers
2_PROYECTO	02_02_SUBCAPITULO	300 only for HS discipline/350	TEXT	Subchapter of the budget for the work unit referred to in the element
2_PROYECTO	02_03_LONGITUD	300 only for HS discipline	NUMBER	Element measurement value
2_PROYECTO	02_04_AREA	300 only for HS discipline	NUMBER	Element measurement value

Table 1. *Cont.*

Pset	Property	LOINSH	Type of Data	Description
2_PROYECTO	02_05_VOLUMEN	300 only for HS discipline	NUMBER	Element measurement value
2_PROYECTO	02_06_PESO	300 only for HS discipline	NUMBER	Element measurement value
2_PROYECTO	02_07_UD OBRA	300 only for HS discipline/350	TEXT	Code of the work unit to which the element refers
2_PROYECTO	02_08_INDIRECTO	300 only for HS discipline/350	TEXT	Code of the indirect work unit or units separated by ';'
2_PROYECTO	02_09_FASE DE OBRA	300 only for HS discipline	TEXT	Project phase
3_OBRA	03_01_TAREA	350	TEXT	Code of the task in the work plan to which the element belongs
EvaluacionRiesgo	Riesgo 0i	100/200/300/350	TEXT	Name of risk i according to the classification of the INSST
EvaluacionRiesgo	Prob_R0i	100/200/300/350	NUMBER	Probability of occurrence of risk i
EvaluacionRiesgo	Sev_R0i	100/200/300/350	NUMBER	Severity of the consequence of the occurrence of risk i
EvaluacionRiesgo	Val_R0i	100/200/300/350	NUMBER	Risk assessment i as a result of the product of its probability and consequence
EvaluacionRiesgo	Re_Prob_R0i	100/200/300/350	NUMBER	Probability of occurrence of risk i once preventive measures have been implemented
EvaluacionRiesgo	Re_Sev_R0i	100/200/300/350	NUMBER	Severity of the consequence of the occurrence of risk i once the preventive measures have been implemented
EvaluacionRiesgo	Re_Val_R0i	100/200/300/350	NUMBER	Risk assessment i as a result of the product of its probability and consequence once the preventive measures have been implemented
DocumentosSeguridadSalud	Normativa	100/200/300/350 only for HS discipline	LINK	Link to the folder within the CDE in which the prescriptions that apply to them are found and the procedure for assembly, maintenance, and disassembly of the preventive measures by discipline
DocumentosSeguridadSalud	Memoria	100/200/300/350 only for HS discipline	LINK	Link to the folder within the CDE in which the report of the Health and Safety Study is located
DocumentosSeguridadSalud	Planos	300/350 only for HS discipline	LINK	Link to the folder within the CDE in which the plans by discipline of the Health and Safety Study are found
DocumentosSeguridadSalud	Presupuesto	300/350 only for HS discipline	LINK	Link to the folder within the CDE in which the measurements and prices by discipline and the budget of the Health and Safety Study are found

2.2. Level of Information for Safety and Health (LOINSH)

The objective is to standardize the level of information necessary (LOIN) for health and safety in the design process of a road project using BIM. There will be a work team (or a role) in charge of analyzing health and safety based on the information coming from the rest of the work teams (pavements and earthworks, drainage, structures, etc.). This team will set the different levels of necessary safety information for each BIM object, called LOINSH (Level of Information Necessary for Safety and Health) in order to be able to carry out the analysis of the risk assessment of the road project depending on the type of risk to be analyzed and the stage of the project. The information will refer to certain geometric

and analytical characteristics, either non-graphic or linked, such as links to documents related to the Health and Safety Study

In order to have sufficient and ascending granularity in the information, three levels are proposed, from the one that needs or has little information, LOINSH 100 (for example, in planning or informative study), a phase with more information available, LOINSH 200 (preliminary design), up to the complete information of the construction, LOINSH 300 (construction project), adding one more level for risks that require additional information in their analysis. The LOINSH is not associated with the phase, which implies that, in a preliminary project phase, due to the particularity of a risk, the health and safety technician can set a necessary requirement corresponding to a LOINSH 350.

The first two structure the information necessary for a preliminary design stage and the last two for the construction project. This can vary according to the requirements and nature of the project, and especially the requirements of the health and safety analysis, which is being used interchangeably in each of them.

Following the criteria of the BIM Manual of the Government of Catalunya [66], the accuracy of the BIM objects for health and safety will be schematic for the LOINSH 100, metric for LOINSH 200, and centimetric for LOINSH 300 and 350. In addition, the LOINSH 300 addresses the standard risk assessment information, and the LOINSH 350 deals with the special risks as indicated in the standard [27].

2.3. LOINSH 100

This LOINSH 100 will be applied when, due to the available information on the project or the risks to be assessed, a division into work units is not possible or necessary, either due to the lack of definition or because the risk affects large areas of the project. The level of information required will be as follows:

2.3.1. Graphical Information Level

- Level of detail: Determined by elements that have a conceptual geometry, with some division intended to mark a specific risk and that allows for the association of Alphanumeric Information.
- Dimensionality: BIM objects can be two-dimensional or three-dimensional, but in any case, they must allow for the association of parametric information.
- Location: They must be in absolute coordinates.
- Appearance: BIM objects must have a colour based on the result of the risk assessment and re-evaluation according to the SIOSH methodology to be able to visualize it graphically within the model. If this is not possible due to requirements because a single model with all the information is desired, the BIM object will maintain the colour of the corresponding material. Even so, having the associated parameters, it should be possible to make colour filters through any visualization programme.
- Parametric behaviour: The health and safety team will carry out a risk assessment on fixed information on the design of the road, so parametric behaviour is not necessary. If after the risk assessment it is necessary to make changes in the design, these must be made by the work team of the discipline involved.

2.3.2. Level of Alphanumeric Information

It must include the identification of the BIM object and the information of the associated risks. The first is structured in a group of parameters (Pset) recognizable by the BIM Open Standard (IFC) format to be able to identify the name of the project, the phase, and the discipline, called "1_IDENTIFICACION", based on the BIM Manual of the Directorate-General for Mobility and Road Infrastructure of the Regional Government of Extremadura [67].

The associated information is also structured in the group of parameters "EvaluacionRiesgo", which includes all the parameters to obtain the result of the evaluation and re-evaluation according to the methodology of the SIOSH [27]. The risk assessment values of the units can be based on known theoretical values extracted from documents such as the risk assessment guide of the Navarre Association of Public Works Companies (NAPWC) [65] or other reference bibliographic values. The parameters of these two Pset can be consulted in Table 1, where each of the parameters and their respective LOINSH are indicated.

2.3.3. Level of Documentary Information

The model must have the capacity to host a URL to link to the Technical Report and Regulations on Health and Safety of the Common Data Environment (CDE), which includes the preventive measures proposed based on the risks assessed. This can be consulted through the "Memoria" and "Normativa" parameter of the "DocumentosSeguridadSalud" Pset added to the BIM model globally, specified at the end of Table 1.

2.4. LOINSH 200

This LOINSH 200 will be applied when, due to the available information on the project or the risks to be assessed, granularity in complete work units is not necessary, and the risks may be grouped for sets of work units. The level of information required will be as follows:

2.4.1. Graphical Information Level

- Level of detail: Determined by BIM objects that represent the typology of the element in a generic way, with a level of metric precision. It is possible that the same BIM object encompasses several elements of the project. In particular, about the discipline of pavements and earthworks, the BIM object can be grouped into a basic section in which the same BIM object contains the different layers of the pavement and represents the finished level of the grading together with the cut slopes. It shall also be possible to divide the layout into sections along project axes or when there is a significant geometrical or constructional difference. It is not necessary to resolve road intersections with precision, but the coordination in plan and elevation must be maintained with the required precision. With regard to the disciplines of structures, drainage, and affected services, the BIM objects must be modelled with the external envelopes of their main elements with the precision required for this LOINSH.
- In the case of BIM objects in the discipline of health and safety, objects will be modelled that represent preventive measures (barriers, signage, etc.) with the precision required in this phase.
- Dimensionality: All elements that make up the disciplines must be three-dimensional in order to have a coordinated BIM object in plan and elevation to which the risk information results can be associated.
- Location and Appearance: The same as the LOINSH 100.
- Parametric Behaviour: The same as the LOINSH 100, with the difference that, in the case of the health and safety discipline itself, it is considered necessary to place preventive measures in an agile and effective manner.

2.4.2. Level of Alphanumeric Information

It must include the identification of the BIM object and the information of the associated risks. The identification parameter group is extended until all those considered in the "1_IDENTIFICACION" Pset (Table 1). With respect to the associated information, the "EvaluacionRiesgo" Pset is presented in Table 1. To start the risk assessment, theoretical

values from guides such as the NAPWC [65] or other bibliographic values can be used, which will be reviewed according to the context information of each unit in the BIM model. The units modelled with this LOINSH will have associated the risks of the activities that compose them (Figure 1).

2.4.3. Level of Documentary Information

The same as for LOINSH 100.

2.5. LOINSH 300

This LOINSH will be used when the risk analysis requires complete granularity of the work units and the risks associated with them, as well as a level of centimetre detail, which allows for interference in the execution of activities to be analyzed.

2.5.1. Graphical Information Level

- Level of detail: Determined by objects that have a geometry that defines the typology of the element it represents with centimetre precision. BIM objects must allow for interference analysis. With respect to the discipline of pavements and earthworks, it will be necessary to define a precise and complete section in which its layers are differentiated by materials and units of work. It must also be possible to divide the route into sections so that the risk areas can be precisely differentiated based on the units of work. In addition, embankment and excavation volumes must be obtained, as well as their slopes, to differentiate them, which must be coordinated in plan and elevation with the section of the road surface and with the natural terrain. With respect to the disciplines of structures, drainage, and services affected, it will be necessary to model all the elements that are the object of analysis by means of a BIM object with a geometry with centimetre precision, but it will be necessary to model fabrication details such as armatures, wall bushings, etc.

In the case of health and safety elements, objects representing preventive measures must be modelled unambiguously and with the centimetre precision required at this stage. It will not be necessary to model execution details.

- Dimensionality: All the elements that make up the disciplines must be three-dimensional.
- Location: They must be in absolute coordinates.
- Parametric appearance and behaviour: Same as LOINSH 200.

2.5.2. Level of Alphanumeric Information

Those relating to identification and associated information. The first maintains those indicated in LOINSH 200 plus those in "2_PROYECTO" Pset for objects in the health and safety discipline (Table 1).

The second remains the same "EvaluacionRiesgo" Pset, although it should be noted that there will be differences in its values (not in its structure) related to the granularity of the risk assessment. In general terms, it is proposed that this should last until there is at least one BIM object to which a risk work unit is associated, in this case according to NAPWC [65], as established in Table 2.

2.5.3. Level of Documentary Information

It will be necessary to define the documentary information parameters belonging to the "DocumentosSeguridadSalud" Pset that are specified at the end of Table 1.

Table 2. Association of disciplines with the elements of the road, as well as with the work units of risk of ANECOP [64] in the construction project stage.

Discipline	Road Element	Risks Grouped by Work Units According to [65]
Pavements and earthworks	Hot mix asphalt layers	Hot mix asphalt (HMA)
	Base	Artificial granular base
	Subbase	Natural granular base
	Natural terrain	Topography
	Clearing surface	Clearing
	Excavation volume	Excavation
	Embankment volume	Embankment
	Slope excavation	Revegetation and hydroseeding of slopes
	Slope embankment	Revegetation and hydroseeding of slopes
Structures	Overpass	Overpasses
	Prefabricated frame	Prefabricated frame
Drainage	Gutters	Longitudinal drainage
	Manholes and pipes	Ditches and dug wells
	Cross drainage culverts	Transverse drainage
Affected services	Underground services	Reposición de canalizaciones de servicios
	Overhead power lines	Interference with overhead lines
Signalling, beaconing, and defence	Horizontal and vertical signage	Horizontal and vertical signage
Health and safety	Preventive measures	Signage during the execution of the work

2.6. LOINSH 350

This LOINSH will be applied when the risk to be assessed requires any of the following conditions: 4D information, generation of risk areas associated with the execution of the work unit or any existing element, or there are special risks according to the regulations, for example, the RD 1627/1997 [26].

2.6.1. Graphical Information Level

The same approach as for LOINSH 300 is adopted, increasing the level of detail, allowing the route to be divided into short sections (1 to 10 m) and all road surfaces to be segregated by layers, allowing 4D construction simulation of the sections and layers, associating BIM objects with others that simulate safety zones for the element to be analyzed and risk zones for machinery, and incorporating BIM objects, at least for the envelopes of the machinery necessary for the execution of that work unit. BIM objects must allow for interference analysis.

2.6.2. Level of Alphanumeric Information

In this LOINSH, the BIM objects will incorporate the "1_IDENTIFICACION" and "EvaluacionRiesgo" Pset in the same terms as the LOINSH 300, along with some parameters of the "2_PROYECTO" Pset and "3_OBRA" Pset. The reason for incorporating these parameters is to consult the information related to the machinery, the breakdowns of the work units (02_01_CAPITULO, 02_02_SUBCAPITULO, 02_07_UD OBRA and 02_08_INDIRECTO of the "2_PROYECTO" Pset), and a third parameter (03_01TAREA of the "3_OBRA" Pset) to carry out the construction simulation. This can be found in Table 1.

2.6.3. Level of Documentary Information

As in the LOINSH 300, a URL parameter will be necessary to link the corresponding information from the Health and Safety Study by discipline. In addition, the BIM object will have information associated by one or more URL parameters on the construction process, with information on the assembly, maintenance, and dismantling plan of auxiliary elements such as scaffolding or shoring. This information must be inside the folder whose link is entered to the parameters within the "DocumentosSeguridadSalud" Pset. In order to manage health and safety on roads with BIM, it will be necessary to define the information requirements, which are different depending on the phase. This makes it necessary to establish several levels of information (LOINSH 100, 200, 300, and 350). Finally, according to the disciplines of the BIM manual of the Directorate-General for Mobility and Road Infrastructure of the Regional Government of Extremadura [67], the characteristics of these LOINSH are defined in Tables 1 and 3.

Table 3. Summary of the definition of the LOINSH proposed for the preliminary project and construction project phases.

		Preliminary Design		**Construction Project**	
Level of Information	**Discipline/Work Team**	**LOINSH 100**	**LOINSH 200**	**LOINSH 300**	**LOINSH 350**
Level of Graphic Information					
Detail	Pavements and earthworks	Conceptual objects with some specific division. Schematic accuracy.	Generic objects of the levelling level and of the excavation and embankment slopes. Metric accuracy.	Objects that define the typology with centimetre accuracy. Division and distribution by layers. Incorporate excavation and backfill objects, as well as excavation slope object and backfill with centimetre accuracy.	Objects with centimetre accuracy. Division by layers based on construction simulation.
	Structures	Conceptual objects. Schematic accuracy.	Generic main objects with metric accuracy.	Objects that define the typology with centimetre accuracy.	Objects with centimetre accuracy. Division based on construction simulation.
	Drainage	Conceptual objects. Schematic accuracy.	Generic main objects with metric accuracy.	Objects that define the typology with centimetre accuracy.	Objects with centimetre accuracy. Division based on construction simulation.
	Affected Services	Conceptual objects. Schematic accuracy.	Generic main objects with metrically accurate dimensions.	Objects that define the typology with centimetre accuracy.	Objects with centimetre accuracy. Division based on construction simulation.
	Signage, Beaconing, and Defence	Not required	Not required	Objects that define the typology with centimetre accuracy.	Objects with centimetre accuracy. Division based on construction simulation.
	Health and Safety	Conceptual objects. Schematic accuracy.	Generic objects with metric accuracy.	Objects that define the typology with centimetre accuracy.	Objects with centimetre accuracy. Division based on construction simulation. Delimitation of machinery work areas in accordance with construction simulations, as well as areas of special risk for the safety and health of workers.
Dimensionality	Pavements and Earthworks	2D/3D	3D	3D	3D
	Structures	2D/3D	3D	3D	3D
	Drainage	2D/3D	3D	3D	3D
	Affected Services	2D/3D	3D	3D	3D
	Signage, Beaconing, and Defence	Not required	Not required	3D	3D
	Health and Safety	2D/3D	3D	3D	3D
Location	Pavements and Earthworks	Absolute	Absolute with metric accuracy.	Absolute with centimetre accuracy.	Absolute with centimetre accuracy.

Table 3. *Cont.*

		Preliminary Design		Construction Project	
Level of Information	**Discipline/Work Team**	**LOINSH 100**	**LOINSH 200**	**LOINSH 300**	**LOINSH 350**
	Structures	Absolute	Absolute with metric accuracy	Absolute with centimetre accuracy.	Absolute with centimetre accuracy.
	Drainage	Absolute	Absolute with metric accuracy	Absolute with centimetre accuracy.	Absolute with centimetre accuracy.
	Affected Services	Absolute	Absolute with metric accuracy	Absolute with centimetre accuracy.	Absolute with centimetre accuracy.
	Signage, Beaconing, and Defence	Not required	Not required	Absolute with centimetre accuracy.	Absolute with centimetre accuracy.
	Health and Safety	Absolute	Absolute with metric accuracy	Absolute with centimetre accuracy.	Absolute with centimetre accuracy.
Appearance	Pavements and Earthworks	Colour according to risk assessment or generic.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.
	Structures	Colour according to risk assessment or generic.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.
	Drainage	Colour according to risk assessment or generic.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.
	Affected Services and Complementary Works	Colour according to risk assessment or generic.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.
	Signage, Beaconing, and Defence	Not required	Not required	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.
	Health and Safety	Colour according to risk assessment or generic.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.	Colour according to risk assessment or by material.
Parametric Behaviour	Pavements and Earthworks	Non-existent	Non-existent	Non-existent	Non-existent
	Structures	Non-existent	Non-existent	Non-existent	Non-existent
	Drainage	Non-existent	Non-existent	Non-existent	Non-existent
	Affected Services	Non-existent	Non-existent	Non-existent	Non-existent
	Signage, Beaconing, and Defence	Not required	Not required	Non-existent	Non-existent
	Health and Safety	Non-existent	Partial	Partial	Partial
Level of Alphanumeric Information					
Identification *	Pavements and Earthworks	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION
	Structures	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION
	Drainage	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION
	Affected Services	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION
	Signage, Beaconing, and Defence	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION
	Health and Safety	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION	Pset_1_IDENTIFICACION
Associated Information *	Pavements and Earthworks	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo; Pset_2_PROYECTO; Pset_3_OBRA
	Structures	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo; Pset_2_PROYECTO; Pset_3_OBRA
	Drainage	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo; Pset_2_PROYECTO; Pset_3_OBRA
	Affected Services	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo Pset_2_PROYECTO; Pset_3_OBRA
	Signage, Beaconing, and Defence	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo; Pset_2_PROYECTO; Pset_3_OBRA

Table 3. *Cont.*

		Preliminary Design		Construction Project	
Level of Information	**Discipline/Work Team**	**LOINSH 100**	**LOINSH 200**	**LOINSH 300**	**LOINSH 350**
	Health and Safety	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo	Pset_EvaluacionRiesgo; Pset_2_PROYECTO;	Pset_EvaluacionRiesgo; Pset_2_PROYECTO; Pset_3_OBRA
Documentary Information					
Linked Information	Pavements and Earthworks	Not required	Not required	Not required	Not required
	Structures	Not required	Not required	Not required	Not required
	Drainage	Not required	Not required	Not required	Not required
	Affected Services	Not required	Not required	Not required	Not required
	Signage, Beaconing, and Defence	Not required	Not required	Not required	Not required
	Health and Safety *	Pset_Documentos SeguridadSalud	Pset_Documentos SeguridadSalud	Pset_Documentos SeguridadSalud	Pset_Documentos SeguridadSalud

* In accordance with the criteria established for each LOINSH in Table 1.

3. Results

3.1. Introduction and Application Case

The LOINSH's standardization proposal is validated in the application to a real road project. In addition, different commercial software specialized in the BIM design of roads has been used for its validation. Although standardization can be extrapolated to other software and commercial houses, software from the Autodesk suite has been used, such as InfraWorks 2024 or Civil 3D 2024, specific to infrastructures and Revit 2024 more typical of buildings. Finally, NavisWorks 2024 is used for 4D simulations. Civil 3D 2024 and Revit 2024 are used in different risk assessment processes to demonstrate the applicability of standardization in different software and contrast the scope and limitations of each.

The choice of one or the other depends on the nature of the project, the handling of the tools by the health and safety team and the scope of the risk analysis. Finally, we will also work with models exported from these programmes to an Open Standard BIM format (IFC).

The results of this research aim to validate the proposed methodological framework at a conceptual level to demonstrate the effectiveness of the organization of safety information in a road project using LOINSH, which provides benefits in the automation of risk assessment. Thus, the application of the proposal will be considered in a single example case, the results of which can be extrapolated to projects of other characteristics.

The example project consists of a road located in Miranda de Ebro, Burgos (Spain) to eliminate the level crossing of KP 456 + 727 of the Madrid–Hendaye railway line. To this end, there is a distribution roundabout, an overpass over the National Highway 1 (N-1), a section connecting the underpass with the roundabout, a section connecting the roundabout with the bridge, two sections connecting the roundabout to roads as a replacement for these, four access or exit branches to the N-1, and, finally, a service road parallel to the N-1 (Figure 2). In this investigation, an analysis is carried out of the safety conditions of activities common to road projects regardless of their dimensions, typology, location, etc. For this reason, the case chosen serves as a particular asset on which to demonstrate the viability of applying the methodological framework to a real road so that the results can be extrapolated to any other road project, thus demonstrating the transferability of the proposed LOINSH.

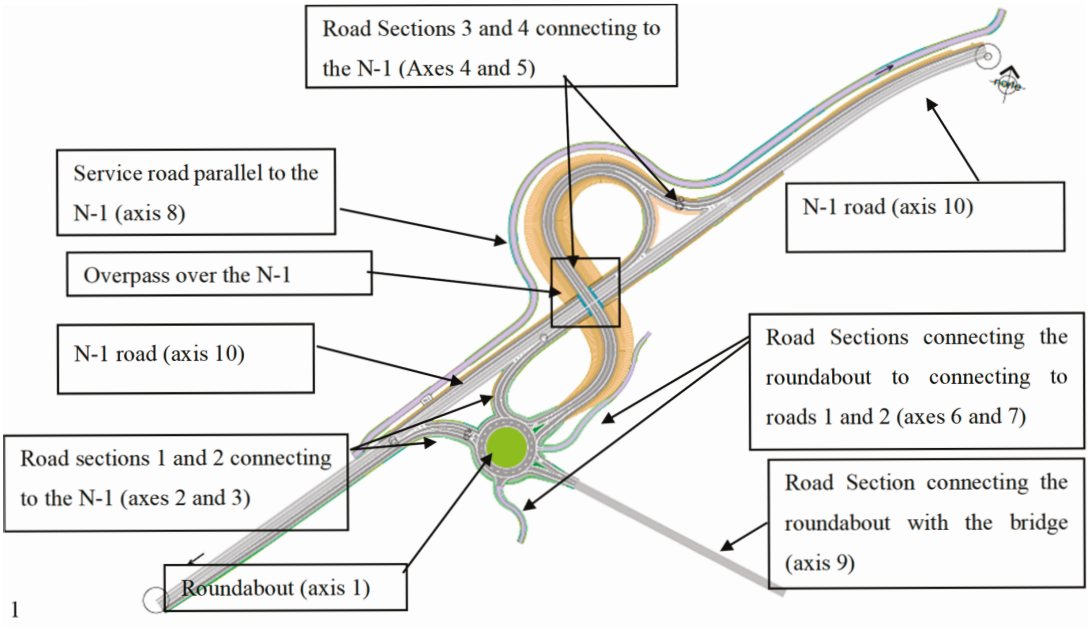


Figure 2. General plan of the project.

3.2. Generation of the BIM Model for the Preliminary Project Phase with LOINSH 100 and 200 Requirements

First, a BIM model for road safety is created, focused on analyzing safety at the preliminary design stage. It contains the following disciplines: pavements and earthworks, structures, affected services, and health and safety.

The information contained in these disciplines is compiled by specific working teams. The health and safety team collects this information and integrates the results of the risk assessment in accordance with the LOINSH that has been established. In this case, the most appropriate thing would be to use the LOINSH 100 or 200, since, at this stage, it would not be necessary to have a centimetre accuracy, as is required for LOINSH 300 or 350, but it would be sufficient to arrange conceptual or generic objects with schematic (LOINSH 100) or metric (LOINSH 200) precision that inform the technicians of the location, position, and interference of these objects with other elements of the project, since the objective of this phase is not to solve all the design problems but to have a vision of the general configuration of the project, so a generic conception of the definition of structures, pavements, Affected Services, drainage works, and others will be sufficient.

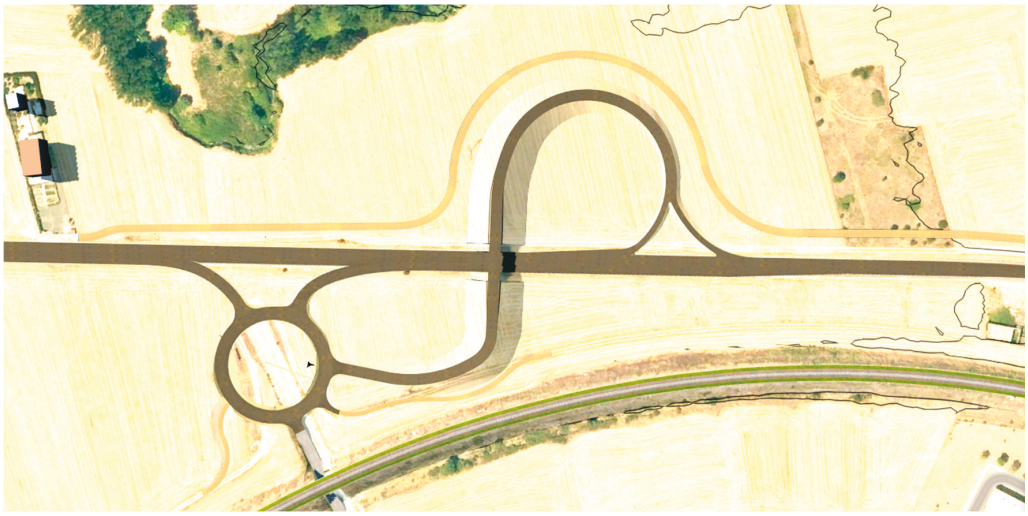
For health and safety assessment, the first step is to create the BIM model of the existing conditions. This was carried out with InfraWorks 2024 with the ETRS89 coordinate system to which vector files were added with information on the lines in the surrounding area of Miranda de Ebro. To this is added the topographic surface, imported as a Digital Terrain Model, and the orthophoto of the area. From this, it is modelled at the preliminary project level, obtaining an approximate geometry of the section and slopes of the necessary earthwork (Figure 3a). In this preliminary design phase, the export to Civil 3D 2024 continues to finalize the geometric fit in plan and elevation.

In this phase of development, the project is defined as a 50 cm package, with no separation between layers. For this reason, the safety technician prescribes a LOINSH 100 for the safety assessment. From this, the modelling team takes from the surface with the axes of the design road in plan and the contour of the work in InfraWorks 2024 a three-dimensional extrusion of 0.50 m thick. This is a first BIM object at a LOINSH 100 level of the pavement and earthmoving discipline (Figure 3b), since its precision is schematic and it is a BIM object with a level of conceptual detail (Table 3). The health and safety team

can then carry out their work through Civil 3D 2024 or through Revit 2024. If it is through the latter, it is necessary that, from Civil 3D 2024, it is exported to IFC format (Figure 3c) and then imported into the software itself (Figure 3d). As can be seen in the figures, this LOINSH 100 incorporates the information of the established Pset (Table 1).

In a more advanced phase of the design in the preliminary design phase, the health and safety technician establishes a LOINSH 200 to have greater precision and division of the road, which allows greater granularity of the risk assessment. To this end, continuing with the discipline of pavements and earthworks, 10 sections of linear works were created, one for each axis of the project, as well as the affected service OPL. At this point, it is not necessary to resolve the road junctions with precision (Figure 4). Figure 4a shows the BIM object of a section with a LOINSH 200 with risk information in relation to earthworks in this phase. The design carried out in the geometry of the road is observed in accordance with the needs of the health and safety team, according to Section 2.4. In this case, it was carried out in Civil 3D 2024, differentiating main axes and in sections of less than 50 m. In addition, these BIM objects do not define any typology, presenting a generic 3D geometry that gives information about the location of the element with metric precision (Table 3).

(**a**)



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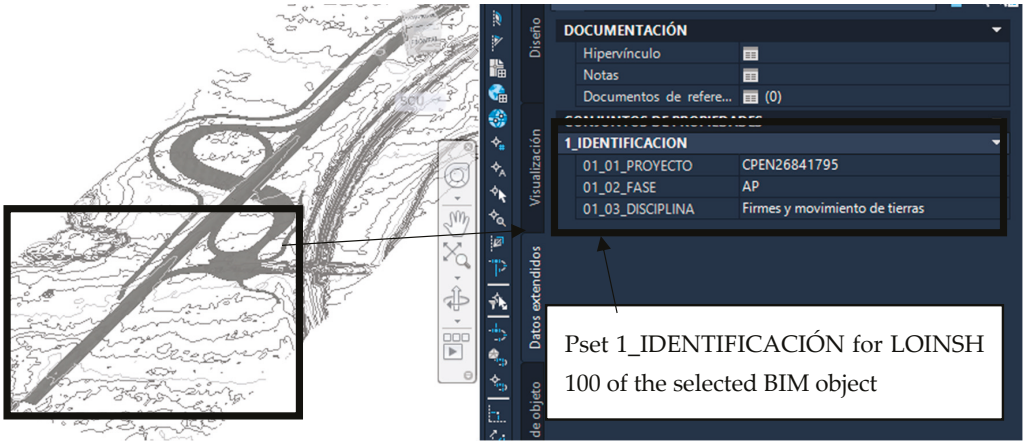
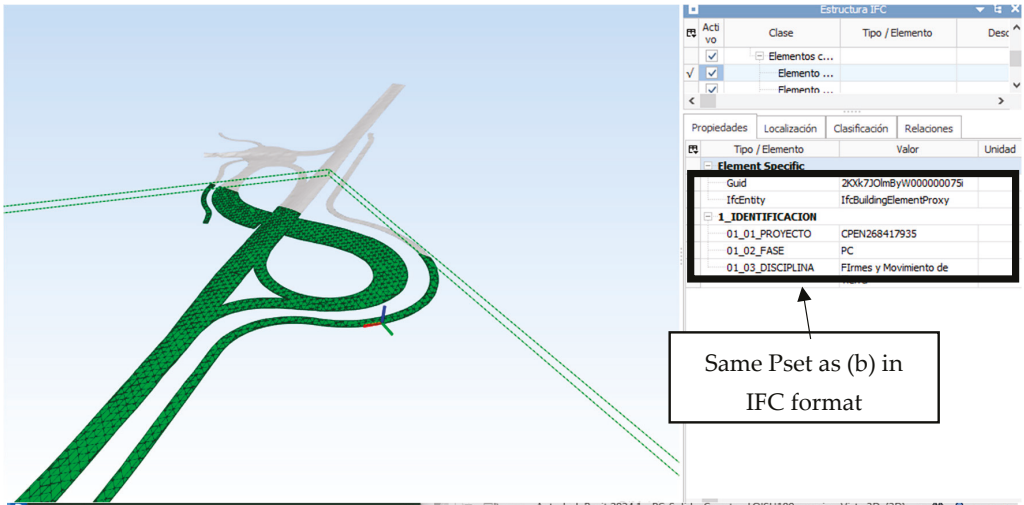


Figure 3. *Cont.*

(**c**)



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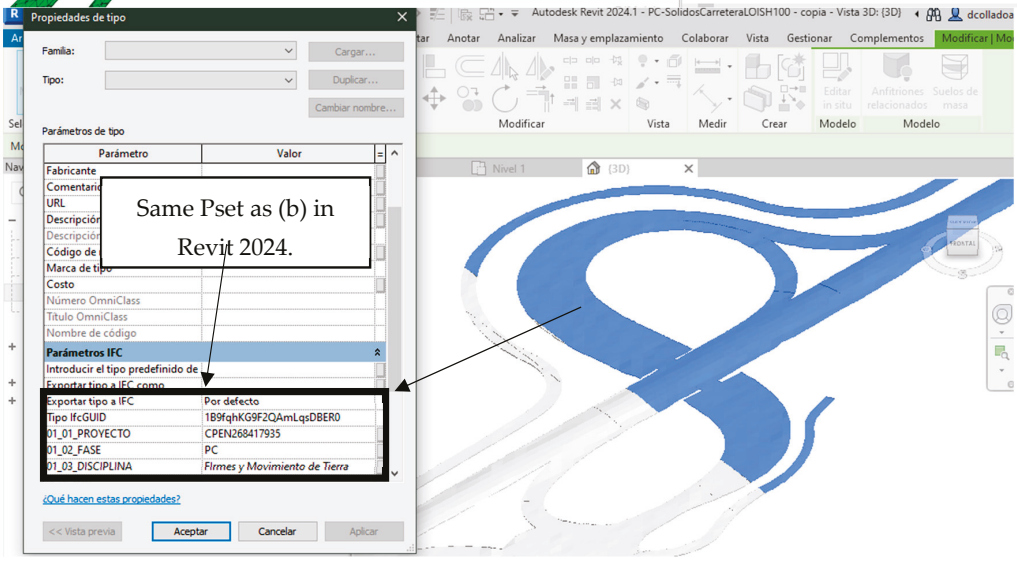


Figure 3. BIM objects of the pavement and earthwork model with a LOINSH 100. (**a**) InfraWorks 2024, (**b**) Civil 3D 2024, (**c**) BIM Vision (IFC), and (**d**) Revit 2024.

(**a**)

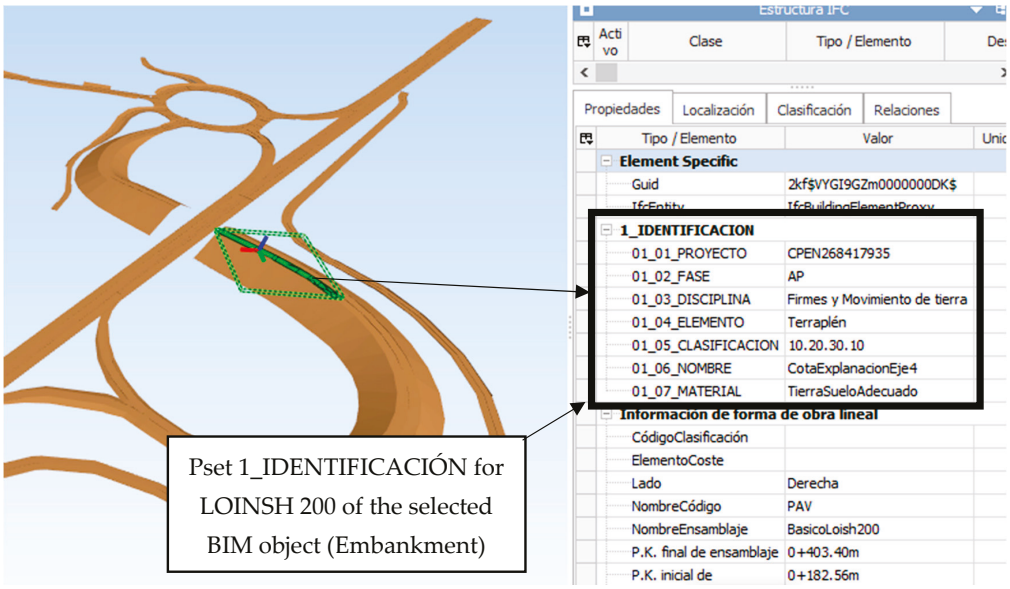


Figure 4. *Cont*.

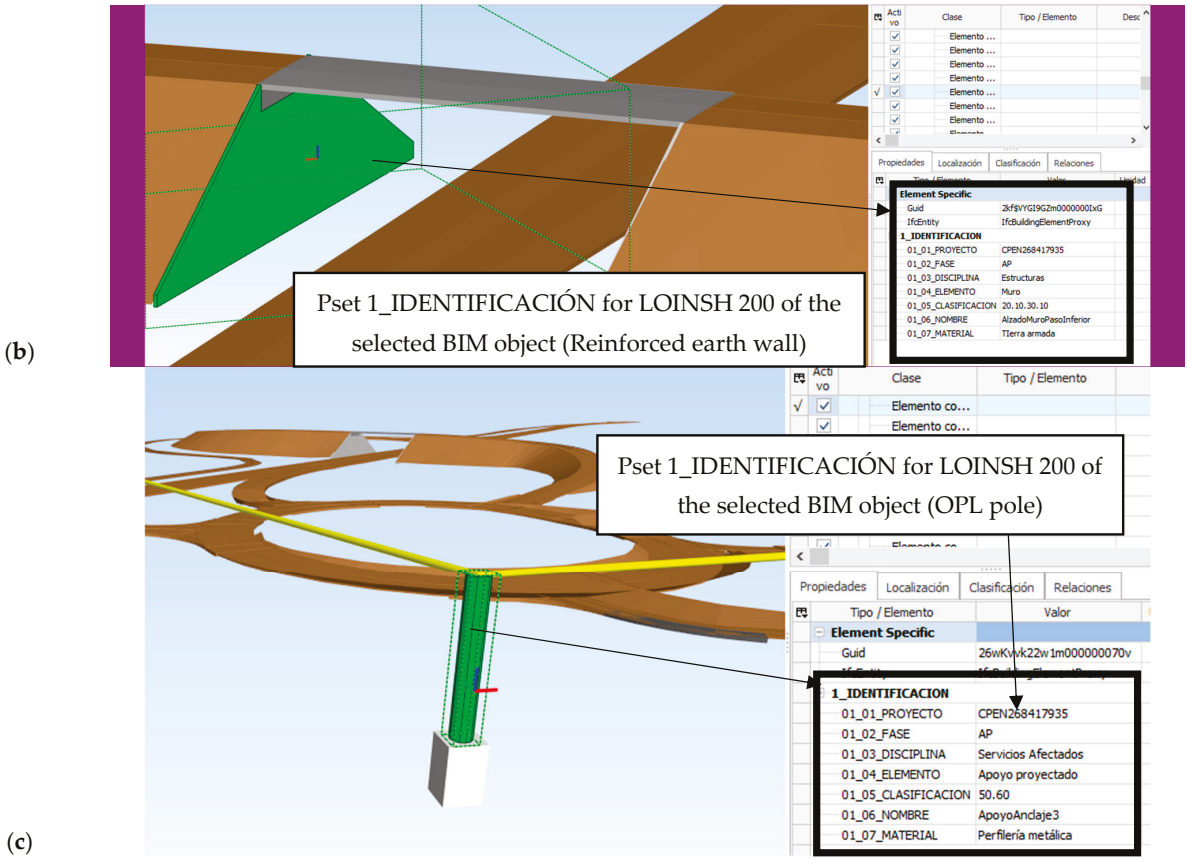


Figure 4. BIM objects of models from different disciplines with LOINSH 200 IFC format in BIM Vision. (**a**) Pavements and earthworks, (**b**) structures, and (**c**) Affected Services (OPL).

It can also be seen that these objects have non-graphic information incorporated. In this way, the health and safety team can manage the information model in a simple way, as well as carry out filters and queries for risk assessment. In this case, the "1_IDENTIFICACION" Pset was added (Table 1), according to the Directorate-General for Mobility and Road Infrastructure of the Regional Government of Extremadura [67], Table 3, and Section 2.4, as well as additional parameters such as the axis, the side, the PK, the volume, etc., which allows for the spatial location of the area to be determined and can be staked on site, if necessary.

With respect to the discipline of structures, in Civil 3D 2024, the geometry of the bridge over the N-1 was developed, modelling the BIM objects that represent the bridge according to LOINSH 200: two reinforced earth walls, the embankment slope, the deck, and the abutments (Figure 4b).

With respect to the discipline of Affected Services, the execution of the road crosses an OPL that is represented by generic BIM objects of the outer envelope of the poles and the route of the high-voltage cables (Figure 4c), as described in Section 2.4.

3.3. Health and Safety Analysis in the Preliminary Design Phase

Once the model has been developed with the BIM objects with the LOINSH 100 and 200, the technician will carry out the risk assessment by entering the information in the parameters of the "EvaluacionRiesgo" Pset (Figure 1).

In this case, and as established in these LOINSH, for the evaluation, a grouping is carried out in the main work units and by previous or habitual work, field work, adverse weather conditions, etc., according to the criteria of the NAPWC [65]. After that, the risk

assessment methodology is applied: identification, assessment of the level of risk based on probability and severity, preventive measures, and reassessment.

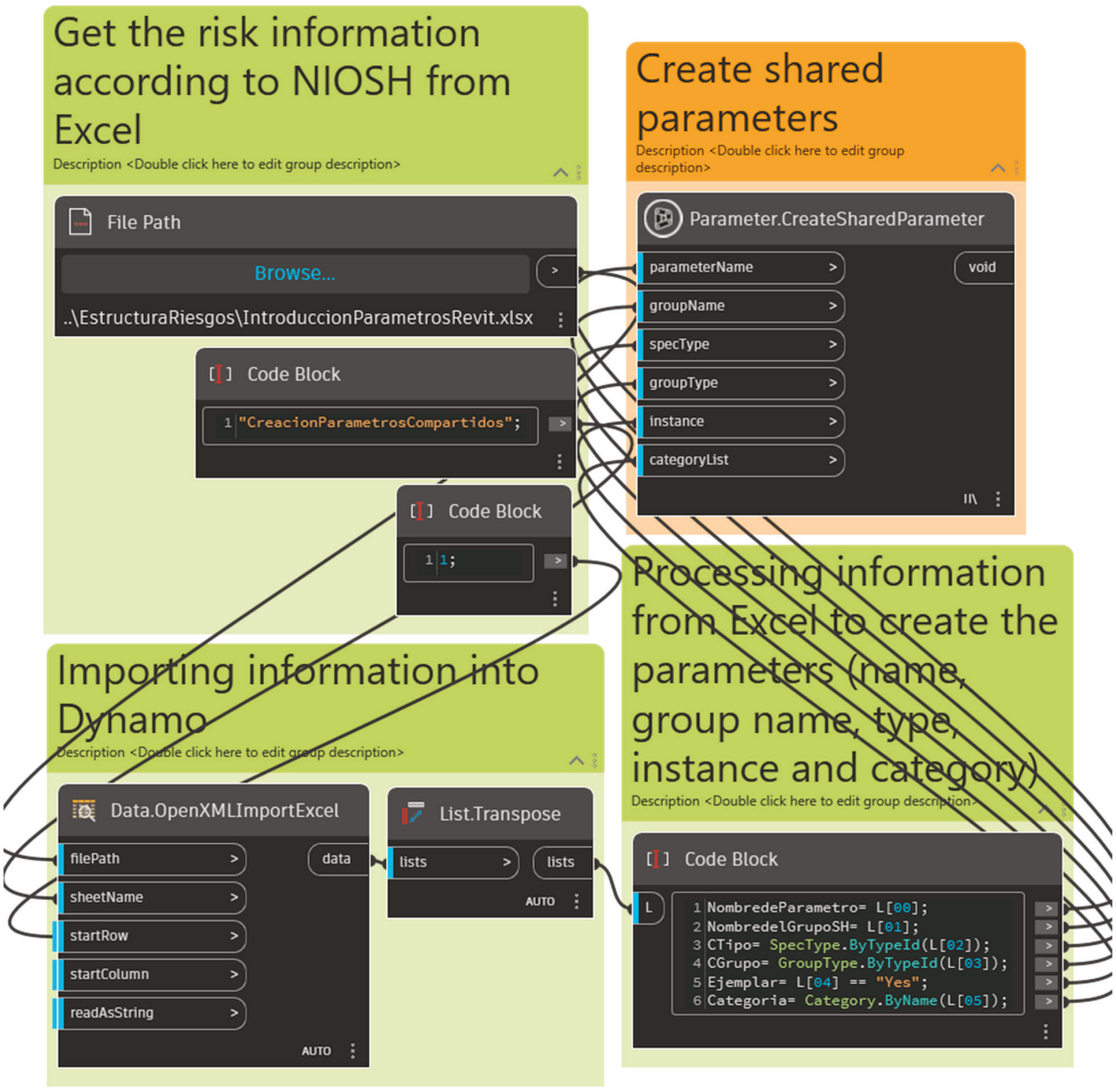
For the validation of the LOINSH, the risk information structures of the work units have been created: excavation, embankment, overpass over N-1, and Affected Services (OPL Replacement). This structure is created by the health and safety technician in Excel.

The association of the parameters to the BIM objects of the work units depends on the software chosen. For example, when using Autodesk Revit 2024, risk information structured in Excel was fed into BIM objects using project parameters. To reduce manual process time and reduce errors, two Dynamo scripts are developed. The first has a code to create a file of shared parameters according to the "EvaluacionRiesgo" Pset (Table 1) from Excel and adds them as project parameters to the Revit 2024 model (Figure 5a), automatically generating the "EvaluacionRiesgo" Pset in the BIM model (Figure 5b).

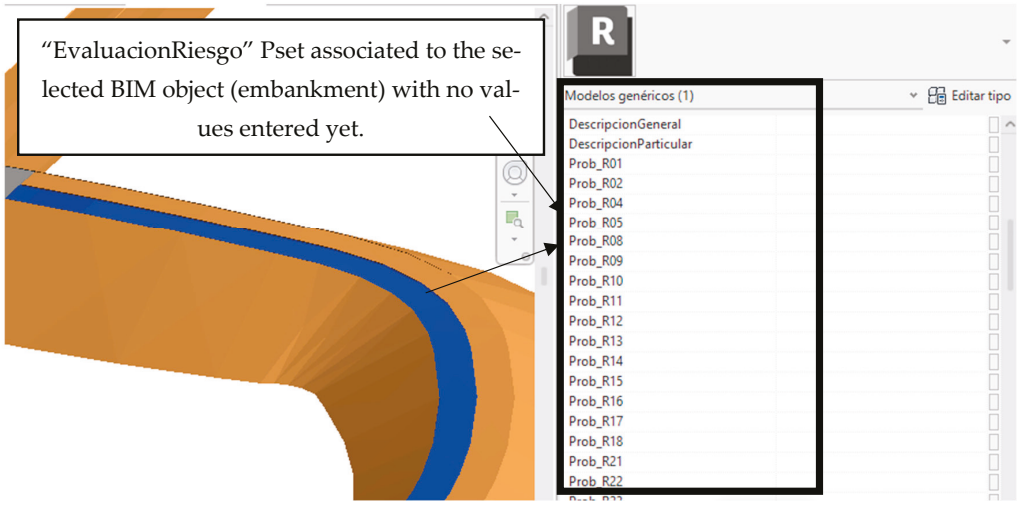
The second script associates the values of each of the parameters of the risk information structure from the Excel sheet to the different BIM objects of the model based on those of the "1_IDENTIFICACION" Pset (Figure 6a). To display only the parameters that apply to that BIM object, a specific category is assigned to that unit of work that represented that BIM object. Figure 6b checks how the category "Site" was associated with the execution of the embankment, and by executing the script, only the parameters of the risk existing in it are associated.

From here, technicians perform risk assessments within the model (Figure 7a). It is worth mentioning that risk values can be managed quickly and efficiently using planning tables in Revit 2024 (Figure 7a) or Project Explorer in Civil 3D 2024 (Figure 7b).

In the case of OPL, when the health and safety technician detects its presence and it is a special risk [26], it is necessary to analyze the execution of works near it, which is not possible with a LOINSH 200, as it has metric accuracy. In addition, as its analysis requires generating the risk areas of the OPL, it will be necessary to apply a LOINSH 350 according to the requirements established, see Section 2.6. However, with the geometry of the LOINSH, the minimum free distance is not met, resulting in an intolerable risk that makes it necessary to divert it.

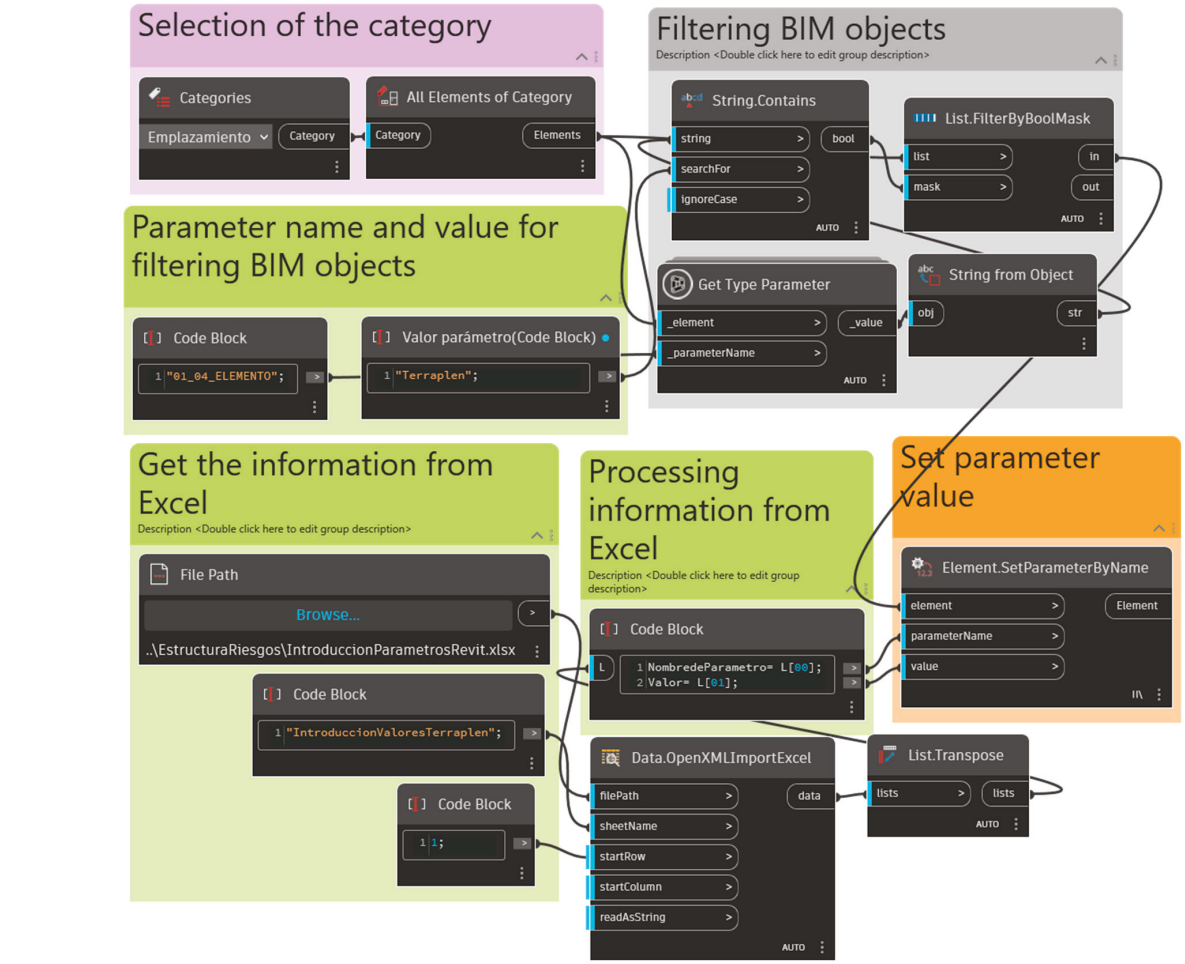


(**a**)

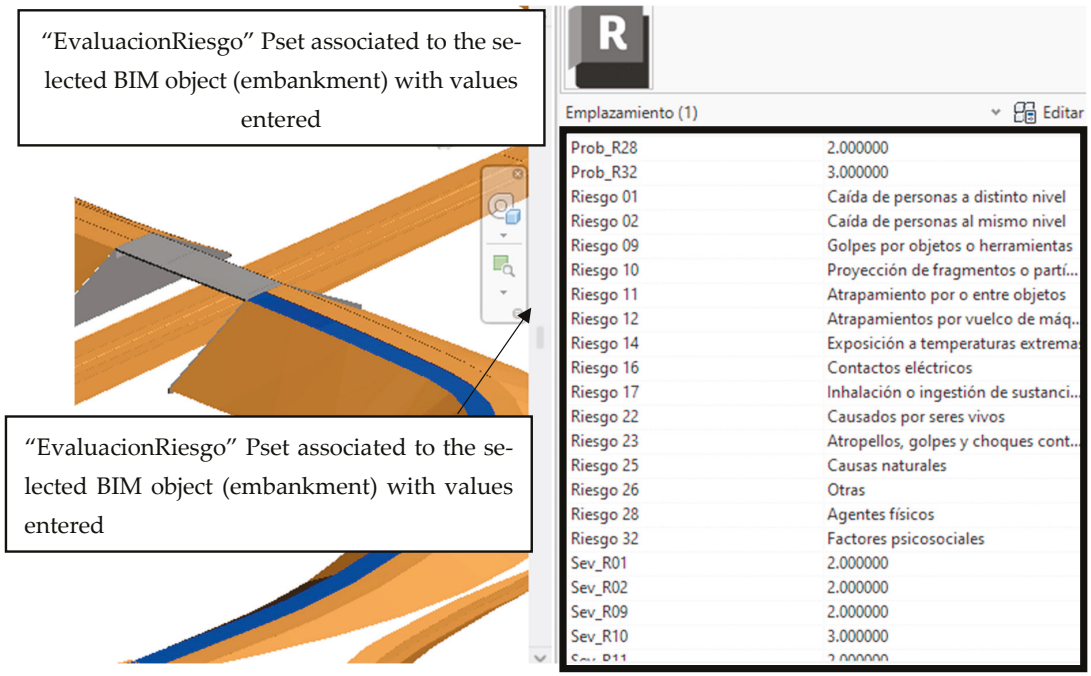


(**b**)

Figure 5. Structure of the "EvaluacionRiesgo" Pset in BIM model. (**a**) Visual programming code in Dynamo to associate parametric information from a sheet in Excel to BIM objects in Revit 2024, (**b**) BIM object of the pavement and earthwork model with the risk assessment parameters incorporated in Revit 2024.

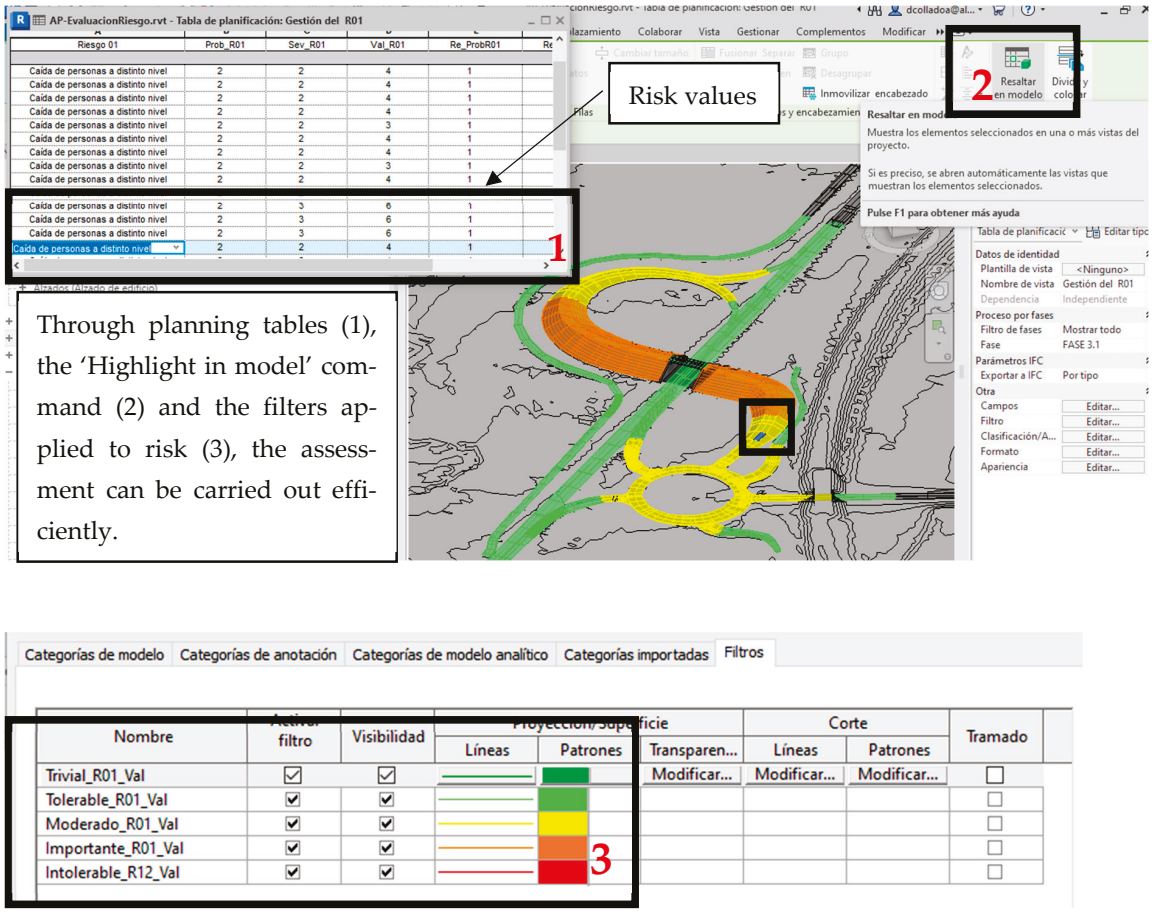


(**a**)

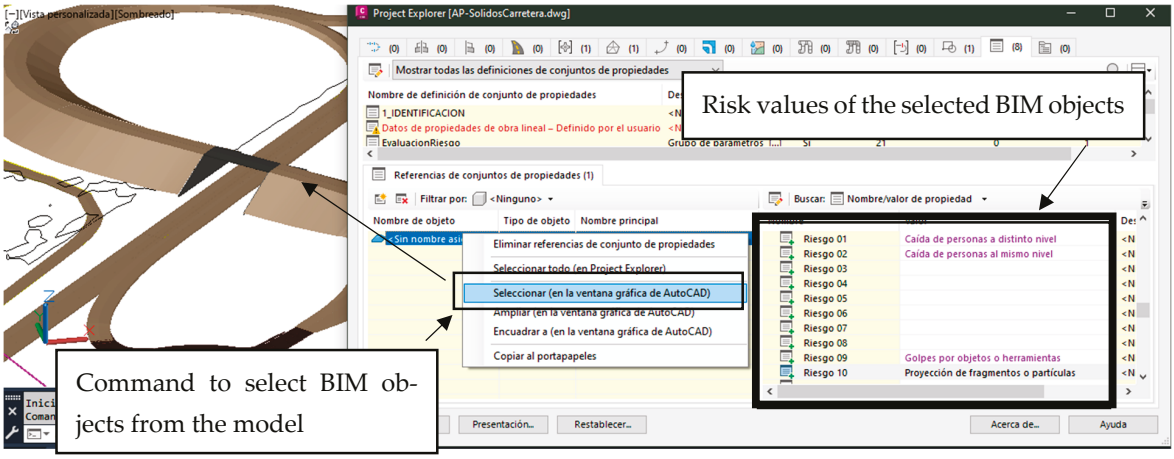


(**b**)

Figure 6. "EvaluacionRiesgo" Pset values in BIM model. (**a**) Visual programming code in Dynamo to associate "EvaluacionRiesgo" Pset values of a sheet in Excel to BIM objects in Revit 2024, (**b**) BIM object of the pavement and earthwork model with the values of the risk assessment parameters.



(a)



(**b**)

Figure 7. Risk assessment within the model. (**a**) Running filters in Revit 2024 for the graphical representation of risk assessment and management using planning tables. (**b**) Managing risk assessment parameter values in Civil 3D 2024 with Project Explorer.

3.4. Generation of the BIM Model for the Project Phase with LOINSH 300 and 350 Requirements

For the validation of the standardization proposed in this phase, the model is developed from the initial one incorporating all the disciplines that are modelled in Civil 3D 2024, except for the structure, which, in order to reach the level of detail required in this phase, the LOINSH has to be modelled in Revit 2024 (Figures 8 and 9). The modelling of BIM objects is centimetre accurate for the resolution of interferences and supervision of the construction process, according to the requirements of Table 3 [67].

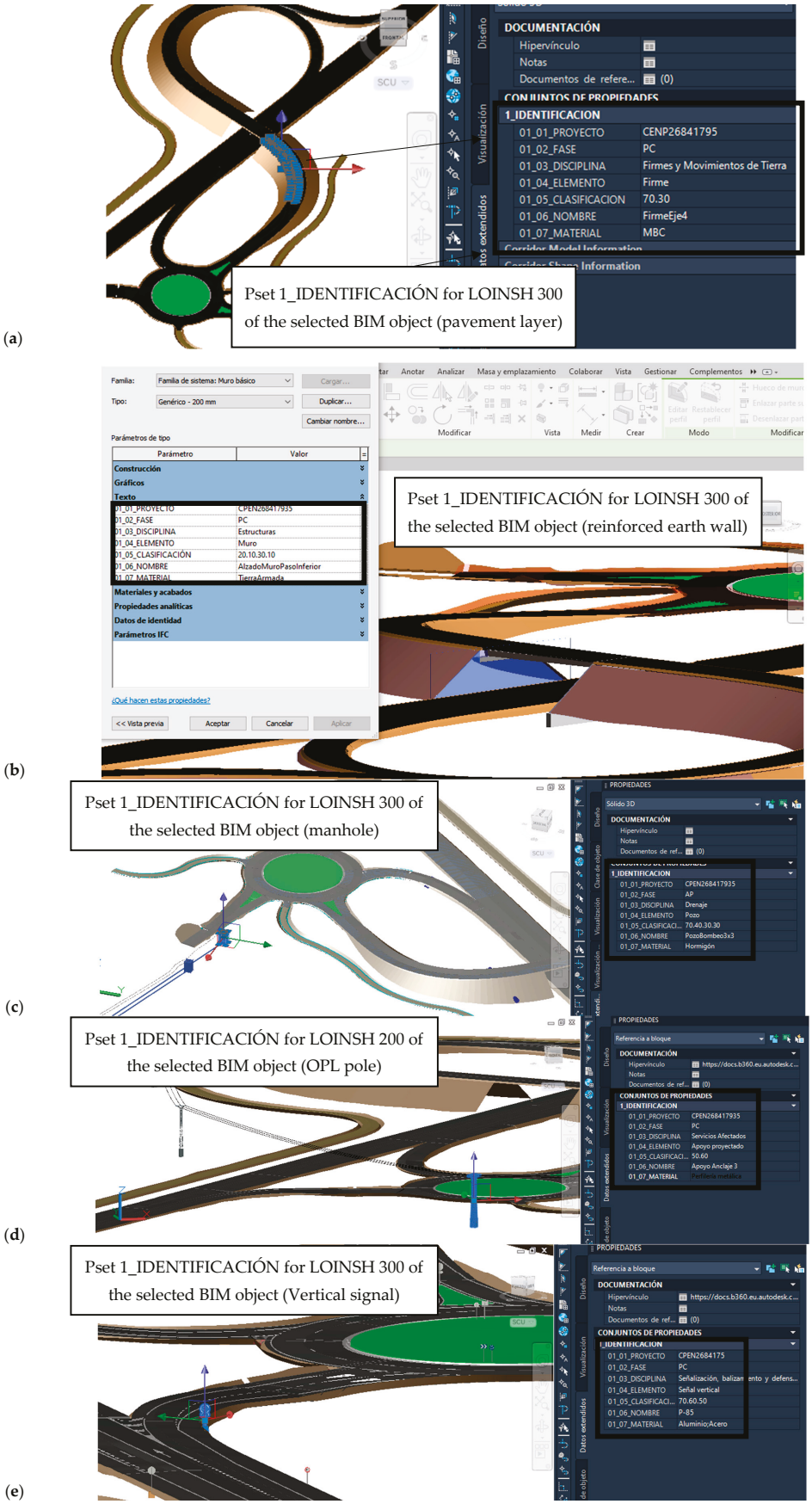
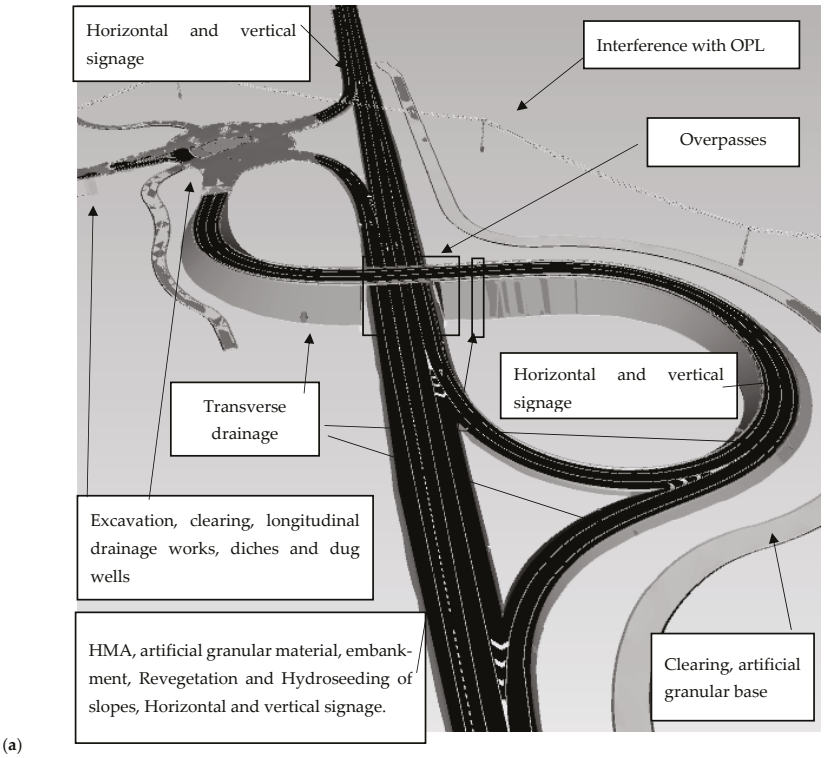
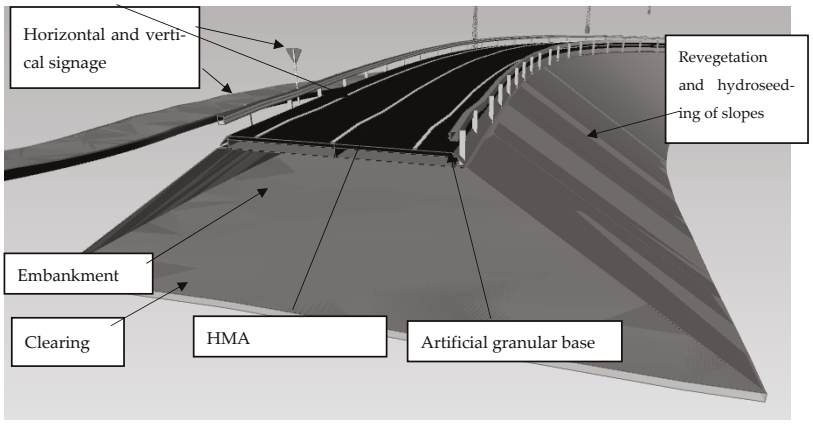


Figure 8. Road model BIM objects with a LOINSH 300 and the "1_IDENTIFICACION" Pset. (**a**) Pavements in Civil 3D 2024, (**b**) structures in Autodesk Revit 2024, (**c**) drainage in Civil 3D 2024, (**d**) Affected Services (OPL) in Civil 3D 2024, and (**e**) horizontal and vertical signage in Civil 3D 2024.



(**a**)



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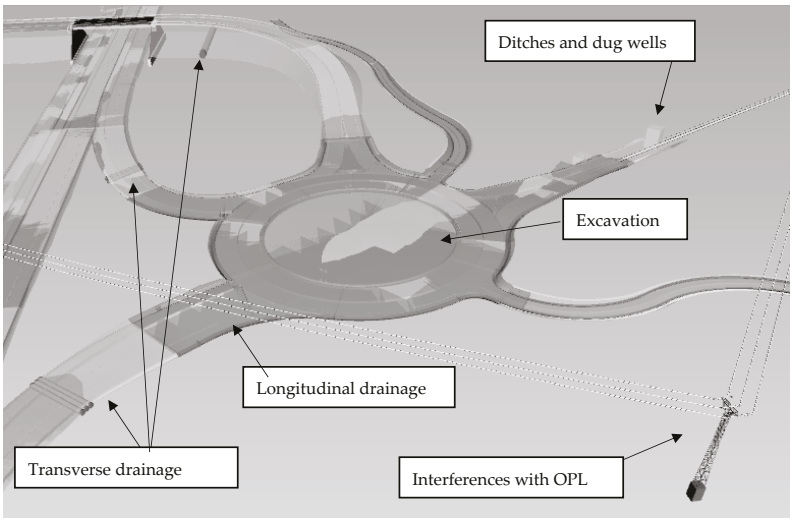


(**c**)

Figure 9. Federated model in NavisWorks 2024, where the work units and their relationship with BIM objects from different disciplines are shown. (**a**) Complete, (**b**) cross-section of the road, and (**c**) roundabout.

For the discipline of pavements and earthworks, pavement sections were defined as follows: width, thicknesses, and ditches (Figure 8a), with the segregation by layers according to Table 3. In the structures discipline, the deck with three trough beams, the neoprene supports, the foundation, and the reinforced earth walls were defined (Figure 8b). The drainage discipline includes the BIM objects of ditches and transverse drainage works, manholes, and collectors until their connection with the existing sewerage network (Figure 8c). In the case of the discipline of Affected Services and the deviation of the OPL, the towers are modelled with a BIM object that defines their precise typology and dimensions and the high-voltage cable with its theoretical catenary curve design (Figure 8d). Given the type of risk when requiring a LOINSH 350, it is necessary to model the risk areas and simulate the construction phases, but this is not possible to do in Civil 3D 2024. Finally, in this phase, the discipline of Signalling, Beaconing, and Defence appears, which is not required for previous LOINSH, modelling the horizontal and vertical signage and barriers (Figure 8e), in accordance with the provisions of Table 3, to assess the risks of the implementation of this discipline.

3.5. Health and Safety Analysis in the Project Phase

The risk information structure follows the "EvaluacionRiesgo" Pset (Table 1) as set out in Section 3.3, the increase in the level of detail of the assessment assumes that there is at least one BIM object to which the risks of a unit are associated [65], as established in Table 2.

Figure 9 shows a federated model of all disciplines in NavisWorks 2024, where the risk work unit associated with the BIM objects marked in that figure is identified, allowing for the management of the associated information.

Based on parameterization, the risk assessment in the BIM model has been automated according to the probability and severity of the area analyzed, which must be determined by the technician according to the section and unit of work analyzed. As an example, the result obtained after incorporating the risk assessment into the model with LOINSH 300 is presented in 01. Falling to different levels for the discipline of pavements and earthworks (Figure 10). It should be noted that the appearance of these models by means of colour coding represents the risk levels proposed by the SIOSH methodology [27] and follows the stipulations of the visualization requirements for the LOINSH 300 in Table 3, which allows the safety technician to obtain quick and visual information on the results of the safety and health assessment carried out on the project.

Within the discipline of pavements and earthworks, in accordance with the initial risk assessment 01 (Figure 10a,b), the configuration of the pavement (composed of two layers) is identical in both work units. Given the division carried out, it is possible to carry out a detailed analysis of the risk according to areas, so in the sections of road connecting to the N-1, the risk is moderate (medium probability (2) and harmful severity (2)), continues as moderate in the area of the roundabout, reaching trivial (probability 1, severity 1) in the execution of lanes on the N-1, due to a lower probability of machinery present is lesser, and tolerable (probability 2, severity 1) at the main road due to the lower height in its execution (Figure 10a,b). In the access ramps to the overpass, the probability is maintained, but the severity is increased if the risk occurs due to the height of the earthwork, becoming important (probability 2, severity 3). The application of the graphic standards allows us to quickly observe that the greatest risk of falling at different levels is around the ramps (axes 4 and 5), leading to the overpass crossing the N-1. It is thus demonstrated how the standardization of the proposed LOINSH allows for greater granularity and ease in the analysis and risk management.

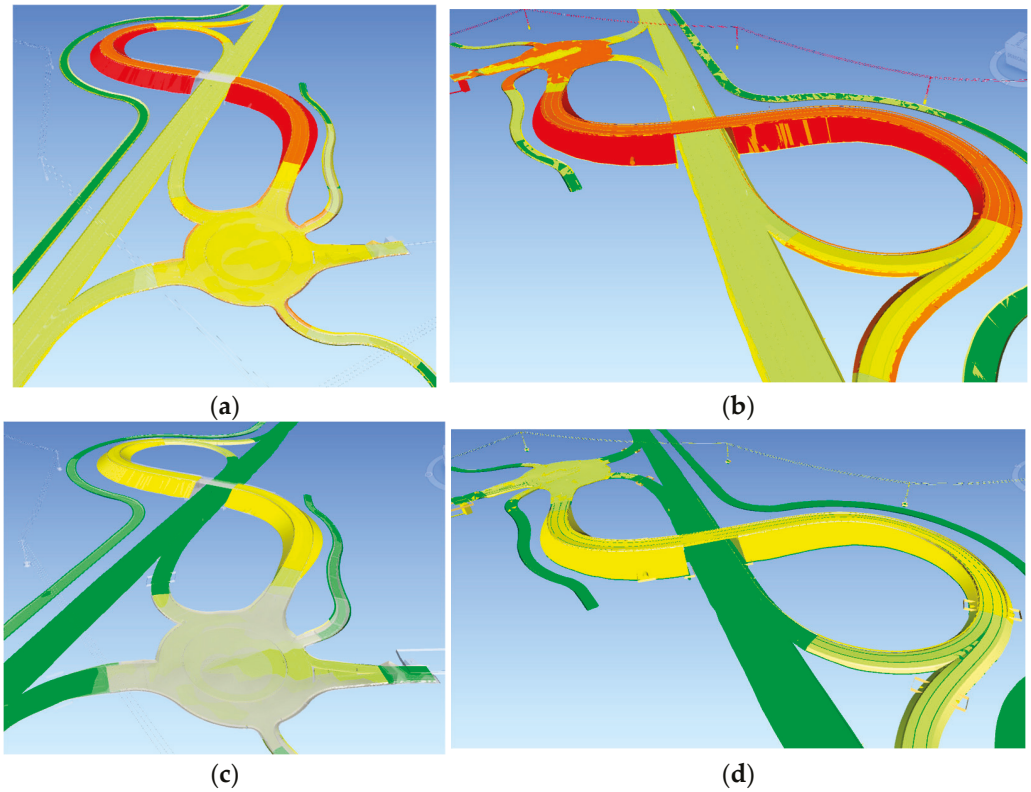


Figure 10. General visualization in NavisWorks 2024 of the BIM model of the discipline of pavements and earthworks (BIM objects of the HMA pavement and granular material base, excavation slopes, and embankment) in the construction project phase of the assessment of the risk of falling at different levels. Red (intolerable), orange (important risk), yellow (moderate risk), light green (tolerable risk), and green (trivial risk). (**a**) Initial risk assessment, perspective 1, (**b**) initial risk assessment, perspective 2, (**c**) reassessment with provision of preventive measures, perspective 1, and (**d**) reassessment with provision of preventive measures, perspective 2.

After the evaluation, preventive measures are applied in areas of important risk: construction signage, 1-metre-high polypropylene mesh barrier, railings, and the corresponding documentary information. After that, when carrying out the risk reassessment (Figure 10c,d), the probability of the risk is modified from the pavement layers and the embankment so that the important risk (probability 3 and severity 2) becomes moderate (reassessed probability 2 and reassessed severity 2), what was assessed as moderate became tolerable (reassessed probability 1 and reassessed severity 2), and what was tolerable became trivial (reassessed probability 1 and reassessed severity 1) (Figure 10c,d).

3.6. Health and Safety Analysis of Special Risks in the Project Phase

The 380 kV OPL that crosses perpendicular to the main road and some road sections is a special risk. In the preliminary design stage, the BIM object that represents the discipline of pavements and earthworks included the risks associated with an OPL. The proposed standardization for the LOINSH 100 of the BIM object of the area (level of detail by sections Table 1), allows for traceability of the risk assessment by allowing the area of impact of the OPL (Civil 3D 2024) electrical risk to be marked. On the other hand, the standardization of risks in the LOINSH ("EvaluacionRiesgo" Pset parameters, Table 1–Figure 11a) allows for the result of the evaluation to be graphically displayed (in this case red, as it is intolerable). This parameterization enables automation using Dynamo (Figure 11b).

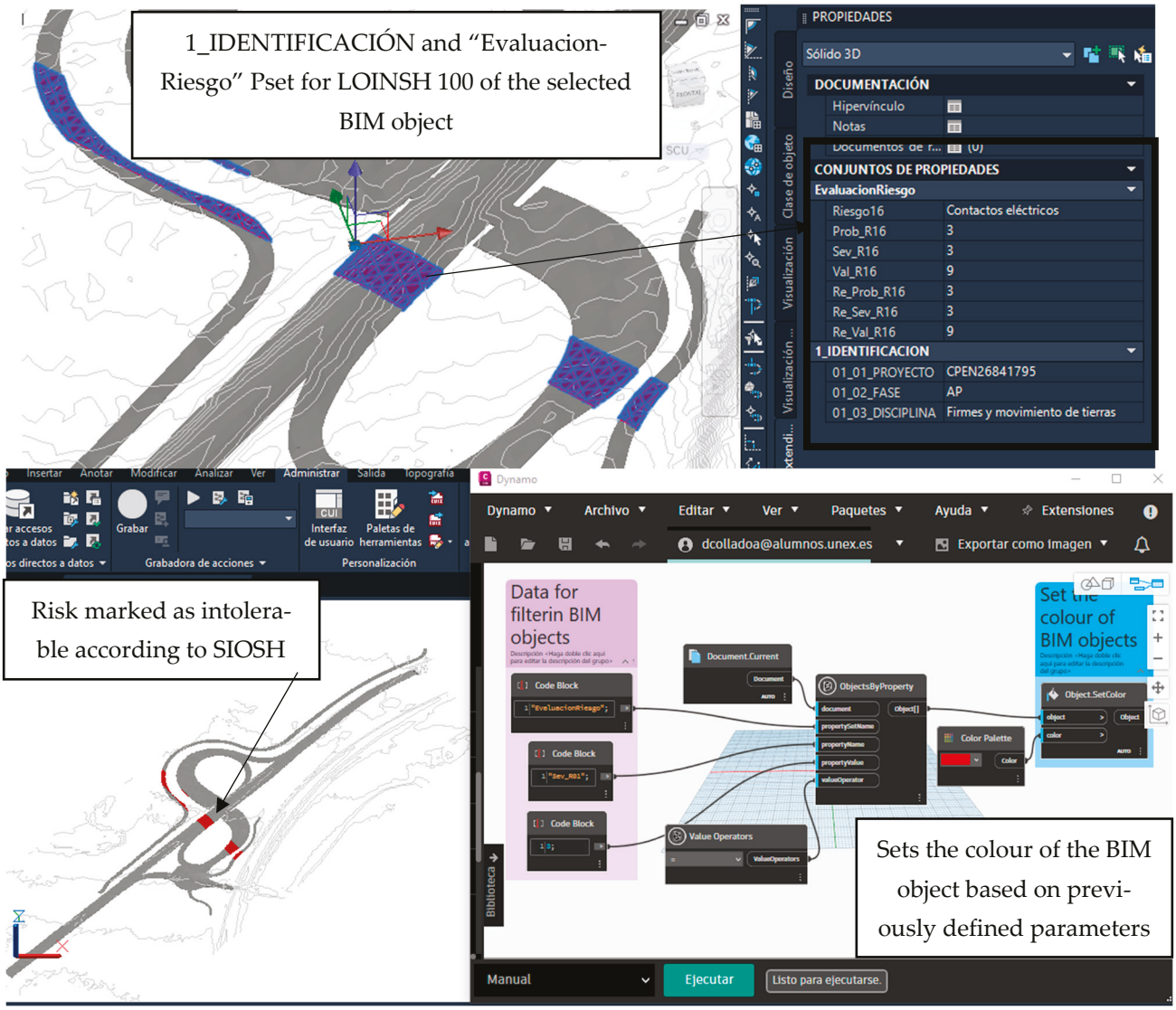
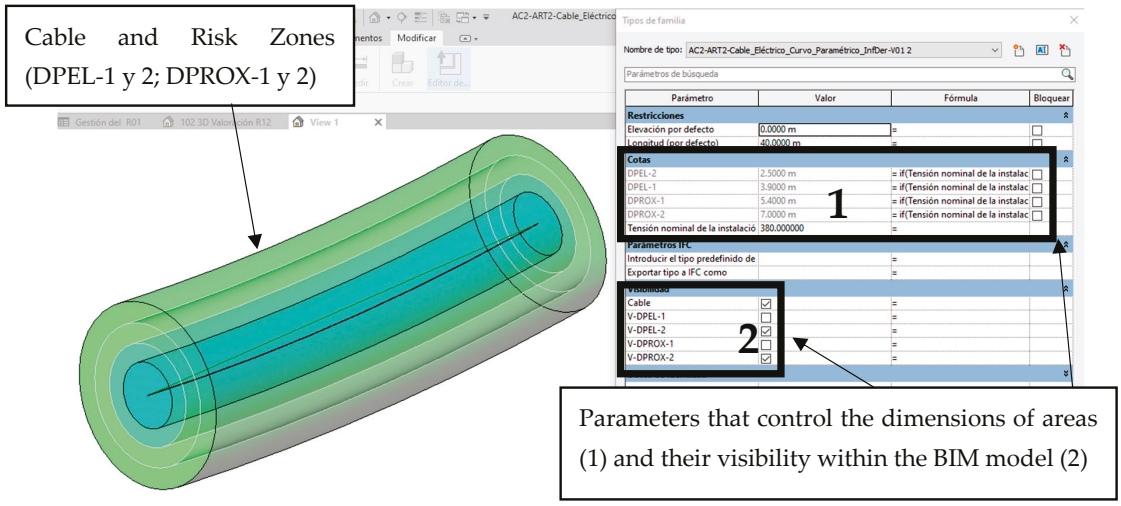
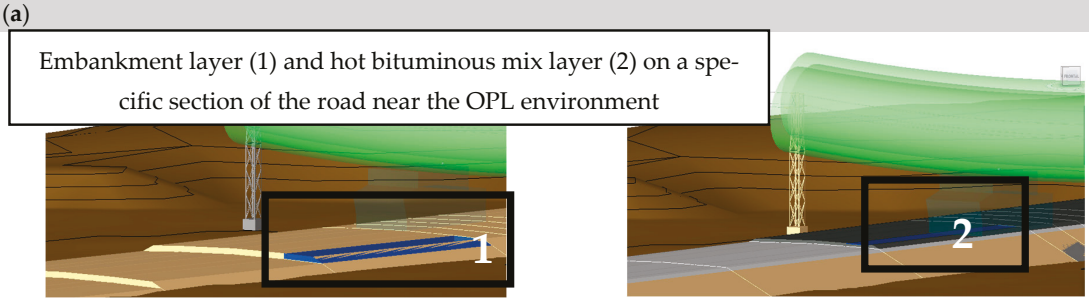


Figure 11. Special risk assessment in the preliminary design phase with a LOINSH 100 in Civil 3D 2024. Need to set back the OPL Route due to an intolerable risk in the execution of the first section of axis 4 of the project. (**a**) "EvaluacionRiesgo" Pset, (**b**) Dynamo script for colour mapping.

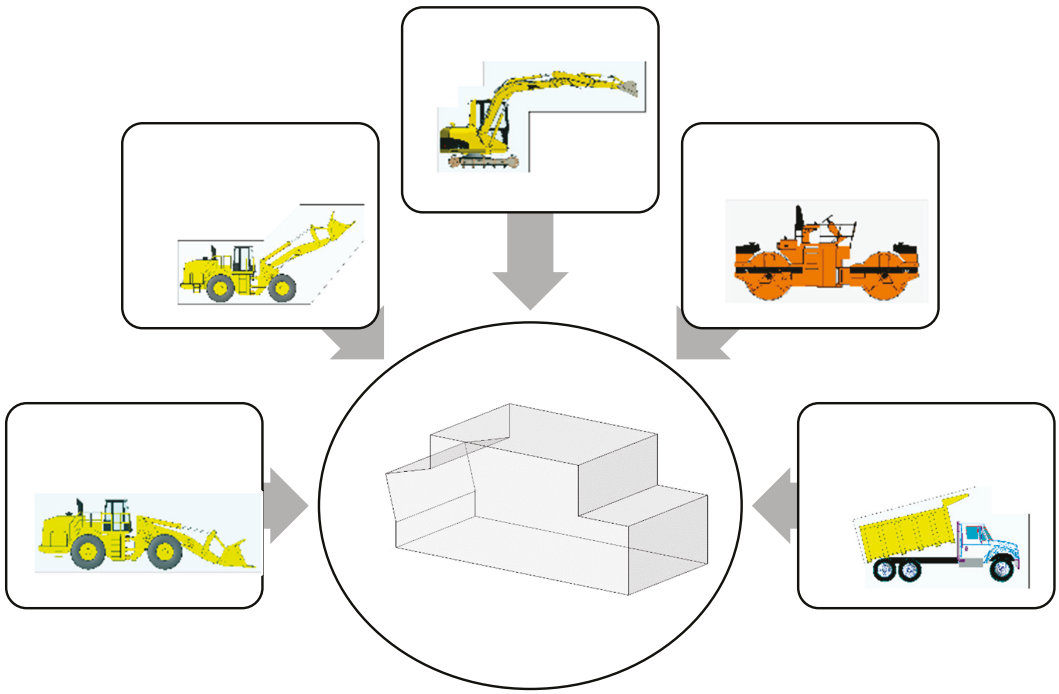
The analysis has been carried out in Revit 2024, considering it is more suitable to meet the requirements of LOINSH 350 (Table 3) by allowing, for example, the creation of BIM objects for risk zones. Among them are that BIM objects must have associated risk zones, as is the case of the OPL with its electrical risk zones (Figure 12a), as well as the phases of the execution of the embankment and pavement layers (Figure 12b,c) or the machinery acting and its envelope (Figure 12d) to determine the interaction between the two. Risk management is carried out from the "EvaluacionRiesgo" Pset (Table 1), which, applied to the division of BIM object by layers of the embankment geometry and pavement according to planning, allows for an analysis of the risks by phases, defined in each one by the interference between machinery and the risk area and to the standardization of colours defined (Figure 12e,f). This is performed in sufficient detail because the LOINSH 350 establishes a requirement that the accuracy of the geometry must be in centimetres (Table 3).



(**a**)



(**b**) (**c**)



(**d**)

Figure 12. *Cont.*

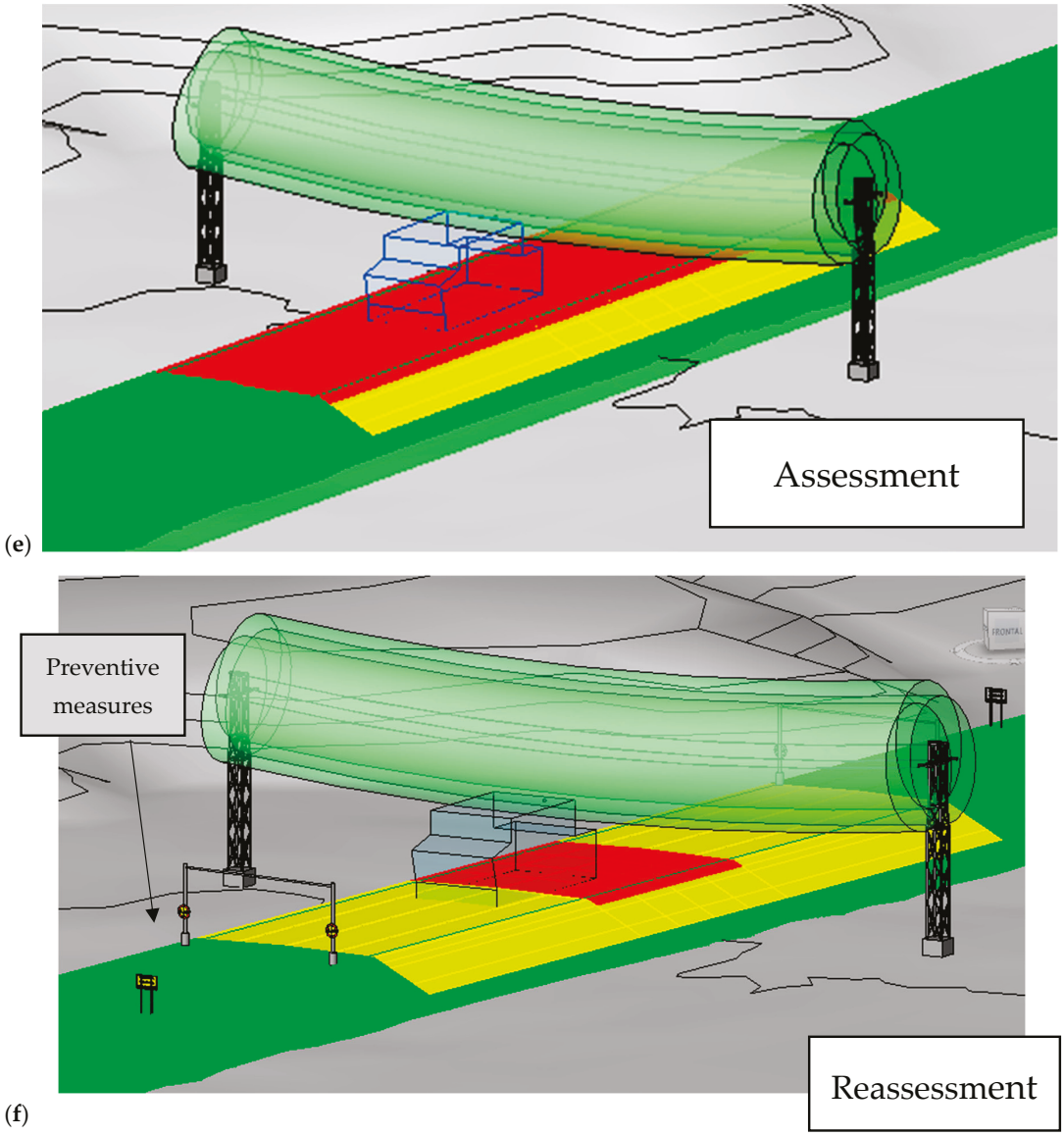


Figure 12. OPL special risk analysis with LOINSH 350. (**a**) BIM object of the OPL with its 4 risk zones and their associated parameters, (**b**) phase of embankment execution by sections and layers according to construction simulation, (**c**) phase of HMA spreading by sections and layers according to construction simulation, (**d**) final envelope based on the set of geometries and positions of the machinery used to execute that section of road, (**e**) risk assessment of the study area for the execution of the embankment and the pavement (red (intolerable), orange (important risk), yellow (moderate risk), light green (tolerable risk), and green (trivial risk)), and (**f**) risk reassessment with preventive measures in place (1 = light green, 2 = dark green, 4 = yellow, 6 = orange, and 9 = red). Note: Delimitation of the zones according to the diagram in Figures 2 and 3.

There are significant risks that can occur on a roadwork due to interference between tasks. To carry out the risk analysis, it is necessary that the BIM objects meet the requirements of the LOINSH 350 to determine the machinery that acts, execution phases, and risk areas. For example, Figure 13 shows the risk analysis of the interaction between the refining of the slopes and the execution of the nearby drainage work. It is shown how the proposed standardization allows one to simulate the interaction between the risk of hitting workers from the backhoe to workers by applying the standards of "1_IDENTIFICACION" Pset information, centimetre accuracy, 3D representation, "EvaluacionRiesgo" Pset (Table 1), and risk areas (Table 3).

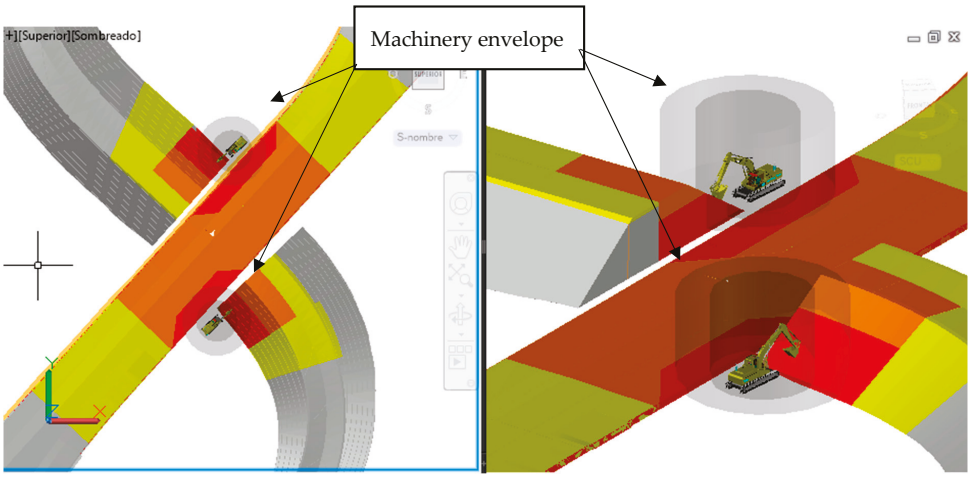


Figure 13. Visualization of the interference analysis model between construction activities in the construction design phase of the risk assessment of collisions, crashes, and impacts with vehicles in Civil 3D 2024 with LOINSH 350. Red (intolerable risk), orange (important risk), and yellow (moderate risk).

3.7. Documentary Information

Figure 14 reflects how the proposed standardization includes information on the aspects that safety equipment must comply with (hygiene and welfare facilities, collective protection equipment, etc.) such as technical specifications, requirements, and regulations. In this case, the "DocumentosSeguridadSalud" Pset is applied according to LOINSH 300 (Tables 1 and 3). Figure 14 shows how Royal Decree 2177/2004, which establishes the minimum health and safety requirements for the use of work equipment by workers in temporary work at height, is linked to the sergeant-type railing.

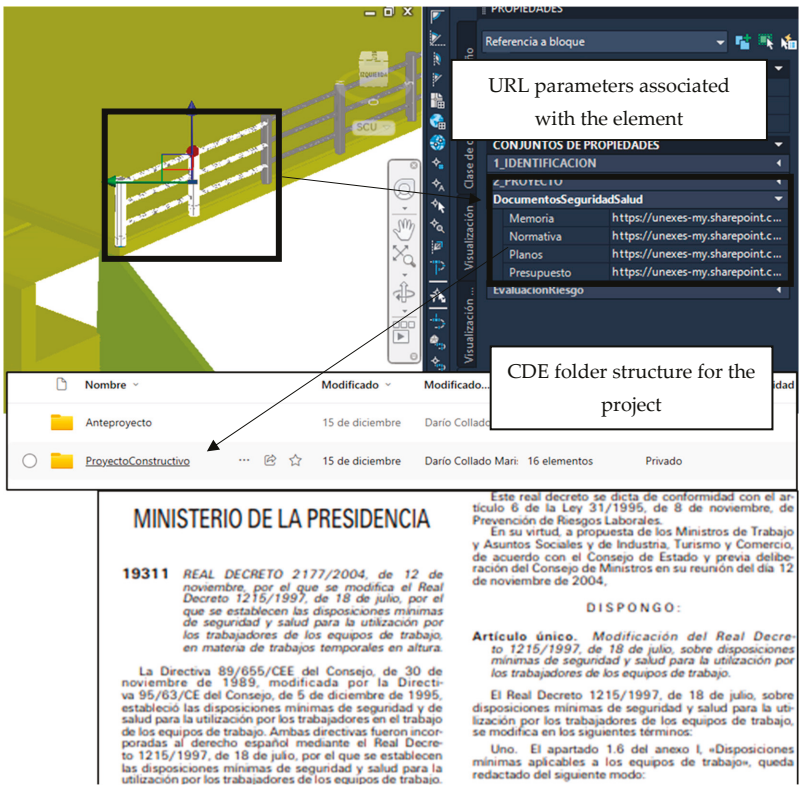


Figure 14. Documentary information with a LOISNH 300 linked to the BIM objects of the model through the CDE that will appear in the specifications of the Health and Safety Study. It shows RD 2177/2004, which establishes the minimum health and safety provisions for use of work equipment by workers in terms of temporary work at height associated with the BIM railing object.

4. Discussion

Construction is one of the economic activities with the highest number of occupational accidents [1–3]. Road construction requires a specific and standardized approach to risk assessment [20–23] and detailed analysis due to special risks such as high-voltage lines [26,27]. Although there are a significant number of investigations focused on reducing this accident rate [21,23,28,29], they have not been efficient [4].

Construction 4.0 technologies make it possible to improve the health and safety of construction sites [35,36], highlighting the BIM methodology [37], encompassing the management of safety information and risk assessment within its eighth dimension [42].

This eighth dimension [43] consists of work processes that pursue objectives that will give rise to requirements [55]. These will define a way forusing BIM [40], which varies depending on the phase [67].

Therefore, anyone considering a working process to address 8D must define a LOINSH that responds to the above. In fact, those authors who have done so have implicitly assumed a LOINSH 300 in the case of [28,49] and 350 in the case of [52] without addressing the issue. A correct definition of LOINSH [55,57] would complete its work, frame it correctly within the project life cycle, and be the link between all of them.

However, there is no methodology and data structure for health and safety (LOINSH) that can be integrated into BIM models, so the objective of this research is to propose the methodology and framework for standardizing workers' health and safety risks to comply with the standard ISO 7817-1:2024 [57]., which responds to ISO 19650-1 [55].

4.1. Safety Information from the Design Phase

In road design, PtD must be applied to reduce accident rates in later phases [32]. This research has shown how it is possible to implement the methodology and information structure in BIM from the design phase when the health and safety technician establishes the LOINSH requirements for each BIM object of the model, which is aligned with these investigations, from the preliminary project as Kamardeen [33] pointed out, thus taking advantage of the benefits of PtD [32]. The early establishment of these LOINSH is aligned with the research of Muñoz and Llamo [41] to develop a preventive strategy for the correction of failures that can occur during the life cycle of the infrastructure, which is economically and technically more feasible than applying corrective measures on the side later.

On the other hand, standardization in four levels avoids the overrepresentation of information and its duplicity [58]. In addition, by increasing the level of detail and granularity of the information, the analysis capabilities increase as the project information progresses and/or the type of risk. This is in line with Massimo-Kaiser et al. [60], who establish this concept as a dynamic and progressive entity to be modified according to changes in the information available and according to the life cycle of the asset.

4.2. LOINSH and Pset Structure

For each of the LOINSH, the way to address Geometric Information (LOG), Alphanumeric Information (LOI), and the (DOC), is in compliance with the ISO 7817-1:2024 [57]. This division of the LOINSH allows for the traceability of the information in different assessments when introducing a risk reassessment, which would help reduce accidents, according to Liu et al. [8].

In addition, with respect to the LOG (Table 3), it should be noted that the LOINSH 100 requires BIM objects with schematic precision and specific ramifications aimed at marking a specific risk. This can be used by safety technicians to carry out risk assessments at a very early stage of the project or work units, which, due to their low complexity, can group

together several risks, requiring conceptual BIM objects, without seeking to be precise in their geometry (Figures 3 and 11). The LOINSH 200 does have a 3D requirement, which has shown benefits for risk detection and task planning, allowing for the development of higher quality proactive prevention [44], so that even when there is no detailed Geometric Information, there will be a view of the overall configuration of project risks (Figure 4). In the project phase, the available information is greater, as well as the requirements of risk analysis, so the BIM objects of the disciplines will be LOINSH 300 or 350. This implies, in addition to 3D, 4D, centimetre precision, division and segregation by layers, or the possibility of defining risk areas (Figures 8 and 12). This allows us to achieve the benefits that Hire et al. [43] indicated for safety and health by applying 3D models and planning.

In addition, as has been demonstrated in the results (Figures 7, 12 and 13), the proposed LOINSH 300 and 350 allow for the achievement of strengths that the BIM provides by being able to detect high-risk tasks [31], as well as the detection of potentially dangerous areas [45].

Regarding the LOI (Table 1), this paper presents a set of Pset parameters recognized by the IFC standard (Figure 4 for the LOINSH 200 and Figure 8 for the LOINSH 300), which allows for the management of security information, as proposed Ait-Lamallam et al. [53].

In the case of DOC, (end of Table 3) by providing the "DocumentosSeguridadSalud" Pset (end of Table 1), it is possible to consult, for example, the Technical Report on Health and Safety in the Common Data Environment (CDE) (Figure 14). These links participate in the automated generation of protocols for the identification and action against risk scenarios based on the security information that is duly organized in the model, as established by Hire et al. [43].

The organization in different LOINSH (Table 3), and the parameter structure of the BIM model (Figures 3, 4 and 8), gives rise to a single database of the project, improving the coordination of safety technicians [40,46], a factor of safety reduction [10]. It also provides an organized structure for the information for safety management, avoiding contradictory, confusing, and disorganized safety protocols, another cause of reduced safety in construction sites [15].

This will solve the gap detected by Taat et al. [13] in regard to the lack of standardization, as well as the lack of innovative strategies for the implementation of security defined by Boadu et al. [14]. All of this will make it possible to overcome the technological limitations that prevent the application of new digital tools indicated by Yap et al. [16].

4.3. LOINSH Risk Assessment

The results have shown how the established LOINSH allows the risk assessment to be carried out by applying validated methodologies both at a general level [27] and in BIM [49,52]. This represents a significant advance in establishing the information requirements to be able to efficiently carry out the analysis according to the type of risk and the stage of development of the project, which are issues not addressed in these investigations.

It has been demonstrated how, with the established LOINSH requirements, each BIM object can represent one or more units of work, the activities for its execution, and the risks (Figure 9). Thus, these are identified and related to activities and units reflected in the BIM model, which solve the problem announced by Mihić [6] on the difficulty of defining and predicting risks in road construction projects.

On the other hand, by establishing the requirements for the association of activities and risks of an ethereal and unobservable nature, with BIM objects (Figures 11–13), it represents an improvement in training and the assimilation of safety information by workers, as well as in risk awareness, since the visual information is much clearer and more direct than the guidelines specified by the prevention technicians orally or by text, as they

highlighted [8,9,47], which can imply an increase in the commitment of workers to comply with safety regulations. These requirements will allow for a more detailed analysis of situations of interference between vehicle and pedestrian traffic in the vicinity of the work, detected as a critical risk factor by Kumar Das et al. [23]. All this will facilitate the performance of analysis of the interaction between external and internal factors, which is a cause of accidents [24,25].

The possibility of automation that allows for standardization (Figures 5, 6 and 11) will reduce errors in the review and information exchange processes that have been announced [61,62], improving the reliability and efficiency processes.

The automation of these processes allows for the identification of high-risk tasks [31] and the detection of potentially dangerous areas [45], such as the high risk of falling at different levels on the overpass in Figure 10, or the automated assessment of risk levels on site for the provision of preventive measures and prevention of risk situations from the design phase [48,49], as can be seen in Figures 10–13; all of these demonstrated benefits of integrating risk prevention into BIM.

It should be noted that the standardization of the appearance requirements of the LOINSH by colour-coding according to risk levels [27] improves the understanding of risks by offering accurate, clear, and direct visual information [8,9,47], helping to raise awareness among workers [17] and increasing commitment, motivation, and responsibility to apply risk prevention protocols [18].

It should be noted that the evaluation mentioned [27] is qualitative in nature. For this reason, despite the automatic input of preliminary risk values (Figures 5 and 6), this must be reviewed and further developed by the health and safety technician graphically within the BIM model (Figure 7). At his discretion, he can divide some risk zones or others and more or less information (Figure 10). Introducing a LOINSH (Table 3) helps to standardize the assessment and subtracts subjectivity, resulting in a higher quality risk assessment.

Reducing the significant accident rate is urgent in the construction sector [1,4,5] and especially in road construction [8,25]. As it has been demonstrated through LOINSH in road projects, it is possible to integrate occupational risk management into BIM; the improvement it will produce in the organization will contribute to risk reduction. By following BIM standards such as the ISO 19650-1 [55] and the ISO 7817-1 [57], the application of this methodology in the sector, especially with the growth that the use of BIM is having in road projects [38], is allowed for.

In this sense, this research for the improvement of occupational risk prevention contributes to the achievement of the United Nations Sustainable Development Goals (SDGs) 2030, in particular, SDG3 “Good Health and Well-being” and SDG8 “Decent Work and Economic Growth” [7].

4.4. Limitations and Future Lines of Research

The following limitations should be considered when applying the methodology presented:

- The correct establishment of the LOINSH required at each milestone and for each risk is key to the correct application of the methodology. Oversetting can lead to inefficiencies that will become exponential as the project becomes larger.
- This definition of LOINSH is based on the qualitative SIOSH methodology. If another methodology of the same type is used, it should be adapted accordingly with regard to the identification and assessment of risks. The methodology would not be valid if a quantitative risk assessment is used.
- The general frameworks of the methodology are transversal to any BIM software, making minor adjustments regarding the introduction of non-graphical information,

modelling, and discretization of BIM objects. However, if this software does not allow for the use of visual programming such as Dynamo, Grasshopper, or similar, the processes to be automated will have to be performed manually. This will result in increased time and errors due to the human factor.

- The assessment methodology used is qualitative and does not allow for sensitivity analysis.

Furthermore, as a result of the research carried out, the following lines of future research have emerged:

- Extend the LOINSH data structures to address the other phases of a road's life cycle: construction, maintenance, and operation.
- To contrast the reduction in on-site accidents in a road project through the application of the methodology presented in this thesis, a comparison with a project carried out in the traditional way must be performed in order to obtain metrics that allow for the quantitative validation of the effectiveness of the proposed standardization of information. This will serve to reinforce the conclusions of this study and the research referenced.
- Create new automations that allow us to move from one LOINSH to another with ease, as well as to transfer the codes developed in Dynamo to an internal programming software so that it is integrated as a command within it, facilitating its application.
- Analyze the development of LOINSH in relation to quantitative risk assessment.

5. Conclusions

This research represents an advancement in the management of health and safety information in road construction projects using the BIM methodology according to ISO 19650-1 [55] from the design phase through the creation and proposed structure of the safety LOINs, known as LOINSH. Following the provisions of ISO 7817-1:2024 [57] in relation to the components of this information and the requirements to which they must respond, this study proposes four different levels that will mark the level of granularity of the BIM objects in the model and their accuracy: LOINSH 100 and 200 for the preliminary design phase, LOINSH 300 and 350 for the project phase.

The study contributes to the standardization of safety information by developing the data structure requirements for each of these LOINSH. Therefore, first of all, the context in which each of these LOINSH should be used is established according to the stage of the construction project. For the preliminary design phase, LOINSH 100 will be used when division into work units is not necessary, requiring schematic precision; while for LOINSH 200, risks must be grouped into sets of work units, whose BIM objects will have metric precision. For the project phase, LOINSH 300 will be used when the complete granularity of risks in work units is required, as well as a centimetric level of detail for the analysis of interference in the execution of activities; while LOINSH 350 will be applied when the risk to be assessed requires 4D information, the generation of risk zones associated with the execution of the work unit is required, or when there are special risks. Thus, it can be seen how each of these LOINSH respond to different needs at different stages of the project life cycle, which makes the management of security information a dynamic, progressive, and adaptive activity to changes that will require continuous review by those responsible for security, which will ensure the uniqueness of the required data at each stage, thus avoiding the overrepresentation of information and problems of duplication, as established by ISO 7817-1:2024 [57].

Likewise, for each of the LOINSH presented, the level of graphic information for each BIM object has been established, justifying the level of detail, dimensionality, location, appearance, and parametric behaviour. In addition, the standardization of Alphanumeric

Information is proposed through Pset, sets of parameters recognizable by the IFC format, which ensures the management of security information in an open format without proprietary software restrictions. BIM objects that include LOINSH have a parameter structure definition for identifying information related to the project, phase, discipline, or work unit referred to through "1_IDENTIFICACION" Pset. Likewise, the risk assessment information is included in the "EvaluacionRiesgo" Pset, which contains all the parameters for obtaining the assessment and reassessment results according to the methodology of the SIOSH. Thus, in order to carry out the risk assessment proposed in the previous Pset on the model, it is established as a requirement that each BIM object represents one or more work units to which a series of activities are linked in order to execute it with its associated risks, which will be the assessment objectives. This risk parameter structure takes advantage of BIM's automated assessment of risk levels on site to enable preventive measures and error correction from the design phase onwards. Regarding the Associated Documentation, the "DocumentosSeguridadSalud" Pset has been proposed to link the information contained in health and safety regulations or technical studies to the model using URL parameters.

Thus, this research has demonstrated how, based on the established LOINSH and the parameter structure presented, it is possible to manage safety information and assess risks during different stages of the road construction life cycle, analyzing the risks arising from the interference of work activities, those linked to the execution of different disciplines, and even those risks considered special, such as the interaction with overhead power lines (OPL), thus justifying that the integration of the BIM methodology through a parameter structure with standardized safety information that benefits occupational risk management in road projects and leads to improved communication flow between agents through the traceability of this information. This research has therefore proposed a framework for standardizing the health and safety risks of road construction workers based on the ISO 7817-1:2024 [57] standard using the BIM methodology in accordance with ISO 19650-1 [55], which will result in a reduction in the high accident rates suffered by workers on road projects. This study therefore aims to lay the foundation for the standardization of safety information for other types of projects in the construction sector in order to reduce their high accident rates and enable the application of the aforementioned standards, thereby extending the benefits of BIM to the safety management of construction projects.

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Abbreviations

CDE	Common Data Environment
DOC	Associated Documentation
HMA	Hot Mix Asphalt
IFC	Industry Foundation Classes
LOG	Level Of Geometric Information
LOI	Level of Information
LOIN	Level Of Information Necessary
LOINSH	Level Of Information Necessary for Safety and Health
NAPWC	Navarre Association of Public Works Construction Companies
SIOSH	Spanish Institute for Occupational Safety and Health
Pset	Property Set
PtD	Prevention Through Design

References

1. ILOSTAT. Statistics on Safety and Health at Work. Available online: https://ilostat.ilo.org/topics/safety-and-health-at-work/ (accessed on 10 July 2025).
2. Choi, J.; Gu, B.; Chin, S.; Lee, J.S. Machine Learning Predictive Model Based on National Data for Fatal Accidents of Construction Workers. *Autom. Constr.* **2020**, *110*, 102974. [CrossRef]
3. Xu, Q.; Xu, K. Analysis of the Characteristics of Fatal Accidents in the Construction Industry in China Based on Statistical Data. *Int. J. Environ. Res. Public Health* **2021**, *18*, 2162. [CrossRef]
4. U.S. Bureau of Labor Statistics Census of Fatal Occupational Injuries News Release. Available online: https://www.bls.gov/news.release/cfoi.htm (accessed on 21 July 2025).
5. Eurostat Accidents at Work Statistics. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Accidents_at_work_statistics (accessed on 21 July 2025).
6. Mihić, M. Classification of Construction Hazards for a Universal Hazard Identification Methodology. *J. Civil Eng. Manag.* **2020**, *26*, 147–159. [CrossRef]
7. UNO Spain. *EL Sector Construcción e Ingeniería Civil: Contribuyendo a la Agenda 2030 La Creación de Ciudades Sostenibles y Resilientes*; UNO: Madrid, Spain, 2022.
8. Liu, J.; Tang, H.; Feng, R. Unraveling the Evolutionary Patterns of Construction Accidents: A Risk Assessment Framework Based on Average Mutual Information Theory. *Sci. Rep.* **2025**, *15*, 13457. [CrossRef]
9. Buniya, M.K.; Othman, I.; Sunindijo, R.Y.; Kineber, A.F.; Mussi, E.; Ahmad, H. Barriers to Safety Program Implementation in the Construction Industry. *Ain Shams Eng. J.* **2021**, *12*, 65–72. [CrossRef]
10. Tezel, A.; Dobrucali, E.; Demirkesen, S.; Kiral, I.A. Critical Success Factors for Safety Training in the Construction Industry. *Buildings* **2021**, *11*, 139. [CrossRef]
11. Memon, A.H.; Soomro, M.A.; Memon, N.A.; Abassi, M.N. Factors Causing Health and Safety Hazards in Construction Projects in Pakistan. *Mehran Univ. Res. J. Eng. Technol.* **2017**, *36*, 559–568. [CrossRef]
12. Abdul Nabi, M.; El-adaway, I.H.; Fayek, S.; Howell, C.; Gambatese, J. Contractual Guidelines for Construction Safety–Related Issues under Design–Build Standard Forms of Contract. *J. Constr. Eng. Manag.* **2020**, *146*, 04020074. [CrossRef]
13. Taat, N.H.M.; Abas, N.H.; Hasmori, M.F. The Barriers of Building Information Modelling (BIM) for Construction Safety. In Proceedings of the 3rd International Conference on Green Environmental Engineering and Technology, Penang, Malaysia, 8–9 September 2021; Mohamed Noor, N., Sam, S.T., Abdul Kadir, A., Eds.; Springer: Singapore, 2022; pp. 121–130.
14. Boadu, E.F.; Wang, C.C.; Sunindijo, R.Y. Challenges for Occupational Health and Safety Enforcement in the Construction Industry in Ghana. *Constr. Econ. Build.* **2021**, *21*, 1–21. [CrossRef]
15. Binhomaid, O.; Hegazy, T. Agent-Based Simulation of Workers' Behaviors, Productivity, and Safety around Construction Obstacles. *Can. J. Civ. Eng.* **2021**, *48*, 969–978. [CrossRef]
16. Yap, J.B.H.; Lam, C.G.Y.; Skitmore, M.; Talebian, N. Barriers to the adoption of new safety technologies in construction: A developing country context. *J. Civil Eng. Manag.* **2022**, *28*, 120–133. [CrossRef]
17. Shepherd, R.; Lorente, L.; Vignoli, M.; Nielsen, K.; Peiró, J.M. Challenges Influencing the Safety of Migrant Workers in the Construction Industry: A Qualitative Study in Italy, Spain, and the UK. *Saf. Sci.* **2021**, *142*, 105388. [CrossRef]
18. Maliha, M.N.; Abu Aisheh, Y.I.; Tayeh, B.A.; Almalki, A. Safety Barriers Identification, Classification, and Ways to Improve Safety Performance in the Architecture, Engineering, and Construction (Aec) Industry: Review Study. *Sustainability* **2021**, *13*, 3316. [CrossRef]

19. Sarvari, H.; Edwards, D.J.; Rillie, I.; Roberts, C. Barriers, Bottlenecks, and Challenges in Implementing Safety I- and Safety II-Enabled Safe Systems of Working in Construction Projects: A Scoping Review. *Buildings* **2025**, *15*, 347. [CrossRef]
20. Marhavilas, P.K.; Koulouriotis, D.; Gemeni, V. Risk Analysis and Assessment Methodologies in the Work Sites: On a Review, Classification and Comparative Study of the Scientific Literature of the Period 2000–2009. *J. Loss Prev. Process Ind.* **2011**, *24*, 477–523. [CrossRef]
21. Das, D.K. Exploring the Factors and Measures to Improve Safety in Road Construction in India. *J. Constr. Dev. Ctries.* **2022**, *27*, 139–152. [CrossRef]
22. Kim, N.; Yan, N.; Grégoire, L.; Anderson, B.A.; Ahn, C.R. Road Construction Workers' Boredom Susceptibility, Habituation to Warning Alarms, and Accident Proneness: Virtual Reality Experiment. *J. Constr. Eng. Manag.* **2023**, *149*, 04022175. [CrossRef]
23. Kumar Das, D.; Olatunji Aiyetan, A.; Mostafa Hassan Mostafa, M. A Systemic Archetype for Enhancing Occupational Safety in Road Construction Projects through Worker Behavior. *Transp. Res. Interdiscip. Perspect.* **2024**, *26*, 101154. [CrossRef]
24. Mohammadi, A.; Tavakolan, M.; Khosravi, Y. Developing Safety Archetypes of Construction Industry at Project Level Using System Dynamics. *J. Saf. Res.* **2018**, *67*, 17–26. [CrossRef] [PubMed]
25. Bilim, A.; Çelik, O.N. Estimating the Possibility of Workday Loss Accidents in Road Construction. *Gradjevinar* **2023**, *75*, 1183–1192. [CrossRef]
26. Ministerio de la Presidencia. *Real Decreto 1627/1997, de 24 de Octubre, Por el Que se Establecen Disposiciones Mínimas de Seguridad y de Salud en Las Obras de Construcción*; Ministerio de la Presidencia: Madrid, Spain, 1997; pp. 1–24.
27. Instituto Nacional de Seguridad e Higiene en el Trabajo. *Evaluación de Riesgos Laborales*; Instituto Nacional de Seguridad e Higiene en el Trabajo: Madrid, Spain, 2000.
28. Collado-Mariscal, D.; Cortés-Pérez, J.P.; Cortés-Pérez, A.; Cuevas-Murillo, A. Proposal for the Integration of Health and Safety into the Design of Road Projects with BIM. *Buildings* **2022**, *12*, 1753. [CrossRef]
29. Chong, D.; Wang, C.; Hao, G.; Jia, S.; Guo, X. Prediction and Quantification of Occupational Health Risk in Road Construction Workers Exposed to Asphalt Emissions. *J. Clean. Prod.* **2024**, *434*, 140328. [CrossRef]
30. López Valcárcel, A. Panorama Internacional de La Seguridad y Salud En El Trabajo de Construcción. *El Criterio de La OIT* **2003**, 1–12. Available online: https://www.cplp.org/Admin/Public/Download.aspx?file=Files/Filer/MIC_IT/Ficheiros/Biblioteca/Saude_Seg/Segurana_e_sade_construcao_2.pdf (accessed on 19 October 2025).
31. Yuan, J.; Li, X.; Xiahou, X.; Tymvios, N.; Zhou, Z.; Li, Q. Accident Prevention through Design (PtD): Integration of Building Information Modeling and PtD Knowledge Base. *Autom. Constr.* **2019**, *102*, 86–104. [CrossRef]
32. Landis Floyd, H.; Valdes, M.E. Leveraging Prevention through Design Principles (PtD) in Electrical Installations. *IEEE Trans. Ind. Appl.* **2021**, *57*, 1212–1221. [CrossRef]
33. Kamardeen, I. 8D BIM Modelling Tool for Accident Prevention Through Design. In Proceedings of the 26th Annual ARCOM Conference, Leeds, UK, 6–8 September 2010; Association of Researchers in Construction Management; pp. 281–289.
34. Al-Bayati, A.J.; Bazzi, K.; Karakhan, A.A.; Jensen, E. Clearing the Path: Overcoming Barriers to Prevention through Design (PtD) Utilization in the US Construction Industry. *Safety* **2024**, *10*, 74. [CrossRef]
35. Forcael, E.; Ferrari, I.; Opazo-Vega, A.; Pulido-Arcas, J.A. Construction 4.0: A Literature Review. *Sustainability* **2020**, *12*, 9755. [CrossRef]
36. Adriaensen, A.; Decré, W.; Pintelon, L. Can Complexity-Thinking Methods Contribute to Improving Occupational Safety in Industry 4.0? A Review of Safety Analysis Methods and Their Concepts. *Safety* **2019**, *5*, 65. [CrossRef]
37. Musarat, M.A.; Alaloul, W.S.; Irfan, M.; Sreenivasan, P.; Rabbani, M.B.A. Health and Safety Improvement through Industrial Revolution 4.0: Malaysian Construction Industry Case. *Sustainability* **2023**, *15*, 201. [CrossRef]
38. Olugboyega, O.; Oseghale, G.E.; Aigbavboa, C. Multiple Holistic Case Study of Project-Level Building Information Modelling (BIM) Adoption in Nigeria. *Constr. Innov.* **2023**, *23*, 567–586. [CrossRef]
39. European Parliament Directive 2014/24/EU of The European Parliament and of The Council of 26 February 2014 on Public Procurement and Repealing Directive 2004/18/EC (Text with EEA Relevance). *Bruss. Comment. EU Public Procure. Law* **2014**, *28*, 29–126. [CrossRef]
40. Castañeda, K.; Sánchez, O.; Peña, C.A.; Herrera, R.F.; Mejía, G. BIM Uses for Mitigating Deficiencies in Road Scheduling Planning. *Sustainability* **2025**, *17*, 2729. [CrossRef]
41. Muñoz, S.; Llamo, J. Revisión sistemática de la implementación BIM basada en modelos de diseño para la construcción de obras viales. *Cuad. Act.* **2023**, *14*, 119–133. [CrossRef]
42. Sampaio, A.Z.; Constantino, G.B.; Almeida, N.M. 8D BIM Model in Urban Rehabilitation Projects: Enhanced Occupational Safety for Temporary Construction Works. *Appl. Sci.* **2022**, *12*, 577. [CrossRef]
43. Hire, S.; Sandbhor, S.; Ruikar, K. A Conceptual Framework for BIM-Based Site Safety Practice. *Buildings* **2024**, *14*, 272. [CrossRef]

44. Petrullo, M.; Morton, B.; Jones, S.A.; Laquidara-Carr, D.; Lubrano, S.; Lorenz, A.; Yamada, T.; Buckley, B.; Logan, K.; Barnett, S. SmartMarket Report Chief Executive Officer Safety Management in the Construction Industry 2017 SmartMarket Report Executive Editor Chief Marketing Officer SmartMarket Report. 2017. Available online: https://www.cpwr.com/wp-content/uploads/Dodge_Safety_Report_2017.pdf (accessed on 19 October 2025).
45. Farghaly, K.; Collinge, W.; Mosleh, M.H.; Manu, P.; Cheung, C.M. Digital Information Technologies for Prevention through Design (PtD): A Literature Review and Directions for Future Research. *Constr. Innov.* **2022**, *22*, 1036–1058. [CrossRef]
46. Hee Lee, D.; Young Park, J.; Sang Youm, H. A Study on the Effect of Improvement of Safety Management on the Promotion of Safety and Health of Workers in Construction Sites. *J. Soc. Disaster Inf.* **2021**, *17*, 568–578. [CrossRef]
47. Tariq Shafiq, M.; Afzal, M. Evaluating 4D-BIM and VR for Effective Safety Communicaton and Training: A Case Study of Multilingual Construction Job-Site Crew. *Buildings* **2021**, *11*, 319. [CrossRef]
48. Lee, Y.; Kim, I.; Choi, J. Development of BIM-Based Risk Rating Estimation Automation and a Design-for-Safety Review System. *Appl. Sci.* **2020**, *10*, 3902. [CrossRef]
49. Cortés-Pérez, J.P.; Cortés-Pérez, A.; Prieto-Muriel, P. BIM-Integrated Management of Occupational Hazards in Building Construction and Maintenance. *Autom. Constr.* **2020**, *113*, 103115. [CrossRef]
50. Belcher, E.J.; Abraham, Y.S. Lifecycle Applications of Building Information Modeling for Transportation Infrastructure Projects. *Buildings* **2023**, *13*, 2300. [CrossRef]
51. Cavieres-Lagos, S.; Muñoz La Rivera, F.; Atencio, E.; Herrera, R.F. Integration of BIM Tools for the Facility Management of Railway Bridges. *Appl. Sci.* **2024**, *14*, 6209. [CrossRef]
52. Collado-Mariscal, D.; Cortés-Pérez, J.P.; Cortés-Pérez, A.; Cuevas-Murillo, A. Proposal for the Integration of the Assessment and Management of Electrical Risk from Overhead Power Lines in BIM for Road Projects. *Int. J. Environ. Res. Public Health* **2022**, *19*, 13064. [CrossRef]
53. Ait-Lamallam, S.; Yaagoubi, R.; Sebari, I.; Doukari, O. Extending the Ifc Standard to Enable Road Operation and Maintenance Management through Openbim. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 496. [CrossRef]
54. *ISO 16739-1:2024*; Industry Foundation Classes (IFC) for Data Sharing in the Construction and Facility Management Industries—Part 1: Data schema. International Organization for Standardization (ISO): Geneva, Switzerland, 2024. Available online: https://www.iso.org/es/contents/data/standard/08/41/84123.html (accessed on 19 October 2025).
55. *BS EN ISO 19650-1: 2018*; Organization and Digitization of Information About Buildings and Civil Engineering Works, Including Building Information Modelling (BIM). Information Management Using Building Information Modelling. Part 1, Concepts and Principles. British Standards Institution: London, UK, 2018; p. 46.
56. Pan, X.; Mateen Khan, A.; Eldin, S.M.; Aslam, F.; Kashif Ur Rehman, S.; Jameel, M. BIM Adoption in Sustainability, Energy Modelling and Implementing Using ISO 19650: A Review. *Ain Shams Eng. J.* **2024**, *15*, 102252. [CrossRef]
57. *ISO 7817-1:2024*; Building Information Modelling—Level of Information Need Part 1: Concepts and Principles. International Organization for Standardization (ISO): Geneva, Switzerland, 2024; p. 23.
58. Godager, B.; Merschbrock, C.; Klakegg, O.J.; Huang, L. Towards an Improved Framework for Enterprise BIM: The Role of ISO 19650. *J. Inf. Technol. Constr. (ITcon)* **2022**, *27*, 1076. [CrossRef]
59. *ISO/AWI TS 7817-2*; Building Information Modelling—Level of Information Need—Part 2: Guidance for Application. International Organization for Standardization (ISO): Geneva, Switzerland. Available online: https://www.iso.org/es/contents/data/standard/08/90/89075.html (accessed on 19 October 2025).
60. Massimo-Kaiser, I.M.; Fröch, G.; Salzgeber, H.; Flora, M. LOIN Für Elemente Des Geologisch-Geotechnischen Baugrundmodells. *Bautechnik* **2025**, *102*, 207–214. [CrossRef]
61. Lindholm, J.; Johansson, P.; Yitmen, I. Toward a BIM Information Delivery Framework Based on Common Data Environment. *Constr. Innov.* **2025**, *25*, 139–157. [CrossRef]
62. Akbas, E.; Bolpagni, M.; Borrmann, A.; Boeykens, S.; Filardo, M.M.; Liu, L.; Beetz, J. A Holistic Approach to Information Requirements: Integration of Level of Information Need and Information Delivery Specification. *J. Inf. Technol. Constr.* **2025**, *30*, 731–744. [CrossRef]
63. Salzano, A.; Cascone, S.; Zitiello, E.P.; Nicolella, M. Construction Safety and Efficiency: Integrating Building Information Modeling into Risk Management and Project Execution. *Sustainability* **2024**, *16*, 4094. [CrossRef]
64. Pham, T.-A.; Likhitruangsilp, V.; Ioannou, P.G. A BIM-Based Digital Twin for Construction Pollution Management in Building Renovation Projects. In *Advances in Information Technology in Civil and Building Engineering, Proceedings of the International Conference on Computing in Civil and Building Engineering, Montreal, QC, Canada, 25–28 August 2024*; Francis, A., Miresco, E., Melhado, S., Eds.; Springer: Montreal, QC, Canada, 2025; pp. 461–477.
65. ANECOP. *Guide to the Evaluation of Labor Risks in the Work Units*; de Navarra, G., Ed.; ANECOP: Comunidad Foral de Navarra, Spain, 2006.

66. Comisión Interdepartamental Para la Implementación de Trabajo y Tecnología Del; Building Information Modelling (BIM) del Comité técnico BIM. In *Manual BIM Modelitzat d'Informació de Construcció*; Generalitat de Catalunya; Departament de Territori: Barcelona, Spain, 2022.
67. Dirección General de Movilidad e Infraestructuras Viarias de la Junta de Extremadura. *Guía BIM*. 2023. Available online: https://www.juntaex.es/w/guia-bim (accessed on 19 October 2025).

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Article

Proposed Safety Control Structure Model for Building Demolition Projects Based on STAMP Model in South Korea

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Abstract

This study developed a safety control structure model to analyze stakeholder interactions to improve safety in Korean building demolition projects. Legal stakeholders and safety measures were systematically incorporated into the System Theoretic Accident Model and Processes (STAMP). The novelty of this safety model is that it provides the first systematic application of STAMP to Korean building demolition, with a specific focus on legal stakeholders and their safety interactions. The results revealed that unsystematic reviews by licensing agencies, the absence of expert reviewers, and the inadequate role of supervisors were key factors contributing to accidents. In particular, the inspection and corrective action of safety measures performed by demolition supervisors directly impacted on-site safety. Furthermore, licensing agencies were identified as key players in determining the overall safety level of demolition projects. The proposed model provides a framework for effectively understanding the roles and responsibilities of stakeholders and supports the identification of non-compliance with safety measures. The use of the proposed model is expected to strengthen the interaction between stakeholders, enhance on-site safety, and contribute to the development of accident prevention strategies for future demolition projects.

Keywords: safety control structure; stakeholder interaction; accident; building demolition; STAMP model

1. Introduction

The construction industry plays a key role in the economic development of countries worldwide but is also recognized as one of the most hazardous sectors in terms of occupational safety [1–3]. Construction project scales have continued to expand in size and complexity, with multiple processes frequently occurring simultaneously at a single site [4,5]. These overlapping activities increase not only the potential for operational interference but also the occurrence of safety-related issues [6,7]. According to accident fatality rates per 10,000 workers in the construction industry across the ten major OECD countries in 2023, the rates were at least twice as high—and in some cases nearly six times higher—than those observed across all industries combined. As shown in Figure 1, the construction industry of South Korea reported an accident fatality rate of 1.59 per 10,000 workers, the highest among OECD countries [8]. Using industrial accident data announced by the Ministry of Employment and Labor of South Korea, the change in South Korea's accident fatality rate is shown in Figure 2.

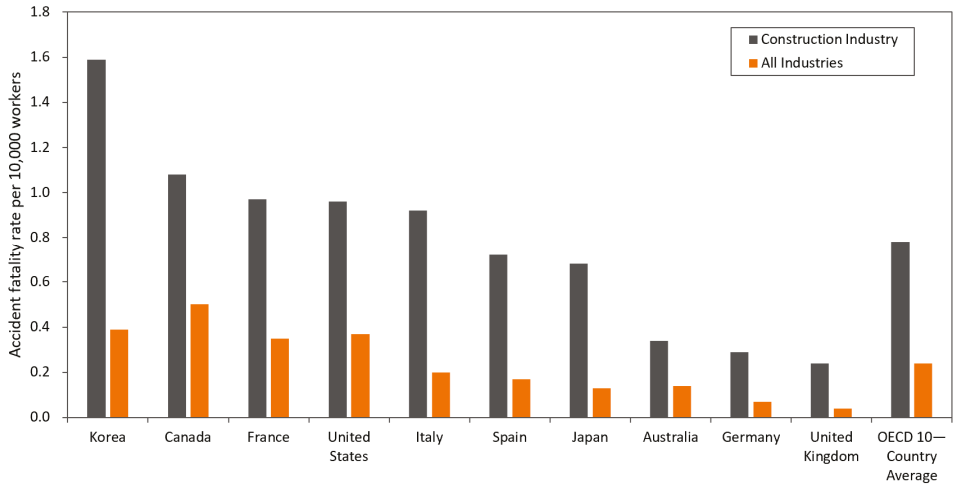

Figure 1. Comparison of accident fatality rates per 10,000 workers in the construction industry [8].

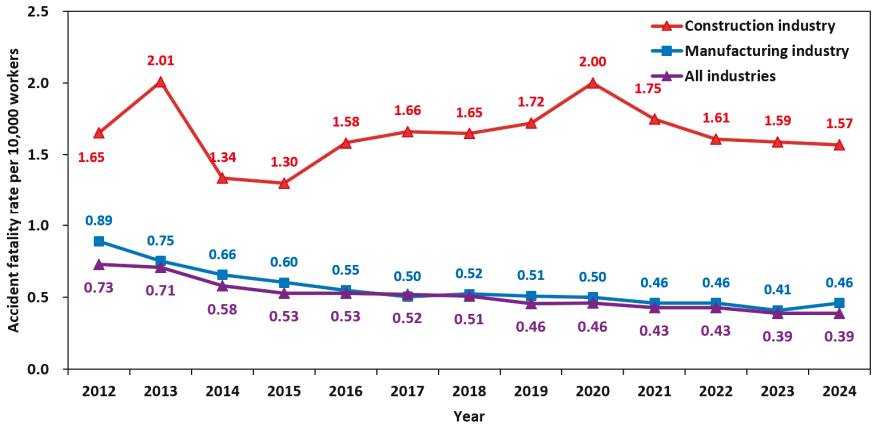

Figure 2. Variation in accident fatality rates per 10,000 workers in South Korea.

The statistics for construction accidents in South Korea between 2021 and 2025 showed that accidents relating to demolition and dismantling accounted for 740 out of a total of 25,647 accidents. In 2023, fatalities increased by 21.1% compared to the previous year, underscoring the escalating risk. Building demolition is recognized as a representative high-risk operation that can result in large-scale casualties, primarily due to structural instability, illegal subcontracting, and insufficient safety management [9]. This is mainly because demolition companies engaged in building demolition works are often small and undercapitalized [10]. Moreover, most workers involved in demolition activities lack proper qualifications, resulting in insufficient implementation of safety systems [11]. Demolition work is not a single, simple process but rather a complex one that simultaneously involves multiple stakeholders, including the client, designer, contractor, supervisor, and permitting authority. Therefore, the causes of accidents cannot be attributed solely to worker error; rather, they are highly likely to arise from systemic and organizational shortcomings, as well as failures in coordination.

Previous studies on accident analysis in demolition operations have primarily focused on two areas: (1) studies using statistical techniques to quantitatively analyze contributing factors, accident causes, and accident types during risk assessment [12–14]; and (2) studies applying sequential models such as FTA and fuzzy models to identify physical causes and human errors [15]. Additionally, a systematic literature review investigated risks associated with demolition waste and factors exacerbating risk elements [16]. Recent international research has also expanded the scope of demolition safety. Fu et al. [17] developed a multi-source data integration method for early warning in bridge demoli-

tion, while Mohammadi et al. [18] reviewed innovative technologies such as robotic and microwave-based demolition with implications for sustainability. Yuzbasi [19] validated numerical simulations of RC building blasting with actual collapse experiments, while Andruszko and Derlukiewicz [20] proposed fatigue assessment methods for demolition robots to enhance equipment reliability. While these studies highlight important advances, they still primarily focus on technical and procedural aspects, paying little attention to institutional and regulatory interactions.

To bridge this gap, systems-theory-based approaches such as STAMP (System Theoretic Accident Model and Processes), AcciMap, and FRAM (Functional Resonance Analysis Method) have recently gained attention in construction accident research. These frameworks are recognized as effective methods for analyzing complex construction environments from a multi-layered perspective [21,22]. However, most applications have focused on general construction projects rather than building demolition. This study applies a STAMP-based framework to Korean building demolition, systematically integrating legal stakeholders and regulatory roles to present a novel systemic perspective.

The STAMP model has been increasingly adopted in research on construction accident analysis. Suraji et al. [23] applied STAMP under the assumption that accidents stem from inappropriate human behavior, using the framework to diagram potential risk factors among project participants. Zhang et al. [24] argued that STAMP elucidates how system complexity contributes to accidents and clarifies stakeholder responsibilities, although they emphasized the difficulty of distinguishing all critical elements in the reviewed construction accidents. Woolley et al. [25] developed an accident investigation template based on STAMP to highlight the limitations of construction systems, particularly the absence of formal communication processes between upper and lower organizational levels. STAMP is regarded as a suitable method for investigating accidents by accounting for all elements associated with construction sites. In South Korea, the coexistence of numerous overlapping systems regulating construction work often leads to limited understanding of stakeholder interactions. However, accident analyses continue to investigate technical causes and human factors in isolation [26]. To date, no studies have applied a systemic approach to building demolition accidents. Therefore, a systemic accident analysis is essential to thoroughly examine accidents in demolition work, which inherently involve complex stakeholder dynamics and multiple overlapping processes. Unlike previous studies that applied STAMP mainly to general construction accidents, this study uniquely integrates legal stakeholders and regulatory roles into the analysis of building demolition accidents in South Korea to find the root and institutional causes, providing a novel systemic perspective.

In South Korea, the demand for demolition work is increasing as the proportion of aging buildings rapidly increases, and this trend has already resulted in major disasters, such as the building collapse accident at Gwangju, South Korea, in 2021 [27]. Investigations into this demolition-related accident identified multiple issues, including illegal subcontracting, unauthorized design modifications, and inadequate safety supervision by the auditing company [28]. These findings highlight a lack of professional competence and safety awareness among stakeholders involved in demolition projects. In particular, the arbitrary alteration of demolition plans during construction was identified as a critical concern. However, efforts to identify fundamental causes that consider institutional and organizational factors remain insufficient. The construction accident cases exemplify the persistent gap between on-site safety practices and institutional implementation. The fact that building demolition accidents continue to occur despite the existence of robust regulatory frameworks underscores their significance as a subject for international research and analysis.

Therefore, this study aims to analyze the interactions between stakeholders involved in building demolition projects using the STAMP framework and to propose a Safety Control Structure. The influence of institutional and organizational factors on demolition projects was identified and directions for strengthening safety management were suggested.

2. Theoretical Background

2.1. Limitations of Accident Investigation System

When a major construction accident occurs, the contractor is required to conduct an accident investigation and report it to the government, while the government investigates whether there has been a violation of the law. Figure 3 shows the serious accident investigation process in South Korea. Examining this process, it is clear that the accident investigation primarily focuses on determining whether the site managers violated the law, as regulated in the Occupational Safety and Health Act (OSH Act). This process, which views determining legal violations by the accident site as a vital control function, has some limitations [29]. It fails to apply the perspective of "Why was adequate control not exercised?" and "Why was improper control exerted?" and is unable to establish preventive measures suitable for the specific characteristics of the site where the accident occurred [30]. Additionally, accident investigation reports have not been publicly released, posing difficulties in their utilization for serious accident reduction. Thus, the current accident investigation methods make it difficult to find the root causes, especially in cases involving various stakeholders, such as dismantling work, making it challenging to identify the fundamental and systematic causes of accidents.

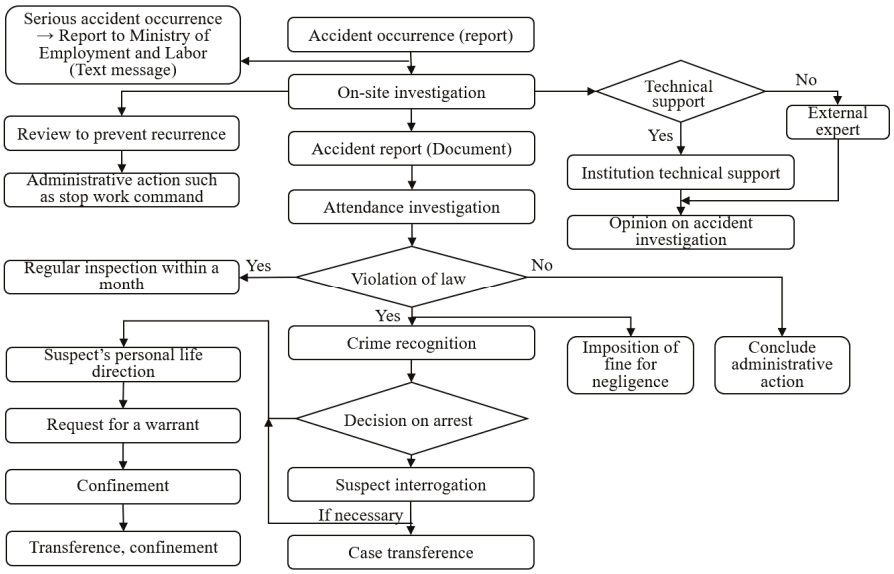

Figure 3. South Korea's serious accident investigation procedure [29].

2.2. STAMP Model

In this study, the STAMP model was used as a basic approach for the systemic accident analysis since it can reflect the overall components of the building demolition process (Figure 4). Leveson's STAMP model, introduced in 2004, is an accident analysis technique that utilizes accident cause models. This approach attempts to address the limitations of past sequential accident analysis techniques, which were difficult to apply when analyzing interactions between components of a system or human factors in a system based on small, simple hardware [21]. The STAMP model considers safety not as a matter of failure prevention but as a control problem and introduces the concept of accidents as a result of inadequately implementing system safety constraints during the design, development,

and operation of the system. The basic control structure of the STAMP model includes the structures for system development and system operation, each of which is organized in hierarchies [22]. Furthermore, through "maintenance and evolution", problems that arise in the system operation structure, such as software and hardware, are fed back into the system development structure for correction and replacement [31].

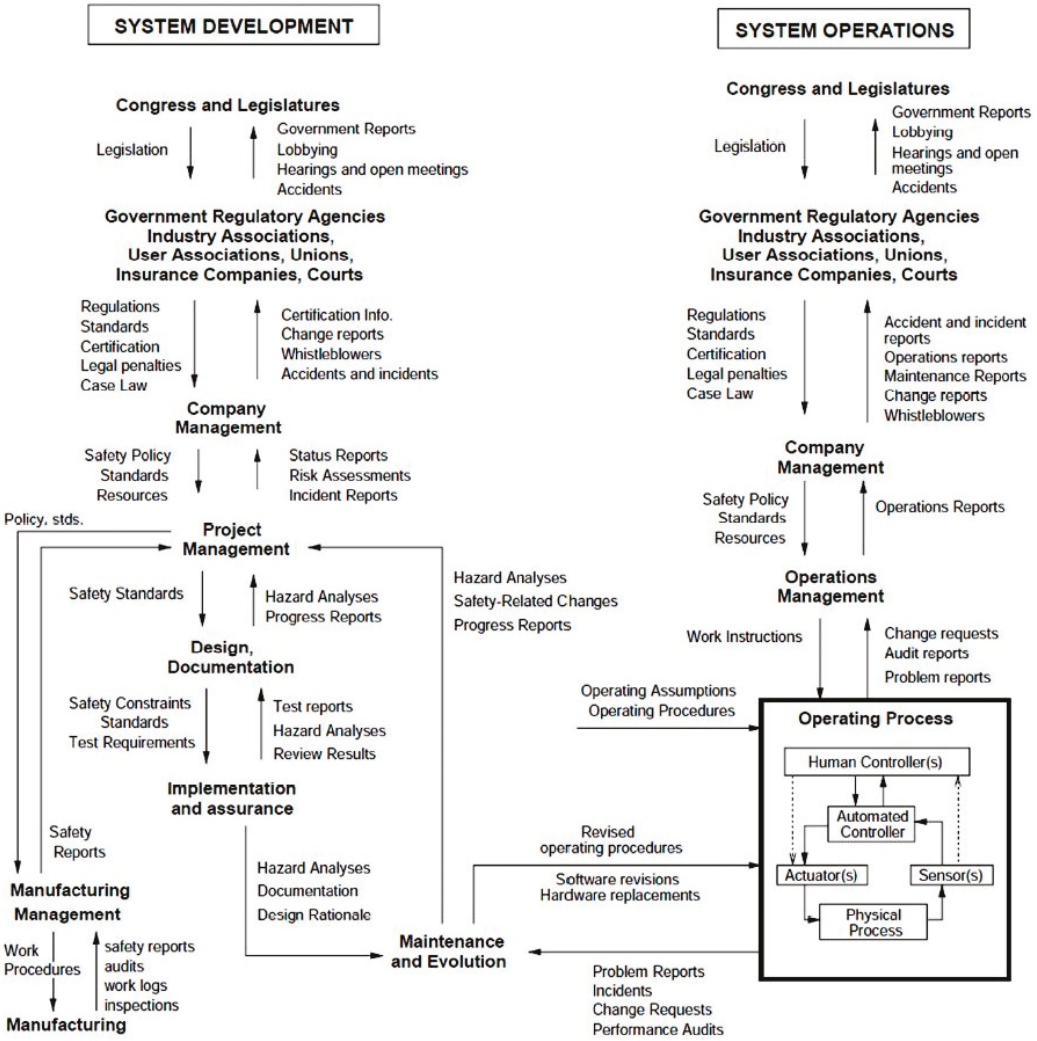

Figure 4. Socio-technical control structure [32].

Systems theory, the foundational theory of STAMP, was developed based on the theory of "Systems Thinking" and according to the concept that a system is formed through the organic interaction of each part that constitutes the system [32]. The components that make up the system are arranged in a hierarchical structure. Each component that makes up the system has its own unique role and properties and interacts with other components in the same layer or in higher or lower layers, such as through control or feedback. When the system is recognized as a single integrated entity formed through the organic interaction between components from an integrated perspective, new properties emerge in addition to the unique roles of each subsystem or component. This characteristic is called emergence. Safety is a representative example of an emergent property [33].

When a system consists of at least two hierarchical structures, components at the upper level in the hierarchy communicate with other components through interfaces to instruct control actions and receive feedback on them, forming a control loop structure. The control loop structure consists of a controller, actuator, sensors, and controlled process. The controller is the entity that issues control commands, including people, software,

and policies, and the controlled process is the controlled object that receives the control commands issued by the controller. The controller determines the process status through measured variables (feedback) and issues control actions to actuators according to a predefined algorithm. Accordingly, the controlled process has a structure that performs the process according to the controlled actions received by the actuator [32].

There are two methods for analyzing risk using the STAMP model: System Theoretic Process Analysis (STPA) and Causal Analysis based on System Theory (CAST). Both STPA and CAST are risk analysis tools based on a robust causal model. STPA's pre-accident analysis can identify not only the scenarios that occurred but also all potential scenarios that could lead to losses. Potential scenarios generated through STPA can be used to prevent accidents before they occur. Conversely, CAST is a useful analytical method for identifying specific accident scenarios that have already occurred. While STPA is used for accident prevention, CAST is used for post-accident analysis. While their purposes are different, they are closely related. Because STPA can be employed early in the accident concept development phase, it can be used to incorporate safety and security into system design from the outset, significantly reducing the cost of designing systems that ensure safety and security. CAST of past accidents can support the STPA process by identifying potential scenarios that must be eliminated or controlled to prevent further losses [34].

While past studies relating to STAMP show its applicability to the overall construction process, there is limited research on accident analysis for specific construction processes such as building demolition work. This study focuses on developing an advanced safety control structure to identify stakeholders participating in building demolition in South Korea and provides a STAMP-based analysis template that can be used in the accident analysis process. The research procedure is presented in Figure 5. First, the work process and stakeholders for demolition work in South Korea were investigated. Next, the safety control structure using the stakeholders and work process was identified at each construction stage, and the advanced model was developed for the whole demolition work process; we verified the model by applying a real accident case that occurred in South Korea.

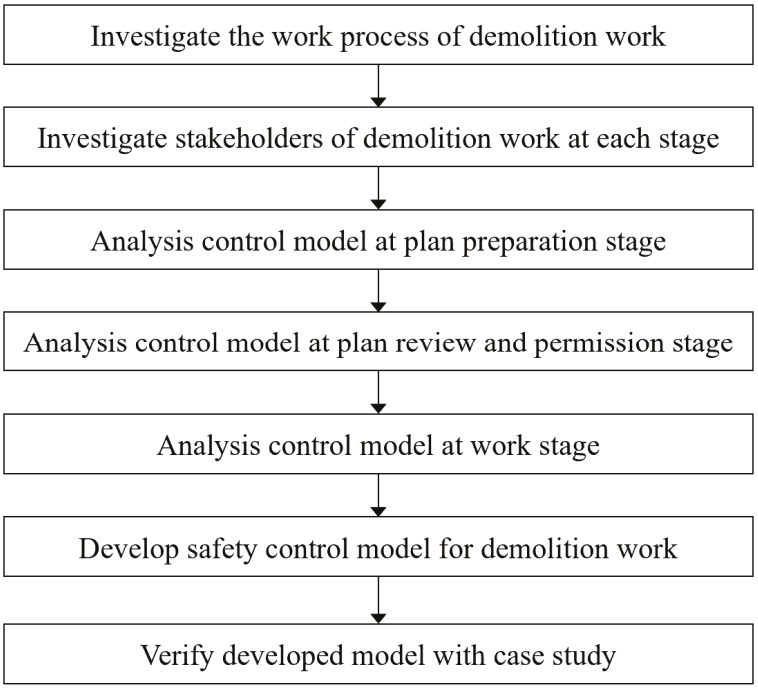

Figure 5. Research procedure.

3. Work Process and Stakeholders of Demolition Work in South Korea

In this section, the procedures and legal stakeholders of Korean demolition work are investigated to develop a safety control structure for the small-scale building demolition process.

3.1. Demolition Process: Permitting Authority

In South Korea, the building demolition process follows the procedure illustrated in Figure 6. The building owner should submit a demolition permit application, demolition notification, demolition plan, and institutional asbestos survey report to the authorizing or permitting agency (authority office) corresponding to the building's address. The application is made to obtain a demolition permit or notify the authorities of the demolition. In the case of small-scale buildings, only notification is required, but for buildings above a certain scale, a permit must be obtained. If a permit is required, a supervisor must be designated. After reviewing all documents, the demolition permit is processed by the district office.

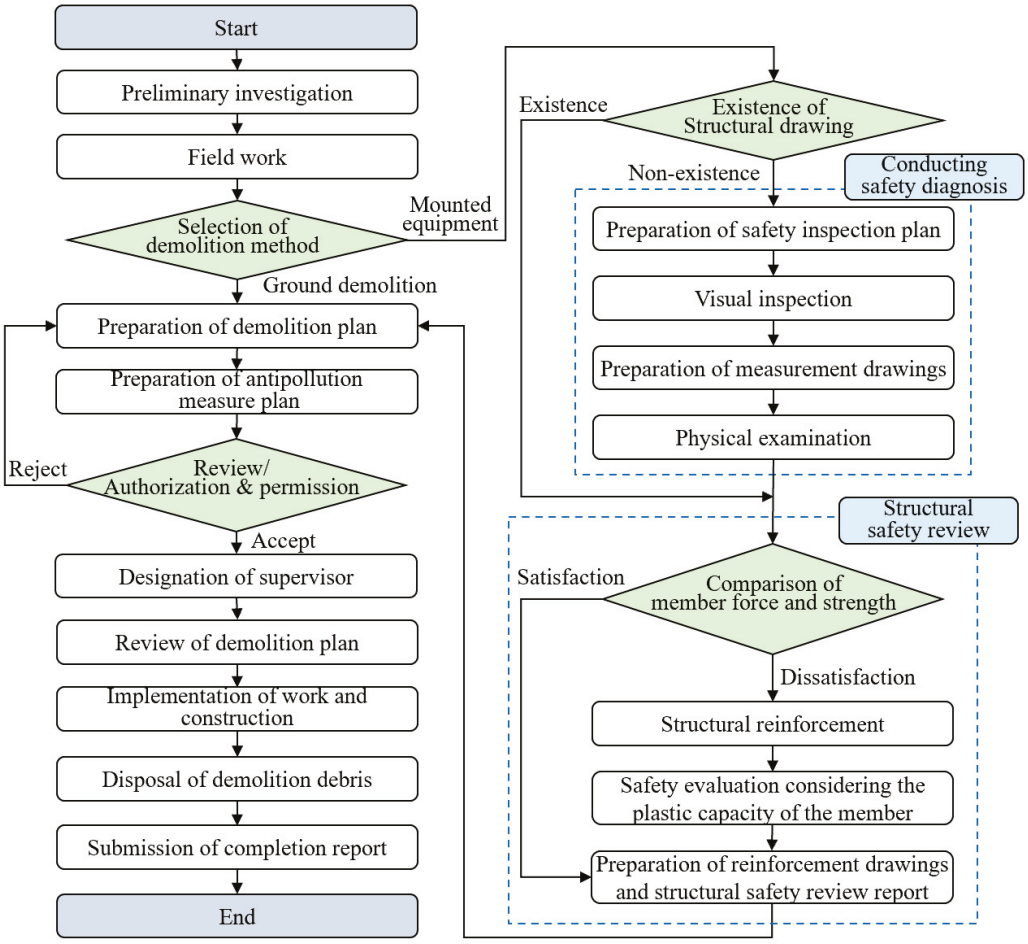

Figure 6. South Korea's demolition work procedure [35].

3.2. Stakeholders According to Demolition Stage

Demolition work was divided into various stages, each involving different stakeholders (see Table 1). These stakeholders participate in accordance with the laws in South Korea. There are various laws related to demolition work, such as the "Building management Act (BM Act)", "Occupational safety and health Act (OSH Act)", and "Construction waste recycling promotion Act (CWRP Act)". These stakeholders must comply with the requirements for their legal roles and implement respective safety measures to ensure a safe demolition.

Table 1. Stakeholders for each stage of demolition work.

Stage	Stakeholders	
Demolition plan preparation	Project owner (building owner), contractor, certified architect, and professional engineer	
Demolition plan review and building permitting	Project owner, authorizing or permitting agency, Korea Authority of Land & Infrastructure Safety (KALIS), certified architect, and professional engineer	
Demolition work	Internal organization	Project owner, main contractor, subcontractor, supervisor
	External organization	Authorizing or permitting agency Government - Ministry of Employment and Labor (MOEL) - Ministry of Land, Infrastructure and Transport (MOLIT) Public institution - Korea Occupational Safety and Health Agency (KOSHA) - Korea Authority of Land & Infrastructure Safety (KALIS) Private institution - Specialized guidance institution for preventing construction industrial accidents

In the plan preparation stage, the project owner, contractor, certified architect, and professional engineer should cooperate to establish a demolition plan. In particular, the demolition plan should be prepared by a certificated architect or a professional engineer. In the review and permitting stage, the specialized review organization is included as a stakeholder. In the case of building demolition that requires a permit rather than notification, a specialized review organization is responsible for the review, and the specialized review organization in South Korea is KALIS (Korea Authority of Land & Infrastructure Safety). The supervisor and external inspectors are included in the process of demolition work to control it.

4. Model Development

The components of the safety control structure of demolition work were derived. To prevent stakeholders from being omitted from the model, the structure of each stage was first analyzed before deriving the final model. Each model was assigned interactions of stakeholders by referring to major laws related to demolition work, such as the BM Act, OSH Act, and CWRP Act. Furthermore, the definitions of "control measures" and "feedback" used in this study were primarily derived from Leveson's STAMP framework (2004) [21] and supplemented with regulatory text analysis of the Building Management Act (BM Act) and the Occupational Safety and Health Act (OSH Act).

4.1. Control Model at the Demolition Plan Preparation Stage

A contractor must conduct a preliminary survey of the demolition work and site and prepare a work plan to prevent risks to workers. However, the demolition plan can only be prepared by a certified architect or professional engineer following the CA Act or PE Act. This requirement aims to prevent accidents resulting from inadequate demolition plans made by contractors. The stakeholders in the demolition plan preparation stage were

determined as shown in Table 2, and the control loop model is shown in Figure 7. In the figure, the solid line represents the control action, while the dashed line indicates feedback.

Table 2. Control loop in the demolition plan preparation stage.

Control Action	Explanation	Feedback	Explanation
Project owner (building owner)	Provide demolition work contract and offer of building design drawings	Contractor	Conduct a preliminary survey of the site and write a work plan
Project owner	Request preparation of demolition plan	Certified architect, professional engineer	Prepare and submit demolition plan

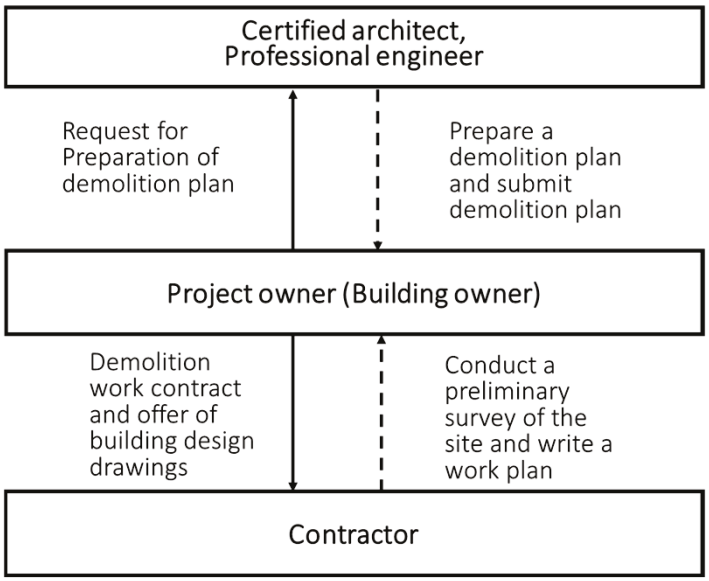

Figure 7. Model of safety control structure in the demolition plan preparation stage.

The safety control structure during the demolition planning phase illustrates the interactions between the owner, contractor, and architect (or engineer). It is a key process that prevents poor design or omission of risk factors from the planning stage. However, in actual construction sites, contractors frequently submit plans formally without sufficient prior research, or owners reduce design reviews for cost-saving reasons. This suggests that if the feedback loop in the early planning stage does not function properly, safety risks can accumulate throughout all subsequent stages. Previous research [30] has reported that when the demolition plan is not appropriate according to building type, the risk of accidents increases dramatically. This model is unique in that it visualizes this observation through a specific interaction structure. Therefore, this model can strengthen the interaction between owners and architects (or engineers) and serve as a basis for institutionally mandating a standardized risk review process during the planning stage. When the project owner issues a demolition contract to the contractor with design drawings, the contractor provides feedback, such as conducting a preliminary survey of the site, to the project owner. Then, the project owner provides site information to the architect (or engineer) and requests that a demolition plan be prepared.

4.2. Control Model at the Demolition Plan Review and Building Permitting Stage

The key stakeholders involved in the building demolition permitting stage include the project owner, the authorizing or permitting agency, KALIS, certified architects, and professional engineers (Table 3). Figure 8 shows the control loop of the demolition plan

review and permitting stages. The project owners must submit a demolition plan to an authorizing or permitting agency. If the submitted demolition plan requires supplementation, the authorizing or permitting agency must request the project owner to amend the plan in accordance with the "BM Act". Furthermore, the authorizing or permitting agency must request KALIS to review demolition plans before providing the permit to demolish the building. This requirement particularly applies when facilities such as bus stops, entrances to urban railway stations, and crosswalks are located near demolition buildings. Additionally, buildings without design documents or explosions used as a demolition method must be reviewed by building committees.

Table 3. Control loop in the demolition permitting stage.

Control Action	Explanation	Feedback	Explanation
Project owner	Request demolition plan review	Certified architect, professional engineer	Review and sign the demolition plan
Project owner	Submit demolition plan	Authorizing or permitting agency	Review the demolition plan
Authorizing or permitting agency	Request review of the demolition plan	KALIS	Review the demolition plan
KALIS	Request deliberation of demolition plan	Building committees	Make decision building permit
Authorizing or permitting agency	Issue demolition permit	Project owner	Receive demolition permit

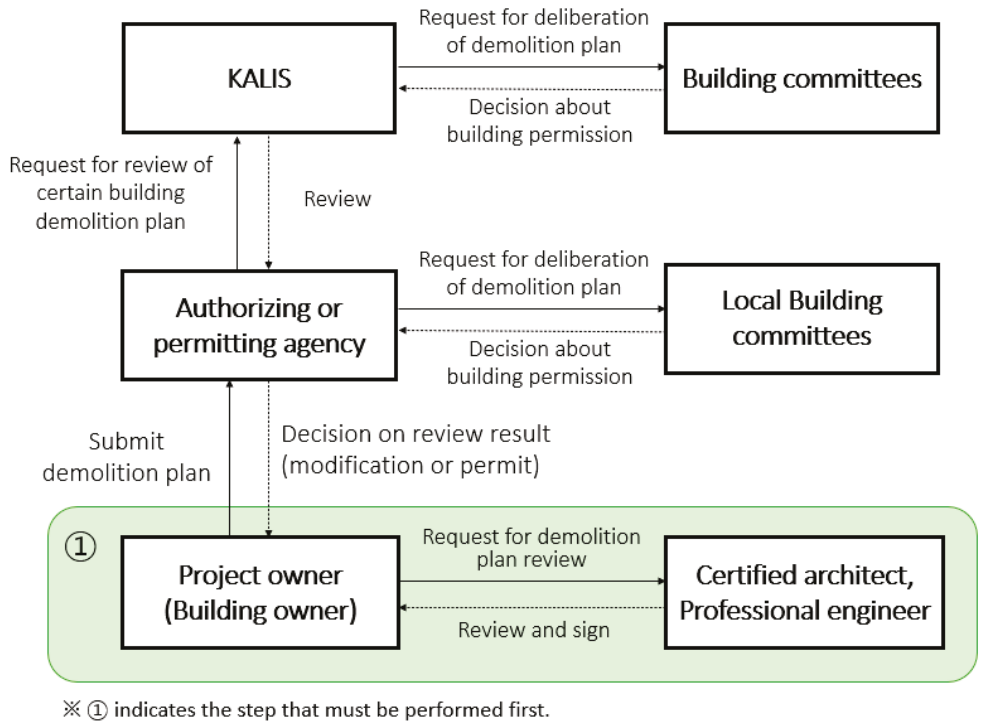

Figure 8. Model of safety control structure in the building demolition permitting stage.

This demonstrates that on-site safety is not simply an administrative process but rather a direct consequence of the control functions of external agencies. As local government officials lack expertise in construction, licensing agencies require additional regulation for higher-risk buildings. Therefore, this model addresses this issue through institutional mechanisms such as the building committee and KALIS. The analysis highlights that the licensing agency's review process is not simply an administrative approval process but rather a core control function directly linked to on-site safety. To strengthen this, policies

should include expanding the participation of external experts, enhancing the transparency of the review process, and clarifying accountability.

4.3. Control Model in the Demolition Work Stage

The construction phase is the most complex, involving numerous stakeholders simultaneously and assigning various roles. The control actions and feedback of stakeholders according to the law were analyzed and the results are shown in Figure 9. A safety control structure can be divided into internal and external organizations (Table 4). Internal organizations include stakeholders directly involved in construction work, such as the project owner, contractor, subcontractor, and supervisors. External organizations mainly include inspectors such as licensing agencies (KOSHA and KALIS) and the government. In South Korea, construction site safety is managed dually by two government ministries: the Ministry of Employment and Labor (MOEL) focuses on ensuring proper implementation of worker safety measures, while the Ministry of Land, Infrastructure, and Transport (MOLIT) monitors the on-site implementation of safety measures documented during the construction permit phase and manages technical safety issues. However, small-scale construction sites often lack specialized safety management personnel, and subcontracting often weakens the contractor's control, increasing the risk of accidents. Previous studies have identified the link between subcontracting and hazardous work as a major cause of serious accidents, and the model presented in this study comprehensively reflects these complex interactions.

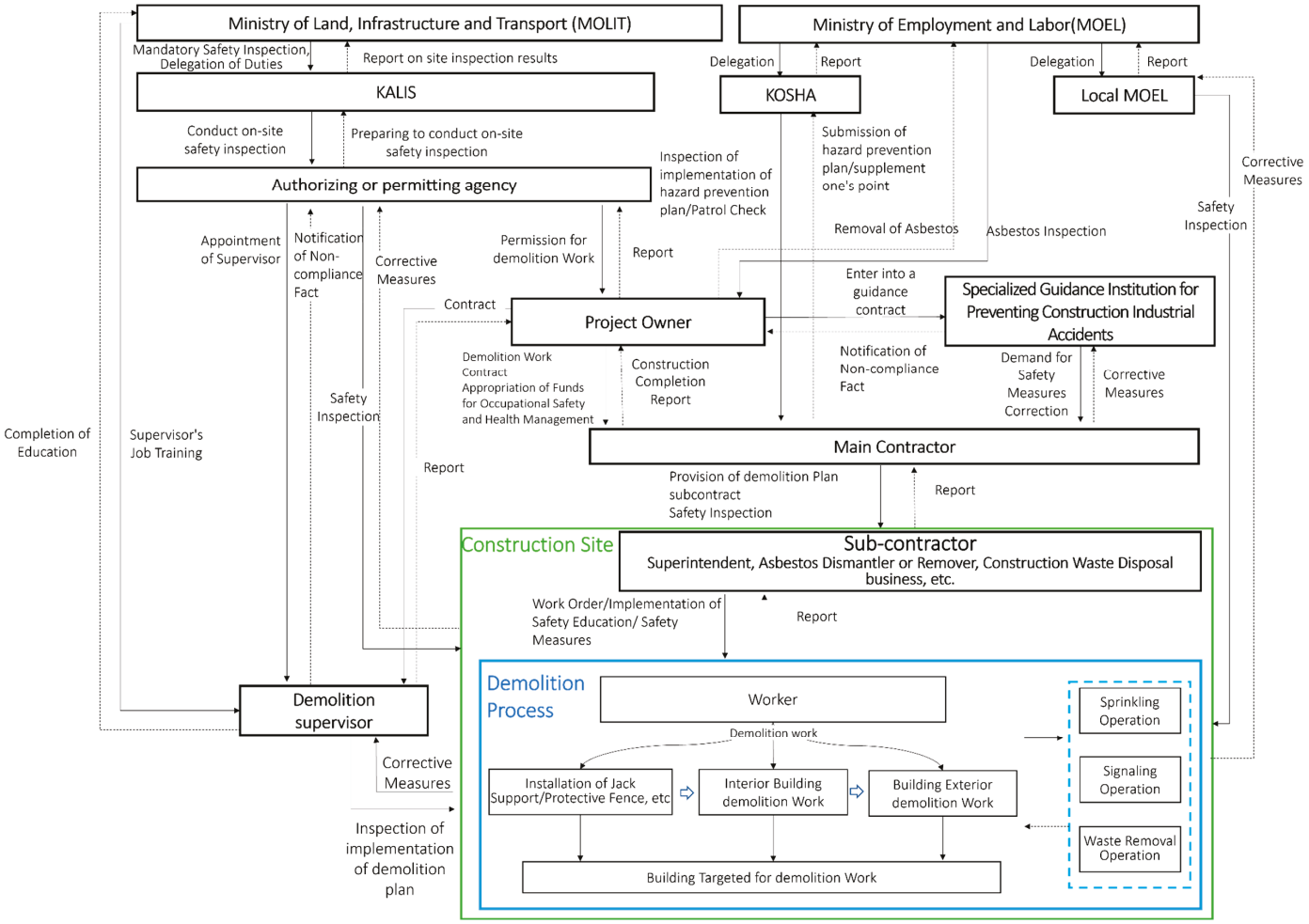

Figure 9. Model of safety control structure in the building demolition work stage.

Table 4. Control loop in the demolition work stage.

Control Action		Explanation	Feedback	Explanation
On-site internal organization	Project owner	Demolition work contract and appropriation of funds for occupational safety and health management	Main contractor	Construction completion report
	Main contractor	Subcontract and offer demolition plan	Subcontractor	Construction completion report Follow demolition plan
	Main contractor	Safety inspection Safety education	Subcontractor	Safety measures
	Subcontractor	Work order Safety education	Construction site	Report work result
	Demolition supervisor	Check demolition plan is followed	Construction site	Corrective measures
	Project owner	Offer site information	Demolition supervisor	Inspection of implementation of demolition plan
External organization	Authorizing or permitting agency	Safety inspection	Construction site	Corrective measures
	Authorizing or permitting agency	Appointment of supervisor	Demolition supervisor	Notification of non-compliance
	Constructor	Submission of hazard prevention plan	KOSHA	Inspection of implementation of hazard prevention plan
	MOEL	Asbestos inspection	Project owner	Removal of asbestos
	Project owner	Covenant	Specialized guidance institution for preventing construction industrial accidents	Notification of non-compliance
	Specialized guidance institution for preventing construction industrial accidents	Demand for safety measure correction	Main contractor	Corrective measures
	MOIT	Mandatory safety inspection	Authorizing or permitting agency	Report on-site inspection results
	MOIT	Supervisor's job training	Demolition supervisor	Completion of education
	KALIS	Conduct on-site safety inspection	Authorizing or permitting agency	Preparing to conduct on-site safety inspection

To enhance safety at small-scale construction sites with construction costs of KRW 100 million to 12 billion, specialized construction industry accident prevention consulting agencies are required to provide safety consulting services under the OSH Act. These experts inspect compliance with safety standards, identify risk factors, and suggest improvement measures, thereby supporting accident prevention. The developed model emphasizes that specialized consulting agencies function as key stakeholders in accident prevention in the small-scale construction industry by incorporating this institutional intervention into the safety control structure. However, if the system is implemented formally, its effectiveness can be limited.

4.4. Development of Safety Control Model for Building Demolition System

The final model can be divided into system development and system operation (Figure 10). The system development portion was structured as a control loop up to the building demolition permit stage, while the operation portion was structured as the construction phase. This control model hierarchically links the entire process, from the client's planning to the permitting process by the licensing authority, to the execution of the construction phase. Specifically, government organizations were placed at the top, including the MOEL and the MOLIT, and a reporting system was added to ensure that issues arising at each stage were circulated to higher-level organizations. Furthermore, by linking the development and operation portions through a supervisor, the impact on site safety could be analyzed, encompassing not only technical and management measures but also safety interactions with external agencies.

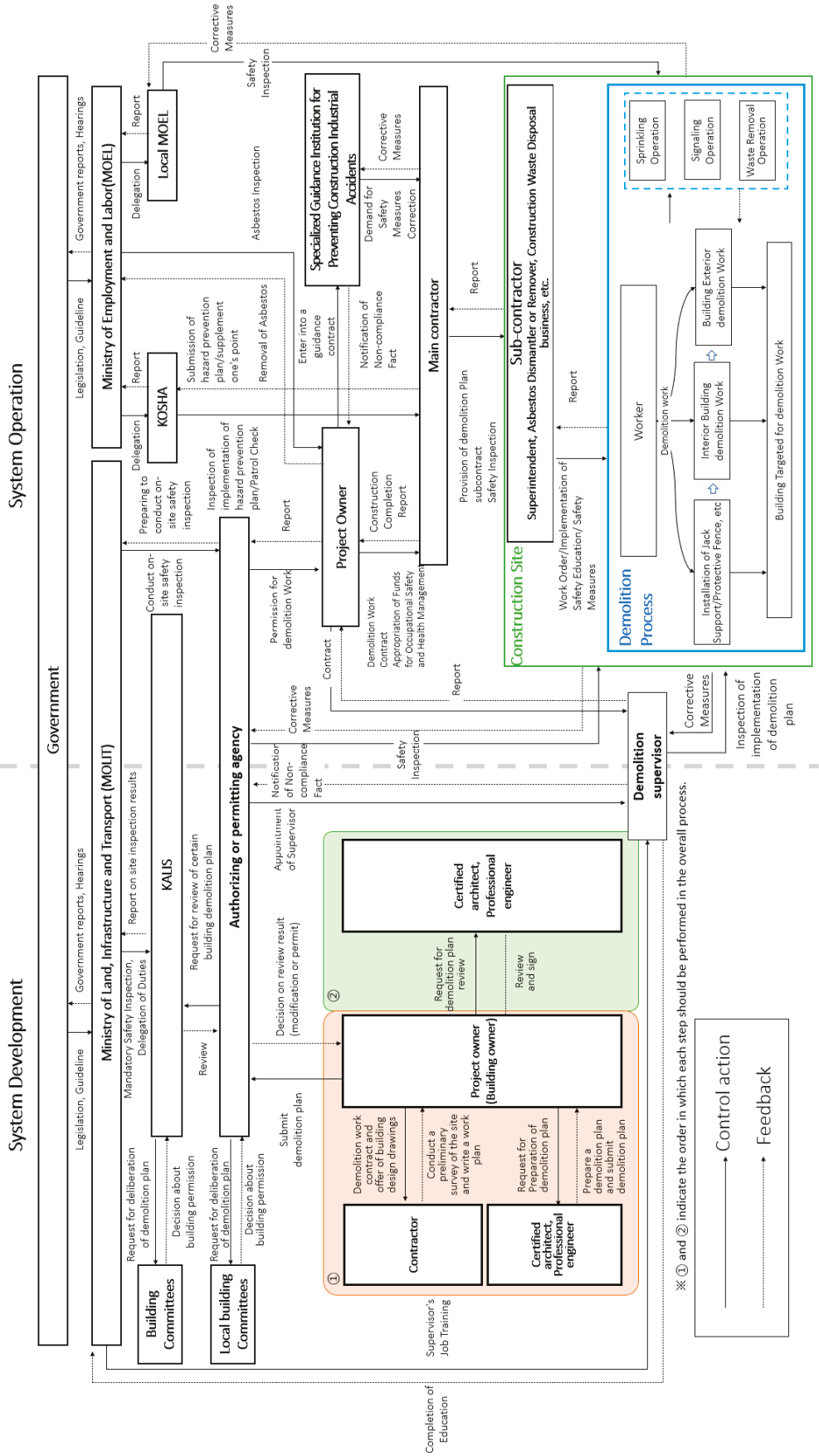

Figure 10. Proposed model of safety control structure for demolition work in South Korea.

This structure is significant in that it clearly reveals the link between control failures by external organizations and site safety, a problem that traditional analysis techniques such as sequential accident models or FTAs and ETAs struggle to address. For example, if a licensing authority issues a poor permit, the impact can be directly transferred to the construction phase, and if the supervisor fails to control this, the structural chain of events leading to an accident can be identified. This provides an analytical framework that can complement the limitations of the accident investigation system in South Korea, which has primarily focused on "on-site violations of regulations". The research results show that demolition collapse accidents can occur due to technical problems as well as interactions between various stakeholders such as the authorizing or permitting agency, demolition supervisors, and the constructor. The authorizing or permitting agency's review of the demolition plan has a significant impact on the demolition work system, and the demolition supervisor's safety measure inspection and corrective actions have a direct impact on the site safety. Therefore, it is essential to recognize that non-implementation of safety measures by external organizations can negatively impact site safety. It is also important to emphasize safety actions by internal and external organizations when managing the demolition work process.

The integrated model in Figure 10 simultaneously reflects the overlapping roles of government agencies and the dual management structure, suggesting areas for improvement in system operation. Currently, the MOEL oversees compliance with worker safety measures, while the MOLIT manages compliance with technical safety measures. However, this duality can lead to confusion in the field. By placing the two agencies at the top, this model visually demonstrates the shared responsibility and cooperative structure between them, emphasizing the need for institutionally integrated management.

The structure that links development (permitting) and operation (construction) through supervisors supports the idea that strengthening supervisors' responsibilities and authority is crucial for ensuring on-site safety during the demolition work. This connects to the issue of "insufficient substantive authority for supervisors", which has been repeatedly raised in previous studies [30,36], and this model highlights the need for institutional improvements to address this issue. Therefore, Figure 10 can be used as an analysis tool that goes beyond simply presenting a structure and can derive directions for institutional improvement and policy implications. However, this final model represents a detailed safety control structure model. The proposed model should be understood primarily as an analytical framework for revealing systemic safety vulnerabilities. For practical use, the model can be simplified by prioritizing critical interactions or consolidating similar roles while maintaining its systemic perspective.

5. Case Study

In this section, using a case study, we verified whether the developed model could serve as a template for understanding interactions between stakeholders during the accident investigation process.

5.1. Selection of Accident

A case study was conducted to determine whether the developed safety control structure model could be applied to actual accident analysis. The Gwangju demolition collapse accident was selected because a reliable accident investigation report was published. The Gwangju demolition collapse occurred on 9 June 2021, during the demolition of a structure using a crusher from the back side. The structure collapsed towards the roadside, causing a casualty event in which, of 17 people waiting at a nearby bus stop, 9 died and 8 were injured (Figure 11).



Figure 11. Collapse during building demolition work in Gwangju, South Korea [36].

The technical root causes of this accident were confirmed by the accident investigation report of the Central Architectural Accident Investigation Committee of the MOLIT along with various news articles. The causes are as follows:

- Collapse of the first-floor slab owing to excessive load from the overburden caused by the soil inside the building.
- Excessive watering operations reduced the internal friction angle of the soil, leading to a rapid impact load.

The root cause mentioned in the accident investigation report referred to technical causes within the site. However, it is necessary to analyze the root cause that influenced the occurrence of technical problems. Therefore, the incorrect interactions of stakeholders that affected the accident were analyzed using the developed model.

5.2. Accident Analysis Results Using the Developed Model

An analysis was conducted to examine safety interactions between stakeholders involved in the considered demolition collapse accident. Figure 12 shows the results and the missing safety interactions between the components are highlighted in red, through which the actions influencing the collapse of each stakeholder can be identified. These missing safety interactions were directly inferred from the official accident investigation report by the Central Construction Accident Investigation Committee [36], which stated that no corrective orders, supervisory inspections, or non-compliance notifications were issued. Moreover, the red color does not imply that all standards were ignored but rather highlights systemic weaknesses where controls were formally present but not effectively implemented. The results were analyzed after deleting stakeholders who were not involved in the accident. An analysis of improper interactions between the authorizing or permitting agency and the project owner revealed that the former did not request that the project owner update deficient items in the demolition plan, and the project owner did not amend or improve the improper demolition plan. The demolition supervisor did not inspect whether the work was being conducted according to the plan or request a correction of the demolition work or report non-compliance despite unauthorized changes in demolition methods. Various subcontractors worked at the demolition site, but the main contractor did not fulfill their responsibilities for communication and control between different tasks. A risk assessment of hazardous duties was not conducted. The subcontractors illegally subcontracted the demolition work again, undertaking the work within a tight schedule and small budget, and thus failed to perform safety management on site properly.

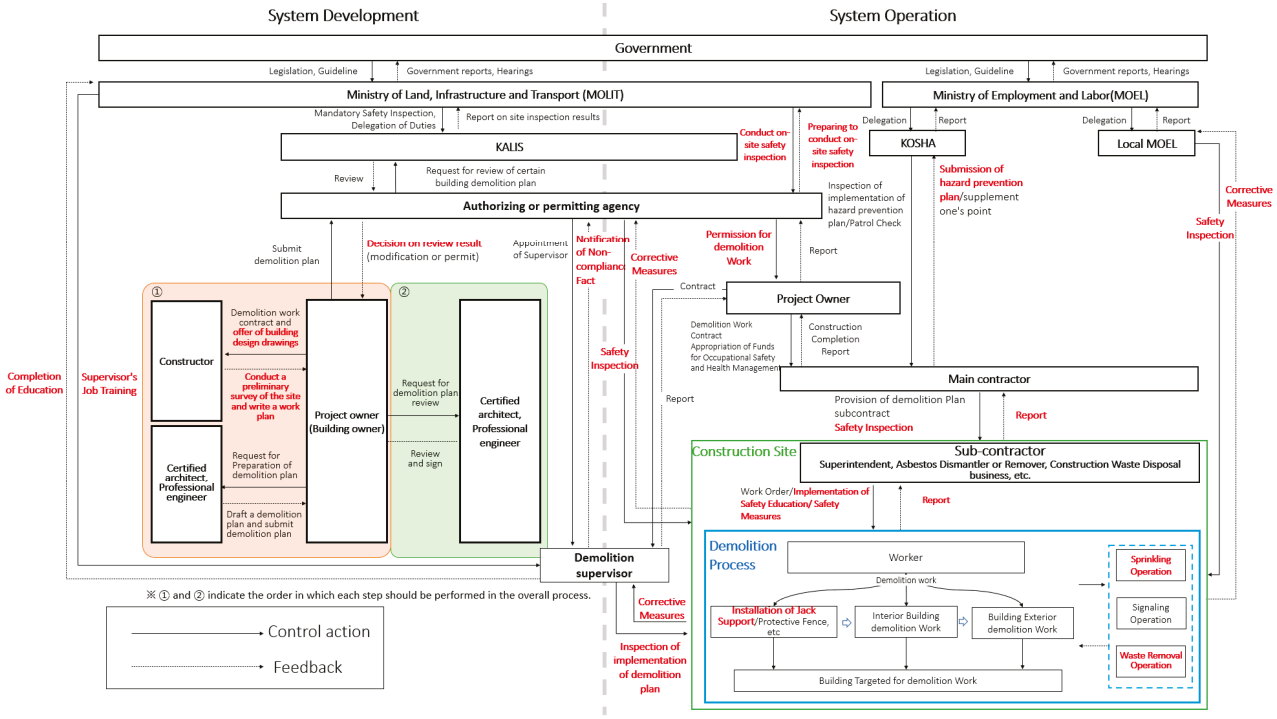

Figure 12. Analysis results of considered demolition collapse accident using developed model.

The results using the proposed model demonstrate that the cause of the accident is not simply a problem of technical factors on site but rather a complex interaction of institutional and organizational flaws. While previous studies [21,22] have pointed out that subcontracting structures and poor communication lead to serious accidents, most have focused on management issues within individual organizations. This study, however, is significant in using a STAMP-based safety control structure to illustrate the direct impact of control failures by external organizations (licensing and supervisory agencies) on on-site safety. In particular, the failure of the authorizing or permitting agency to request improvements and the absence of supervisory inspections and reporting indicate that the legal roles stipulated in the BM Act and the OSH Act were not properly implemented on-site. This goes beyond mere violations of regulations; it reveals structural limitations that prevent adequate safety control within the operational system. This interpretation demonstrates that accident investigation practices still focus solely on "whether or not there was a violation of the law", suggesting the need for future institutional reforms that focus on the question, "Why were appropriate controls not implemented?".

In South Korea, many demolition projects are small in scale, lacking specialized safety management capabilities. The multi-layered division of responsibility among the owner, general contractor, and supervisor is unclear. Therefore, this model goes beyond simply identifying the cause of the accident and can serve as a basis for suggesting future policy improvements, such as strengthening owner training and supervisor qualification requirements, and standardizing licensing agency review procedures. Moreover, responsibilities could be clearly shown by identifying actions that were not implemented by each component. The results obtained using the proposed model can be used to establish measures to prevent recurrence of accidents in the future. Thus, the proposed model is able to improve on the limitation that it is difficult to analyze the impact of policies and regulations of external organizations such as the authorizing or permitting agencies, regulatory agencies, and government agencies in the sequential model commonly used in construction accident analysis.

6. Conclusions

This study proposes an advanced safety control structure model to identify stakeholders participating in building demolition in Korea and analyze the safety interactions between them at each stage of the demolition process. The existing method mainly analyzes the direct causes of collapse accidents during building demolition in terms of nonperformance of demolition management and non-treatment for strength reinforcement. However, this study investigated various problems in the demolition plan approval process and poor work attitudes of demolition supervisors and found that various factors affect accident occurrence in relation to multiple construction participants.

Understanding how stakeholders implement safety measures through their interactions is essential. The safety control structure model developed in this study helps in effectively understanding the safety measures and roles of these stakeholders. It is important to use this model to identify the safety measures that have not been implemented at the site and to find ways to strengthen them through further interactions between stakeholders.

For the considered accident, approval of construction without a systematic review by the authorizing or permitting agency or without review experts was identified as a problem. In addition, the lack of a role for the demolition supervisor, who can control demolition work as a whole, directly contributed to the collapse. The role of the authorizing or permitting agency is important, because it influences the overall demolition system. In addition, the role of the supervisor, who directly affects the safety of the demolition work by checking safety measures and taking corrective actions, is also important. Therefore, to develop practical implementation measures, it is necessary to strengthen the following roles for each stakeholder. The authorizing or permitting agency is advised to adopt standardized demolition plan review checklists and mandate peer reviews for complex projects. Supervisors must be regularly present on site and complete customized training linked to accident scenarios. It is also essential to periodically provide education to enhance their job capabilities by reinforcing qualification standards. Project owners should establish a system where, prior to issuing construction orders, they submit standardized safety checklists or register demolition plans online with permitting authorities, making them accessible to supervisors and all stakeholders. These measures, introduced as pilot programs in high-risk urban demolition projects, can be institutionalized nationwide through regulatory amendments.

The demolition work safety control model developed in this study was verified by applying it to one demolition work accident. Although this study focused on a specific accident case, further research is needed on a variety of accident types and situations.

Key conclusions can be summarized as follows:

- Licensing agencies decisively influence the overall safety of demolition projects.
- Supervisors' inspections and corrective actions directly impact on-site safety.
- Missing safety measures and weak enforcement highlight systemic and organizational deficiencies beyond technical issues.
- Strengthening training, qualification standards, and institutional authority for supervisors is essential.
- The proposed STAMP-based model provides a systematic framework to identify unimplemented safety measures and guide future policy improvements.

This study analyzed the Gwangju collapse accident as a single case to validate the proposed model, thus limiting its generalizability. Future research should apply this model to various types of demolition accidents (e.g., residential buildings, industrial facilities) to enhance its robustness.

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References

1. Shin, S.H.; Won, J.H.; Jeong, H.J.; Kang, M.G. Development of a site information classification model and a similar-site accident retrieval model for construction using the KLUE-BERT model. *Buildings* **2024**, *14*, 1797. [CrossRef]
2. Omer, M.M.; Mohd-Ezazee, N.M.A.; Lee, Y.S.; Rajabi, M.S.; Rahman, R.A. Constructive and destructive leadership behaviors, skills, styles and traits in BIM-based construction projects. *Buildings* **2022**, *12*, 2068. [CrossRef]
3. Wang, D.; Qin, Y.; He, Y. The effect of leader–follower psychological capital congruence on safety behavior. *Buildings* **2024**, *14*, 1. [CrossRef]
4. Igwe, C.; Nasiri, F.; Hammad, A. Construction workspace management: Critical review and roadmap. *Int. J. Constr. Manag.* **2022**, *22*, 1960–1973. [CrossRef]
5. Won, J.H.; Jeong, H.J.; Kim, W.; Kim, S.; Kang, S.Y.; Hwang, J.M. Mechanisms analysis for fatal accident types caused by multiple processes in the workplace: Based on accident case in South Korea. *Int. J. Environ. Res. Public Health* **2022**, *19*, 11430. [CrossRef]
6. Moon, H.S.; Kim, H.S.; Kim, C.H.; Kang, L.S. Development of a schedule-workspace interference management system simultaneously considering the overlap level of parallel schedules and workspaces. *Autom. Constr.* **2013**, *39*, 93–105. [CrossRef]
7. Gwak, H.S.; Shin, W.S.; Park, Y.J. Space-constrained scheduling optimization method for minimizing the effects of stacking of Trades. *Appl. Sci.* **2021**, *11*, 11047. [CrossRef]
8. ILO (International Labour Organization), Statistic on Safety and Health at Work. Available online: https://ilostat.ilo.org/topics/safety-and-health-at-work/ (accessed on 17 August 2025).
9. MOLIT Construction Safety Management Integrated Information. Construction Accident Information Report (2024 Construction Accidents). 2025. Available online: https://www.csi.go.kr/community/dataMain.do (accessed on 1 September 2025).
10. Mitropoulos, P.; Abdelhamid, T.S.; Howell, G.A. Systems model of construction accident causation. *J. Constr. Eng. Manag.* **2005**, *131*, 816–825. [CrossRef]
11. Ertas, H.; Erdogan, A.S. An analysis of occupational accidents in demolition work. *Civ. Eng. Archit.* **2017**, *5*, 37–51. [CrossRef]
12. Takahashi, H. An investigation of fatal accidents in demolition work of buildings. In Proceedings of the International Structural Engineering and Construction Conference, Chicago, IL, USA, 20–25 May 2019. [CrossRef]
13. Patel, D.J.; Patel, D.A. Identification of potential demolition hazard attributes: An exploratory factor analysis approach. *J. Leg. Aff. Disput. Resolut. Eng. Constr.* **2023**, *15*, 04522061. [CrossRef]
14. Patel, D.J.; Ponnana, S.A.; Patel, D.A.; Patel, M.B. Development of a framework for risk assessment in building demolition works. *J. Leg. Aff. Disput. Resolut. Eng. Constr.* **2023**, *15*, 04523016. [CrossRef]
15. Alipour-Bashary, M.; Ravanshadnia, M.; Abbasianjahromi, H.; Asnaashari, E. A hybrid fuzzy risk assessment framework for determining building demolition safety index. *KSCE J. Civ. Eng.* **2021**, *25*, 1144–1162. [CrossRef]
16. Alipour-Bashary, M.; Ravanshadnia, M.; Abbasianjahromi, H.; Asnaashari, E. Building demolition risk assessment by applying a hybrid fuzzy FTA and fuzzy CRITIC-TOPSIS framework. *Int. J. Build. Pathol. Adapt.* **2022**, *40*, 134–159. [CrossRef]
17. Fu, M.; Liang, Y.; Feng, Q.; Wu, B.; Tang, G. Research on the Application of Multi-Source Data Analysis for Bridge Safety Monitoring in the Reconstruction and Demolition Process. *Buildings* **2022**, *12*, 1195. [CrossRef]
18. Mohammadi, M.; Mohammad, S.M.; Roshanbin, M.; Lomboy, G.R.; Abubakri, S. Advances in Concrete Demolition Technologies: A Review of Conventional and Emerging Methods for Sustainable Waste Management. *Eng* **2024**, *5*, 3174–3191. [CrossRef]
19. Yuzbasi, J. Controlled Demolition: Novel Monitoring and Experimental Validation of Blast-Induced Full-Scale Existing High-Rise Building Implosion Using Numerical Finite Element Simulations. *J. Civ. Struct. Health Monit.* **2025**, *15*, 891–914. [CrossRef]

20. Andruszko, J.; Derlukiewicz, D. Enhancing Demolition Works Safety: Integrating Numerical and Experimental Methods for Structural Failure Prevention in Remote-Controlled Demolition Robots. *Eksploat. I Niezawodn.—Maint. Reliab.* **2024**, *26*, 1–16. [CrossRef]
21. Leveson, N. A new accident model for engineering safer systems. *Saf. Sci.* **2004**, *42*, 237–270. [CrossRef]
22. Salmon, P.M.; Cornelissen, M.; Trotter, M.J. Systems-based accident analysis methods: A Comparison of Accimap, HFACS, and STAMP. *Saf. Sci.* **2012**, *50*, 1158–1170. [CrossRef]
23. Suraji, A.; Duff, A.R.; Peckitt, S.J. Development of causal model of construction accident causation. *J. Constr. Eng. Manag.* **2001**, *127*, 337–344. [CrossRef]
24. Zhang, J.; Zhang, W.; Xu, P.; Chen, N. Applicability of accident analysis methods to Chinese construction accidents. *J. Saf. Res.* **2019**, *68*, 187–196. [CrossRef]
25. Woolley, M.J.; Goode, N.; Read, G.J.M.; Salmon, P.M. Have we reached the organisational ceiling? A review of applied accident causation models, methods and contributing factors in construction. *Theor. Issues Ergon. Sci.* **2019**, *20*, 533–555. [CrossRef]
26. Yoon, H.K.; Kwon, Y.J.; Oh, B.H.; Gwon, Y.I.; Yoon, Y.G.; Oh, T.K. A Study on the improvement of safety management of plan/order, design, and construction business management. *J. Korean Soc. Saf.* **2020**, *35*, 56–63. [CrossRef]
27. Yonhap News. 'Gwangju Hakdong Collapse Disaster' Only 3 People, Including the Subcontractor Manager and Supervisor, Were Sentenced to Prison (Comprehensive). 2021. Available online: https://www.yna.co.kr/view/AKR20220907065651054 (accessed on 1 September 2025).
28. Kim, H.K.; Kim, T.H.; Cho, C.G. A Study on the Regulations and Standards for Structural Demolition Safety. *Constr. Eng. Manag.* **2022**, *23*, 8–12. Available online: https://scienceon.kisti.re.kr/commons/util/originalView.do?cn=JAKO202213841032554&oCn=JAKO202213841032554&dbt=JAKO&journal=NJOU00291654 (accessed on 1 September 2025).
29. Lee, S.J.; Lee, H.G.; Shin, D.G. Analysis of the effectiveness and feasibility of accident analysis policy for construction safety from the perspective of system safety. *J. Soc. Disaster Inf.* **2023**, *19*, 146–160. [CrossRef]
30. Shim, Y.K.; Jeong, J.W.; Lee, J.H.; Jeong, J.M. Necessity of improvements on code of practice at the demolition work considering building structure type: Based on demolition work of permission and registration. *Korean J. Constr. Eng. Manag.* **2020**, *21*, 66–74. [CrossRef]
31. Primer, S. An STPA Primer. MIT Cambridge 2013. Available online: https://psas.scripts.mit.edu/home/wp-content/uploads/2013/10/An-STPA-Primer-version-0-4.pdf (accessed on 19 August 2025).
32. Leveson, N.G. Applying systems thinking to analyze and learn from events. *Saf. Sci.* **2011**, *49*, 55–64. [CrossRef]
33. Rising, J.M.; Leveson, N.G. Systems-theoretic process analysis of space launch vehicles. *J. Space Saf. Eng.* **2018**, *5*, 153–183. [CrossRef]
34. Leveson, N.G. CAST Handbook: How to Learn More from Incidents and Accidents. 2019. Available online: http://sunnyday.mit.edu/CAST-Handbook.pdf (accessed on 19 August 2025).
35. MOLIT and Korea Authority of Land & Infrastructure Safety. Building Demolition Plan Preparation and Review Manual. 2024. Available online: https://www.kalis.or.kr/www/brd/m_435/view.do?seq=191 (accessed on 1 September 2025).
36. Central Building Accident Investigation Committee. Gwangju Building Demolition Collapse Accident Investigation Report. 2021. Available online: https://www.molit.go.kr/USR/policyData/m_34681/dtl.jsp?id=4559 (accessed on 1 September 2025).

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Using Safety-Specific Transformational Leadership to Improve Safety Behavior Among Construction Workers: Exploring the Role of Knowledge Sharing and Psychological Safety

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Abstract

Leaders play a crucial role in shaping employees' safety behaviors (SBs). However, research on broader leadership styles has yielded inconsistent findings, emphasizing the need for a more tailored leadership approach, especially in high-risk industries, such as construction. Applying the social exchange theory and the positive organizational behavior framework, this study examined the impact of safety-specific transformational leadership (SSTL) on SB. This study uses a quantitative research design to collect data from employees of Turkish construction firms in Ankara and Istanbul. A cross-sectional research design was employed, with purposive sampling of data collected from 706 construction workers in Türkiye. The findings indicate that SSTL positively influences both SB and knowledge sharing, whereas knowledge sharing enhances SB. Knowledge sharing mediates the relationship between SSTL and SB. This study's findings suggest that implementing safety-specific transformational leadership (SSTL) can significantly improve safety behavior among construction workers by promoting knowledge sharing and psychological safety.

Keywords: transformational leadership; safety behavior; construction; knowledge sharing; psychological safety

1. Introduction

Poor safety records in the construction sector have long been a source of criticism [1], particularly in developing nations such as Turkiye [2]. In 2023 alone, 1932 workers lost their lives in work incidents, with the construction industry accounting for the majority of these workplace fatalities [3]. Globally, the construction industry accounts for approximately 30 to 40% of work-related fatalities, despite employing only 7% of the global total workforce [4]. For example, in the United States and China, the construction industry significantly poses a higher danger and has more fatalities than other industries, such as mining, commercial, and industrial sectors [5].

Despite progress in technological innovations, safety regulations, and training initiatives, unsafe behavior remains a significant contributor to adversarial safety outcomes. While leadership plays a critical role in shaping employee behaviors and attitudes [2], traditional leadership approaches often fail to address the unique challenges of enhancing safety in high-risk industries, such as the construction sector. Specifically, existing studies have investigated several factors, such as benevolent leadership [2] and servant leadership [6], as critical approaches for improving safety behavior. Thus, it is critical to

research safety-specific leadership styles that may improve employee safety behavior in the construction sector.

Safety behavior is a critical challenge for most firms globally [7], particularly within the construction sector. Based on this, there are numerous research calls to investigate the link between leadership and employee safety behaviors (SB) [2,8]. Transformational leadership is among the most extensively researched leadership styles due to its potential to initiate, maintain, or promote SB across various occupations and disciplines [9–11]. Safety-specific transformational leadership (SSTL) integrates transformational leadership techniques and approaches while placing strong emphasis on occupational safety [12]. Compared with general transformational leadership, SSTL may serve as a more effective predictor of safety behavior, where leaders focus on their motivational and inspirational efforts to foster positive safety-related outcomes [13,14]. Despite this, there is a lack of empirical studies on the impact of SSTL on employee SB in the construction context.

In the general literature, an emerging study on context-specific safety leadership (i.e., SSTL) has been demonstrated to promote safety outcomes such as SB [14]. If SSTL indeed influences employee safety behavior, more research is needed to address questions concerning the mechanisms that govern this relationship. Knowledge sharing relates to the process by which subordinates mutually exchange information and their knowledge [15]. Prior studies highlight that leadership fosters knowledge-sharing behaviors and collaborative learning [16,17]. Safety-specific transformational leadership clearly outlines the interactive process by which leaders exert their influence on subordinates to accomplish organizational safety practices [14]. Moreover, leadership has also been argued to motivate followers to engage in knowledge-sharing behaviors [17], which, in turn, enhances safety behavior [2]. Thus, there are conceptual reasons for expecting knowledge sharing to mediate the relationship between SSTL and SB. Accordingly, the current research partly responds to the recent research call [14] to investigate knowledge sharing as a mechanism through which SSTL influences SB.

With SSTL, leaders motivate followers through a vision centered on safety and intellectual stimulation, such as encouraging employees to develop safer procedures, and are likely to promote knowledge sharing by presenting it as a significant contribution to the organization's safety objectives [12]. Moreover, leaders serve as facilitators of knowledge-sharing behavior [18], and safety-specific transformational leadership may be adept at ensuring this. The rationale behind this is that SSTL motivates and inspires followers with safety values [12]. Despite the distinctive characteristics of SSTL, Agarwal and Anantatmula [19], Siemsen et al. [20], and Yin et al. [21] argued that psychological safety is an enabler of knowledge sharing. However, the extant literature has yet to establish its interaction with knowledge sharing as a moderator concerning other employee behaviors, such as safety behaviors. In addition, in this study, psychological safety relates to the work context in which employees feel secure to interact with organizational structures in the workplace, grounded in conviction; they will not face punishment for doing so [22]. Accordingly, based on social exchange theory [23] and the positive organizational behavior perspective [24], this study develops a moderated mediation framework (Figure 1) to investigate the impact of SSTL on SB through the mediating role of knowledge sharing and the moderating role of psychological safety in the Turkish construction industry.

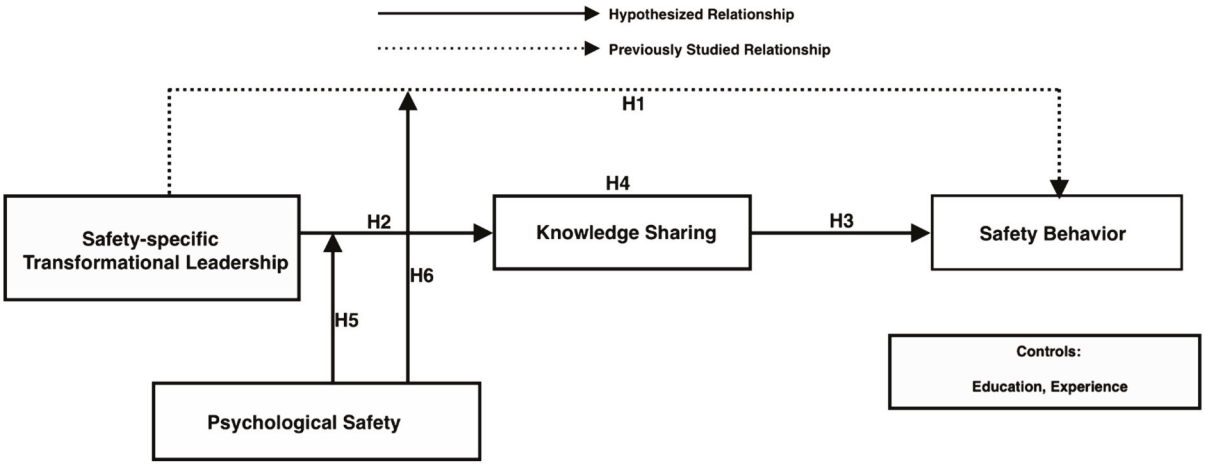

Figure 1. Research framework.

This study's research framework (Figure 1) explores how safety-specific transformational leadership influences safety behavior in construction workers, mediated by knowledge sharing and moderated by psychological safety. It suggests that leaders who inspire a shared safety vision and encourage safe practices support a climate of psychological safety, where workers feel comfortable sharing knowledge and concerns. This positively impacts their safety behavior. The variables used in this research are explained below:

1. Safety-specific transformational leadership (independent variable):

This leadership style, where leaders champion a safety vision and encourage employees to actively participate in achieving it, is the starting point.

2. Safety behavior (dependent variable):

This encompasses the actual actions and practices of workers related to safety, such as adhering to safety protocols, using personal protective equipment, and reporting hazards.

3. Knowledge sharing (mediating variable):

This refers to the exchange of safety-related information, best practices, and lessons learned among workers.

4. Psychological safety (moderating variable):

This is the belief that one can take risks, speak up with ideas or concerns, and admit mistakes without fear of negative consequences.

Relationships:

Hypothesis 1. *SSTL positively influences employee safety behavior*.

Hypothesis 2. *SSTL positively influences knowledge sharing*.

Hypothesis 3. *Knowledge sharing positively influences employee safety behavior*.

Hypothesis 4. *Knowledge sharing mediates the relationship between SSTL and employee safety behavior*.

Hypothesis 5. *For construction workers with high psychological safety, the positive impact of SSTL on knowledge sharing is stronger than that of those with low psychological safety*.

Hypothesis 6. *The indirect impact of SSTL on safety behavior through knowledge sharing is the strongest at a high level of psychological safety*.

Contributions:

- This study uses four variables: safety-specific transformational leadership, safety behavior, knowledge sharing, and psychological safety. Among these variables, safety-specific transformational leadership is an independent variable, safety behavior is a dependent variable, knowledge sharing is a mediating variable, and psychological safety is a moderating variable.
- Social exchange theory and the positive organizational behavior framework are used to examine the impact of safety-specific transformational leadership (SSTL) on safety behavior.
- The primary objective of this study is to investigate how safety-specific transformational leadership impacts safety behavior among construction workers, specifically exploring the roles of knowledge sharing and psychological safety.
- The research seeks to understand how leaders can encourage a safety-conscious environment in construction by promoting knowledge sharing and psychological safety, which leads to better safety outcomes for workers.

2. Theoretical Background and Hypotheses Development

2.1. Social Exchange Theory (SET)

SET has been widely applied to understand workplace behavior in various fields, such as business management, safety management, and social psychology [14,25]. Social exchange interactions are characterized by the continuous reciprocal transfer of resources between two parties, where these exchanges are interdependent and create future obligations [26]. The interactions in social exchange do not involve a predetermined agreement or explicit bargaining but rather entail discretionary cooperative behavior [27]. Studies indicate that leaders who inspire and motivate employees tend to be passionate about their organizational safety goals [14]. This is described as a reciprocal response from employees to their enterprises' initiative to promote positive emotions (e.g., harmonious passion) and social context (e.g., leadership) [14,25]. However, research has primarily focused on investigating other employee behaviors, such as safety behavior as a reciprocal response to employees' perceptions regarding exchange relationships in a social context (e.g., leadership) [14] and not the actual exchanges that occur among employees. Demonstrating that the organizational social context (i.e., SSTL) exchanges activities that result in employee exchanges (i.e., knowledge sharing) is essential to the idea that SSTL and knowledge sharing stem from social exchange. This understanding is critical for developing strategies that encourage employees' safety behavior in high-risk industries such as the construction sector.

2.2. Positive Organizational Behavior (POB) Perspective

Drawing from SET, this research assumes that when employees perceive leaders' inspiration and motivation in relation to safety goals, they are willing to share safety-related knowledge as reciprocal behavior with other employees, which in turn influences their safety behavior. In addition to SET, this study also integrates the perspective of positive organizational behavior (POB) to explain "when" such a relationship may occur. POB scholars recommend adopting a positive approach in organizational behavior research [25,28,29]. Given that POB places greater emphasis on the significance of individual positive psychological conditions [29], this study used POB to complement the SET assumption. In this study, the POB perspective helps underscore psychological safety beneficiaries (i.e., employees). The POB framework can offer a robust framework for understanding the psychological capacities and states that can moderate the relationship between SSTL and safety behavior. The theory is grounded on the tenet that positive psychological

states can enable individuals to perform at their optimum potential. Applying this framework to safety in the construction industry can shed light on why psychological safety is not merely a desirable attribute but a required catalyst that can unlock the full potential of SSTL on employees' safety behavior. Consistent with the POB perspective, we argue that employees who experience psychological safety are more capable of reciprocating the required safety standards in the workplace.

2.3. SSTL and Safety Behavior

Safety is a major concern for firms globally [2]. More specifically, safety behavior is of great importance in the construction sector because of the enormous proportion of fatalities relative to other industries [2,30]. In this study, safety behavior is defined as the behavior exhibited by individuals concerning safety [31]. Inappropriate safety behaviors are the principal cause of workplace accidents. In this context, enhancing individual safety behaviors may reduce the incidence of workplace accidents [32].

SSTL is a leadership approach that redefines the values of transformational leadership: idealized influence, intellectual stimulation, inspirational motivation, and individualized considerations to optimize and prioritize safety within a firm [12,28]. This safety-focused leadership style motivates employees to prioritize safety in their work activities [33]. Leaders who portray SSTL, such as conveying a clear safety vision, showing dedication to safety, and emphasizing individual safety concerns, play a critical role in shaping actions and behaviors regarding safety [33]. Moreover, previous studies have demonstrated a positive relationship between SSTL and various employee safety outcomes. For example, Irshad et al. [33] reported that safety-specific transformational leaders stimulate favorable interactions with followers by fostering autonomy and individual consideration, which enhances psychological well-being, a critical aspect of safe work behavior. Similarly, based on a sample obtained from airline pilots, Wu et al. [14] demonstrated that leaders with safety-specific transformational behaviors encourage and motivate their subordinates to adhere to safety standards rather than use assertive behavior to enforce safety behavior.

Furthermore, SSTL is associated with improved employee motivation. Research conducted on firefighters revealed that SSTL increased safety motivation, resulting in improved safety performance, which included the appropriate and efficient use of personal safety gear [34]. These findings highlight the importance of safety-specific transformational leadership in creating an environment that encourages employees to be inherently motivated to comply with safety protocols. However, it is important to note that these studies were conducted outside of the construction industry. Given the high-risk nature of the construction sector, it is crucial to investigate and establish a link between context-specific safety leadership approaches and employee outcomes to ensure workplace safety. However, to our knowledge, there is a lack of empirical research in the extant literature on the link between SSTL and safety behavior in the construction context. Furthermore, SET posits that the relationship between leaders and followers is founded on mutual obligation and reciprocity [23]. Thus, drawing from SET and advancing the current literature, we argue that SSTL can be viewed as a form of social exchange, where leaders prioritize workplace safety and motivate employees to adopt positive behaviors. In return, employees will likely reciprocate by complying with safety procedures and adopting safety behaviors. Hence, we propose the following hypothesis:

Hypothesis 1. *SSTL positively influences employee safety behavior.*

2.4. SSTL and Knowledge Sharing

Knowledge is regarded as one of the most critical assets of a firm [35]. Knowledge sharing involves the sharing of ideas between employees and other relevant individuals [36]. Various researchers have argued that employees often hesitate to share knowledge with others unless they are motivated to do so, because they view their knowledge as a source of authority and advantage [37,38]. From this standpoint, scholars in the knowledge management domain have explored numerous factors that may impact knowledge sharing within a firm, with leadership identified as a significant contributor to fostering knowledge sharing by inspiring employee motivation [39]. However, the literature is filled with studies that examine traditional leadership approaches to knowledge sharing [21,40]. In advancing the existing body of knowledge, this study anticipates that safety-specific transformational leadership can promote knowledge sharing because safety-specific transformational leadership can shape subordinates' attitudes and behaviors while fostering a passion for change [14]. With a new vision regarding safety protocols, subordinates are more inclined to respond positively to safety-specific transformational leaders' calls to share knowledge with other employees to shift the status quo.

Congruent with SET, it is well established that leaders play a critical role in motivating and influencing followers' behaviors and thoughts. From this perspective, numerous studies based on samples collected from nurses in the hospital context argue that proficient safety leadership can enhance safety knowledge when concerns about safety are supported by guidance, solutions, and relevant insights to foster a secure working environment [41,42]. Therefore, safety-specific transformational leaders can guide their subordinates to share acquired safety knowledge with their peers. Motivated by safety-specific transformational leaders' push for collaboration with other employees towards shared safety objectives, this study anticipates that employees will be more willing to share their knowledge with others. Thus, we posit the following hypothesis:

Hypothesis 2. *SSTL positively influences knowledge sharing*.

2.5. Knowledge Sharing and Safety Behavior

An earlier study confirmed that knowledge sharing is crucial because it can curb meaningless learning processes within organizations [43]. It has also been demonstrated that the most prevalent cause of errors and wrongdoings is a lack of experience and knowledge [44]. Based on this, Edmondson [45] argued that appropriate knowledge management encourages learning and work settings that boost employees' safety knowledge and circumvent the repetition of accidents and mistakes.

Based on the framework in [46], safety knowledge determines safety behavior. The study emphasized that safety knowledge influences safety participation and compliance. Within the SET framework, interactions among employees are founded on mutual obligation and reciprocity [23]. From this standpoint, when employees share knowledge, they build a shared reservoir of information that serves the entire organization, fostering a sense of mutual obligation and reciprocity. In return, individuals who gain knowledge are likely to respond by adopting positive behavior, which includes following safety standards and undertaking safety initiatives. Based on this, we argue that, in the construction context, knowledge sharing can be construed as a form of social exchange in which individuals offer their experience and knowledge regarding workplace safety to promote overall safety. This interaction strengthens relationships and may instill a sense of obligation among individuals to prioritize safety behavior. Thus, we posit the following hypothesis:

Hypothesis 3. *Knowledge sharing positively influences employee safety behavior*.

2.6. The Mediation Role of Knowledge Sharing

As discussed in the preceding sections, the relationship between SSTL and knowledge sharing (H2) and between knowledge sharing and employee safety behavior (H3) suggests that SSTL influences safety behavior through knowledge sharing. One of the primary causes of accidents in the construction sector is a lack of knowledge [47]. Shin et al. [48] demonstrated that safety knowledge has the most robust direct influence on safety behavior among various mechanism variables such as affective commitment and safety motivation. Similarly, Neal et al. [46] discovered that safety knowledge significantly predicts safety behavior. Considering these results, management of safety knowledge is essential. As a key aspect of knowledge management, knowledge sharing can be a useful instrument in disseminating knowledge, particularly in high-risk industries such as the construction sector, where a lack of knowledge is one of the primary reasons for safety accidents. Furthermore, unsafe behavior may be addressed or even averted with thorough and extensive safety knowledge sharing [49]. However, this process did not occur automatically. Moreover, leadership plays a critical role in managing knowledge sharing [50]. Despite this, the intervening role of knowledge sharing on the relationship between context-specific safety leadership (i.e., SSTL) and safety behavior remains unexplored.

It has been highlighted that human errors are commonly caused by poor motivation and knowledge related to operating processes [51]. This is relevant in the construction industry because construction workers are constantly exposed to various work hazards and possible fatalities. Hence, acquiring and disseminating knowledge on safe operating techniques and procedures is essential for workers in the construction sector to avert such incidents. To accomplish this, it has been highlighted that leaders who portray safety-specific transformational leadership behaviors often create an environment that facilitates collaboration and open communication [26], which can encourage knowledge sharing among employees. This collaborative environment may promote employees' awareness of safety measures, which can translate into better safety behaviors.

In safety-specific transformational leadership, genuine care for employee well-being and safety is clearly perceived and understood [13,14]. Congruent with SET, this fosters a sense of mutual obligations and collaboration between leaders and followers, encouraging employees to adopt leaders' safety standards and practices, which lowers self-restraint to comply with safety regulations. We contend that knowledge sharing can further promote safety adherence and collaboration because employees share safety information with each other to advance safety goals. Thus, we posit the following hypothesis:

Hypothesis 4. *Knowledge sharing mediates the relationship between SSTL and employee safety behavior*.

2.7. The Moderation Role of Psychological Safety

Despite decades of policy overhaul and wide-ranging safety research, the construction industry remains alarmingly dangerous in different regions of the world [3]. Statistics for developing nations are notably worse, albeit still unreliable, than those for advanced nations, where injuries and fatalities are nevertheless a cause for worry [52–54]. For example, Turkiye conservatively reported that 1932 workers lost their lives in 2023, with most occupational fatalities occurring in the construction sector [3]. Li et al. [55] stated that the primary cause of numerous accidents in the construction sector is human behavior. In this respect, various studies have examined behavior-based safety in the past decades [56]. These studies highlight the role of human behavior in preventing unsafe behaviors and accidents [55]. Although psychological safety acknowledges this human aspect, studies on psychological safety in the construction industry are limited [57,58]. Moreover, owing to its

risky tasks, the construction sector needs a psychologically safer workplace to minimize safety risks and occupational health hazards [57], which is a major challenge for leaders and firms in the construction sector. Despite this, the literature lacks research exploring psychological safety as a positive individual condition for the proposed predictor of safety behavior in the construction sector. Hence, psychological safety is proposed as a driving force that can weaken or strengthen research within our research framework (Figure 1).

Previous research has highlighted that psychological safety is crucial and valuable in high-risk and dangerous industries, where employee safety is essential [57]. Consistent with the positive organizational behavior perspective, individuals with more positive psychological resources (i.e., psychological safety) tend to deal with work-related challenges with more positivity, perseverance, and motivation [59,60]. Simply put, employees must possess a certain degree of motivation and positivity before sharing knowledge [25]. While safety-specific transformational leaders encourage, inspire, and motivate their followers to adopt workplace safety goals and foster safety citizenship behavior [14,61], employees need more positivity to share knowledge [25]. From this standpoint, Demirkesen et al. [57] highlighted that psychological safety promotes a positive environment, enabling individuals to feel more empowered to engage in knowledge sharing and undertake proactive behaviors. Hence, in this study, we anticipate that when employees have higher psychological safety, they are more likely to engage in greater knowledge sharing (i.e., sharing safety-related insights among their peers).

Furthermore, Edmondson [62] argues that psychological safety can determine the difference between a near miss and a catastrophic incident. Psychological safety fosters a collaborative work environment that enhances employee absorption [63]. It provides an environment in which employees feel safe expressing their opinions without fear of reprisal [22]. From this standpoint, Quansah et al. [64] highlighted that in a workplace with psychological safety, employees do not suffer negative outcomes such as ridicule or embarrassment, which could affect their sense of self and social standing when they express themselves. Thus, it can be inferred that such an enabling environment can further promote employees' self-confidence and morale. For example, in a highly psychologically safe work setting, highly motivated workers may be passionate about adhering to safety protocols and sharing safety-related insights acquired from safety leaders. Consistent with the positive organizational behavior perspective, they may also feel energized and inspired to report unsafe behaviors without experiencing distress or fear. Moreover, such individuals exhibit higher engagement in undertaking extra-role initiatives to accomplish firm objectives (e.g., safety performance) [3,64]. Hence, we posit the following hypotheses:

Hypothesis 5. *For construction workers with high psychological safety, the positive impact of SSTL on knowledge sharing is stronger than that of those with low psychological safety.*

Hypothesis 6. *The indirect impact of SSTL on safety behavior through knowledge sharing is the strongest at a high level of psychological safety.*

3. Methods

3.1. Participants and Data Collection

This study uses a quantitative research design to collect data from employees of Turkish construction firms in Ankara and Istanbul. Before data collection, permission was obtained from the senior management of the construction firms. The construction firms targeted were listed under the Turkish Contractors Association (https://www.tmb.org.tr (accessed on 2 August 2025)). Therefore, this study adopted a purposive sampling method (i.e., non-probabilistic sampling). Following approval from the senior management of the

targeted firms, the construction workers (i.e., the targeted respondents of this study) were offered an explanation regarding the objectives of the research [65]. Workers who consented to participate in the survey were assured of complete anonymity and were required not to disclose any identifiable or personal information in the survey [66]. Moreover, they were free to withdraw from participation without any consequences during the survey process. Following a recent similar study in the construction sector [1] and in recognition of their participation, participants were provided with a souvenir: a pair of protective gloves. An incentive approach was employed to promote collaborative interaction with the participants and encourage them to complete the survey based on their own experiences [67]. Data were collected between September 2024 and October 2024. The survey was administered electronically and through in-person visits based on the respondents' preferences. Owing to the possible influence of common method bias in survey-based research, the survey was administered in two waves with a one-month interval [68].

In the first wave, respondents completed questions related to SSTL, knowledge sharing, and psychological safety. In the second wave, respondents completed questions related to safety behavior. Before administering the first wave, each respondent was assigned a unique identifier (i.e., a code). This unique identifier was used to match the respondents in the second wave.

A total of 1060 questionnaires were administered, of which 753 were recovered. However, owing to incomplete responses, 47 responses were removed, resulting in a response rate of 66.60%. Table 1 presents the sample characteristics. The sample consisted of 677 (95.89%) males and 29 (4.11%) females. Based on experience, the majority of the respondents, 492 (69.68%), had at least five years of work experience. With regard to education, 213 had a high school education or less 213 (30.17%), 441 had a bachelor's degree/equivalent (62.47%), 14 had a master's degree or higher (1.98%), and 38 (5.38%) had other degrees. Based on age, 201 respondents were less than 25 (28.47%); 317 were 26–30 (44.90%); 144 were 31–35 (20.40%); 24 were 36–40 (3.40%); and 20 were above 41 (2.83%).

Table 1. Sample attributes.

Demographic Characteristics (n = 706)	Frequency	Proportion (%)
Gender		
Male	677	95.89
Female	29	4.11
Experience (years)		
Less than one	23	3.26
1–3	102	14.45
3–5	89	12.61
5–10	364	51.55
Above 10	128	18.13
Education		
High school or less	213	30.17
Bachelor's degree or equivalent	441	62.47
Master's degree or higher	14	1.98
Others	38	5.38

Table 1. *Cont.*

Demographic Characteristics (n = 706)	Frequency	Proportion (%)
Age (years)		
Less than 25	201	28.47
26–30	317	44.90
31–35	144	20.40
36–40	24	3.40
Above 41	20	2.83

3.2. Survey Instruments

Since the items used in the survey were originally in English, we followed Brislin's [69] translation and back-translation approach. The SSTL was measured using 10 items adapted from Kelloway et al. [70]. A sample item is "My supervisor provides a clear vision of what needs to be done to work safely". Knowledge sharing was measured using eight items adapted from Ni et al. [71]. A sample item is "I often discuss and exchange safety training contents with my co-workers". Psychological safety was measured using seven items adapted from Edmondson [22]. A sample item is "I am not afraid of the consequences of questioning the company's safety practices". Safety behavior was measured using 11 items adopted from Neal and Griffin [72] and Ye et al. [73]. A sample item is "I uphold the use of safety protection equipment at work". All participants completed the survey using a 7-point Likert scale from 1 (not at all) to 7 (very much). The questionnaire used for data collection is presented at the end of the manuscript.

3.3. Data Analysis Procedures

The questionnaire survey was thoroughly reviewed for inconsistencies and errors before data analysis. Data analyses were conducted using SPSS 29.0 and AMOS 26.0. Furthermore, the data collected were thoroughly screened to detect any cases of outliers, missing values, and multicollinearity issues, ensuring that the factors were suitable for statistical procedures [74]. Pearson's correlation was used to establish correlations among the measures. Subsequently, a confirmatory factor analysis (CFA) was performed to examine and test the measures' reliability and validity and establish the overall fitness of the proposed research model [75]. After validating the measurement model, the proposed research framework was tested using the Hayes PROCESS macro v5.0 [76]. Specifically, Model 4 was employed to test the direct and mediation (with 5000 bootstrap resamples). Model 8 was used to test the moderating hypotheses. Model 4 represents a mediating variable model, where an independent variable influences a dependent variable through a third mediating variable. Model 8 could refer to a moderating variable model, where the relationship between an independent and dependent variable is affected by a third moderating variable [76]. Furthermore, a significant effect was determined when the 95% confidence interval (CI) did not contain zero.

3.4. Non-Response Bias

A pre-test was performed to assess the quality of the data collected. Wave analysis was employed to assess the non-response bias [77]. Based on this approach, the survey responses were classified into two categories: early and late. Subsequently, an independent t-test was performed on the items for SSTL and safety behavior. The t-values for the measurement items revealed no significant differences between the two categories, indicating the absence of non-response bias in the data collected.

3.5. Common Method Bias (CMB)

Procedural and statistical approaches have been employed to control and test CMB [78,79]. The survey was presented to two experts and two professors in the construction and safety management fields for recommendations. The feedback received aided in the refinement of measurement items. Harman's one-factor test and the marker variable approach were employed for the statistical analysis. Harman's one-factor test results indicated that the first factor represented only 25.58% of the total variation [80]. Given this result, CMB is not a serious concern in the collected data [79]. This study also adopts the marker variable technique. This approach involves adding a theoretically unrelated construct to the main variables of the research framework. The results indicated that the highest correlation between the study's main and theoretically unrelated constructs was 0.04. This offers further evidence that CMB was not a serious concern in this study [81].

4. Analysis and Results

4.1. Reliability and Validity of the Measurement Model

The reliability and validity of measurement items are critical for establishing the quality of empirical research [82]. Accordingly, appropriate tests were conducted to examine the reliability and validity of the measures, specifically internal reliability, convergent validity, and discriminant validity. Hence, Cronbach's alpha (α), factor loading, composite reliability (CR), and average variance extracted (AVE) were used.

The confirmatory factor analysis results (demonstrated in Table 2) indicated that the factor loadings exceeded the minimum value of 0.6 [83] (see Figure 2). The loadings for all items are also shown in Table 2, ranging between 0.618 and 0.887. This range depicts robust connections between the observed indicators and their corresponding latent variables. Furthermore, Cronbach's alpha was used to test scale reliability. For all variables, the Cronbach's alpha values were between 0.895 and 0.964. The squared multiple correlation (SMC) values supported the measurement reliability of the items. Similarly, for all the variables, the CR values were between 0.905 and 0.965. Both the Cronbach's alpha and CR values exceeded the minimum threshold of 0.7. Moreover, the AVE values were above 0.5 (between 0.513 and 0.717). Taken together, the measurement model demonstrated sufficient convergent validity [84,85]. Accordingly, the items within the model capture the underlying variables that were measured.

Table 2. Confirmatory factor analysis results.

Construct/Item	Factor Loadings	SMC	α	CR	AVE
Safety-specific transformational leadership (SSTL)			**0.909**	**0.913**	**0.513**
SSTL1	0.653	0.504			
SSTL2	0.733	0.537			
SSTL3	0.717	0.514			
SSTL4	0.667	0.510			
SSTL5	0.758	0.575			
SSTL6	0.693	0.508			
SSTL7	0.815	0.665			
SSTL8	0.802	0.643			
SSTL9	0.618	0.502			
SSTL10	0.678	0.508			

Table 2. *Cont.*

Construct/Item	Factor Loadings	SMC	α	CR	AVE
Knowledge sharing (KS)			**0.926**	**0.925**	**0.608**
KS1	0.799	0.638			
KS2	0.831	0.691			
KS3	0.783	0.612			
KS4	0.794	0.631			
KS5	0.854	0.729			
KS6	0.748	0.559			
KS7	0.729	0.532			
KS8	0.685	0.510			
Psychological safety (PS)			**0.895**	**0.905**	**0.578**
PS1	0.795	0.632			
PS2	0.863	0.744			
PS3	0.748	0.560			
PS4	0.841	0.707			
PS5	0.727	0.528			
PS6	0.654	0.504			
PS7	0.667	0.507			
Safety behavior (SB)			**0.964**	**0.965**	**0.717**
SB1	0.800	0.639			
SB2	0.820	0.672			
SB3	0.858	0.736			
SB4	0.886	0.785			
SB5	0.819	0.672			
SB6	0.854	0.729			
SB7	0.854	0.729			
SB8	0.821	0.674			
SB9	0.887	0.786			
SB10	0.882	0.779			
SB11	0.826	0.682			

Note: α = Cronbach's alpha; CR = composite reliability; extracted; SMC = squared multiple correlation; AVE = average variance extracted.

Furthermore, consistent with Fornell and Larcker [84], the correlation matrix among the variables is lower than the nearby values of the square root of the AVE for each construct (Table 3), demonstrating discriminant validity. Finally, the overall fit of the measurement model was evaluated by applying various indices [86], presented in Table 4. These indices consisted of the normed chi-square, Tucker–Lewis Index (TLI), Comparative Fit Index (CFI), Goodness of Fit Index (GFI), Normed Fit Index (NFI), and Root Mean Square Error of Approximation (RMSEA). Table 4 shows that all indices were above the recommended thresholds, indicating that the model fit the data collected.

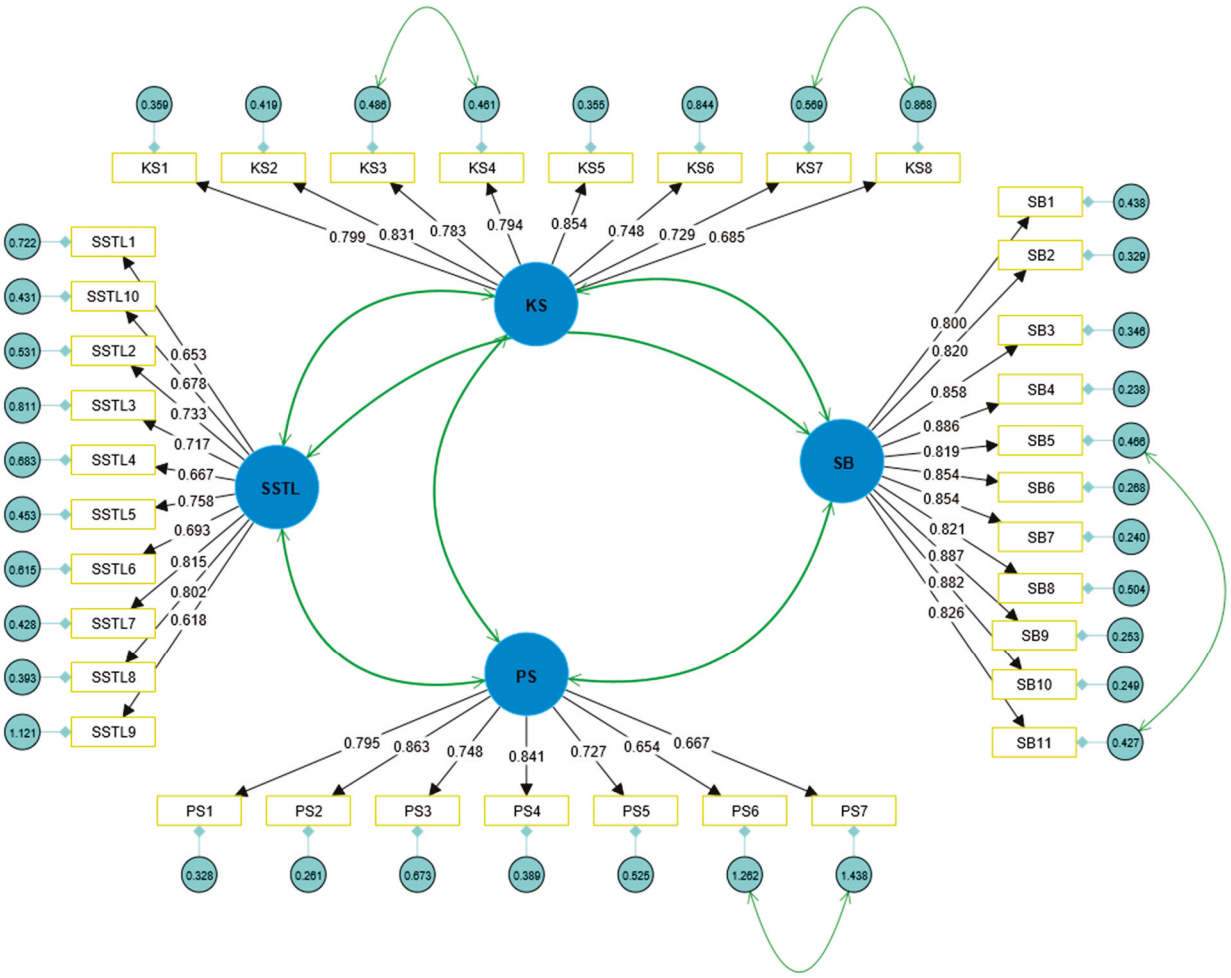

Figure 2. Factor loadings of the measurement items.

Table 3. Discriminant validity and descriptive statistics.

Construct	M	SD	SSTL	KS	PS	SB	Edu	Exp
SSTL	5.740	0.830	**(0.716)**					
KS	5.601	0.948	0.702 **	**(0.780)**				
PS	4.408	0.613	0.665 **	0.729 **	**(0.760)**			
SB	5.570	0.938	0.681 **	0.670 **	0.748 **	**(0.846)**		
Edu	-	-	0.004	0.012	0.009	0.016	-	
Exp	-	-	0.009	0.018	0.041	0.003	0.017	-

Note: Values in diagonal parentheses are square roots of AVEs; Exp = experience; Edu = education; SD = standard deviation; M = mean; ** = Significant correlations ($p < 0.01$).

Table 4. Research model goodness of indices.

Goodness of Fit Indices	Recommended Threshold	Reference	Results	Goodness of Fit
CMIN/df	<3	[74,86,87]	2.601, $p < 0.001$	Fit
GFI	>0.9		0.905	Fit
TLI	>0.9		0.936	Fit
IFI	>0.9		0.940	Fit
CFI	>0.9		0.941	Fit
NFI	>0.9		0.937	Fit
RMSEA	<0.08		0.061	Fit

4.2. Direct and Indirect Effect Results

Model 4 embedded in the Hayes PROCESS macro was used to test the direct and indirect effects [76]. The direct effects are possible and significant (i.e., H1–H3), as shown in Table 5. The results confirm that SSTL positively influences safety behavior (β = 0.470, t = 18.366, $p < 0.001$). SSTL positively influences knowledge sharing (β = 0.802, t = 41.582, $p < 0.001$). Safety knowledge positively influenced safety behavior (β = 0.374, t = 16.699, $p < 0.001$). Accordingly, support was found for H1–H3.

Table 5. Test of direct effects and mediation in the hypothesized model.

Outcome Variable	Independent Variable	Estimates (β)	Standard Error	t-Values	*p*-Values	95% CI
M1: KS	Intercept	0.999	0.112	8.939	0.000	[0.780, 1.219]
$R^2 = 0.493$	SSTL	0.802	0.019	41.582	0.000	[0.764, 0.840]
M2: SB	Intercept	0.774	0.108	7.156	0.00	[0.562, 0.986]
	SSTL	0.470	0.026	18.366	0.000	[0.420, 0.520]
$R^2 = 0.537$	KS	0.374	0.022	16.699	0.000	[0.330, 0.418]
The indirect impact of SSTL on safety behavior via knowledge sharing						
Direct effect of X on Y		0.470	0.026	18.366	0.000	[0.420, 0.520]
Total effect		0.770	0.020	39.296	0.000	[0.732, 0.809]
SSTL → KS → SB		0.300	0.024			[0.255, 0.348]

Note: CI = confidence interval.

Using the bootstrapping technique (a reliable method) for testing indirect effects [76,88], we examined whether SSTL leads to safety behavior through knowledge sharing. The results of the bias-corrected percentile confirm that knowledge sharing mediates the SSTL–safety behavior relationship (β = 0.300, BootSE = 0.024, BootLLCI = 0.255, BootULCI = 0.348). Moreover, Table 5 demonstrates that the main effect remained significant in the presence of the mediator. Thus, partial mediation was observed, supporting H4.

Moderation test results

The moderation and mediation hypotheses were tested using Model 8 embedded in the Hayes PROCESS macro [76]. The results for moderation and moderated mediation are presented in Table 6. Following recent research [89,90] and to prevent multicollinearity issues, all constructs were mean-centered before conducting the analysis. Experience and education were also included as covariates.

Table 6. Test of the moderating effect of psychological safety in the hypothesized model.

Relationships	Sample Estimate	Standard Error	t-Values	*p*-Values	95% CI	
					Lower	Upper
M1: knowledge sharing						
Intercept	5.578	0.016	340.281	0.000	5.546	5.610
SSTL	0.440	0.023	19.369		0.396	0.485
PS	0.466	0.020	23.852	0.000	0.428	0.505
SSTL × PS	0.044	0.017	2.690	0.000	0.012	0.077
Experience	0.049	0.028	1.781	0.075	−0.005	0.104
Education	−0.015	0.014	−1.045	0.295	−0.042	0.0127

Table 6. *Cont.*

Relationships	Sample Estimate	Standard Error	t-Values	*p*-Values	95% CI	
					Lower	Upper
The conditional direct effect of SSTL on KS at different levels of PS						
−1SD (Low)	0.397	0.025	15.655	0.000	0.347	0.447
+1SD (High)	0.483	0.030	16.107	0.000	0.424	0.542
R^2 = 0.625 ***						
M2: Safety behavior						
Intercept	4.905	0.129	38.381	0.000	4.697	5.203
SSTL	0.303	0.024	12.509	0.000	0.255	0.350
KS	0.110	0.023	4.770	0.000	0.065	0.155
PS	0.487	0.022	22.418	0.000	0.444	0.530
SSTL × PS	0.012	0.016	0.727	0.469	−0.020	0.043
Experience	−0.008	0.027	−0.312	0.755	−0.061	0.044
Education	0.020	0.013	1.513	0.130	−0.006	0.047
R^2 = 0.642 ***						
The conditional indirect effect of SSTL on SB through KS at different levels of PS						
−1SD (Low)	0.044	0.012			0.020	0.068
+1SD (High)	0.053	0.015			0.023	0.082
Index of moderation mediation						
	0.005	0.028			0.001	0.011

Note: CI = confidence interval; M = model; *** = Correlation is significant at $p < 0.001$. Consistent with the study's proposed hypothesis (Model 1), SSTL positively influenced knowledge sharing (β = 0.440, t = 19.369, $p < 0.001$), and the link was moderated by psychological safety (β = 0.440, t = 19.369, $p < 0.001$, [0.396, 485]). Further insights into this moderation analysis using simple slope analysis revealed that the conditional relationship varies at different levels of psychological safety (i.e., one standard deviation below the mean and one standard deviation above the mean). Specifically, the relationship was significant for different values of psychological safety. However, the relationship is weaker for construction employees with a low level of psychological safety (β = 0.397, t = 15.655, $p < 0.001$, [0.347, 447]), and the relationship becomes stronger for construction employees with a high level of psychological safety (β = 0.483, t = 16.107, $p < 0.001$, [0.424, 0.542]). Figure 3 depicts a visualization of the aforementioned conditional direct effect, supporting H5.

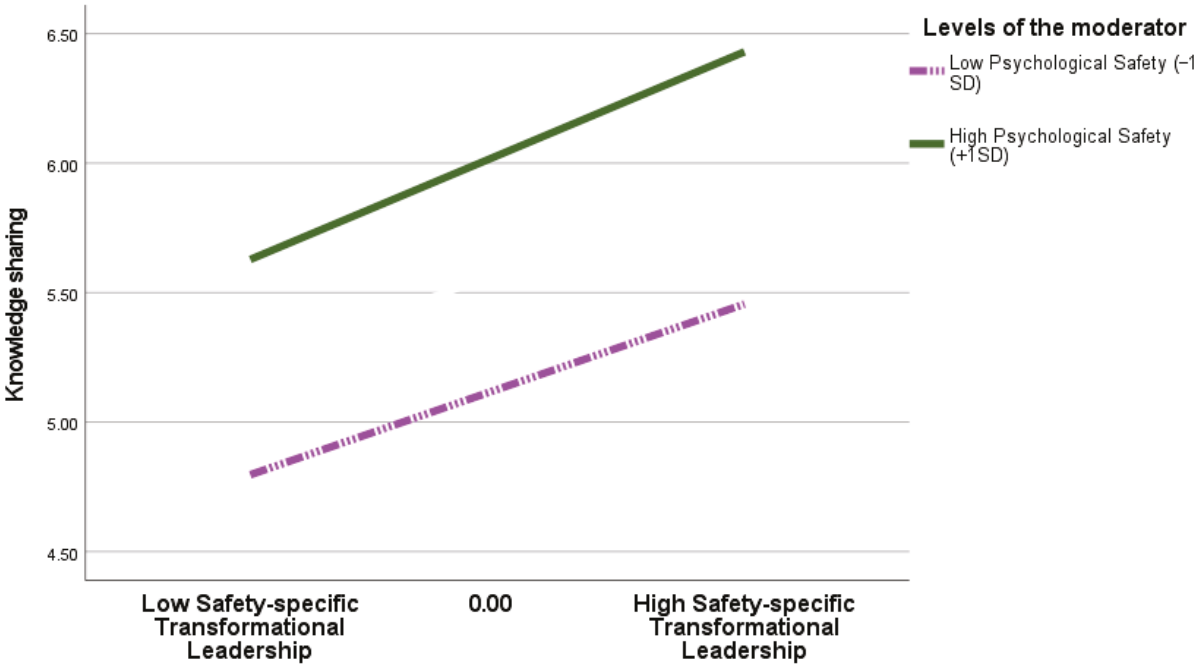

Figure 3. The interaction effect of SSTL and psychological safety on knowledge sharing.

Table 6 demonstrates the moderated mediation results. The conditional indirect effect indicates that psychological safety moderates the mediated relationship between SSTL and safety behavior through knowledge sharing. To gain further insight into the moderating pattern, the conditional indirect effect was plotted for different values of psychological safety (Figure 4). Specifically, the conditional indirect effect of SSTL on safety behavior through knowledge sharing was stronger at a high level of psychological safety (β = 0.044, SE = 0.012, [0.020, 0.068]), and the mediated relationship became weaker at a low level of psychological safety (β = 0.053, SE = 0.015, [0.023, 0.082]). Accordingly, we found that H6 was supported.

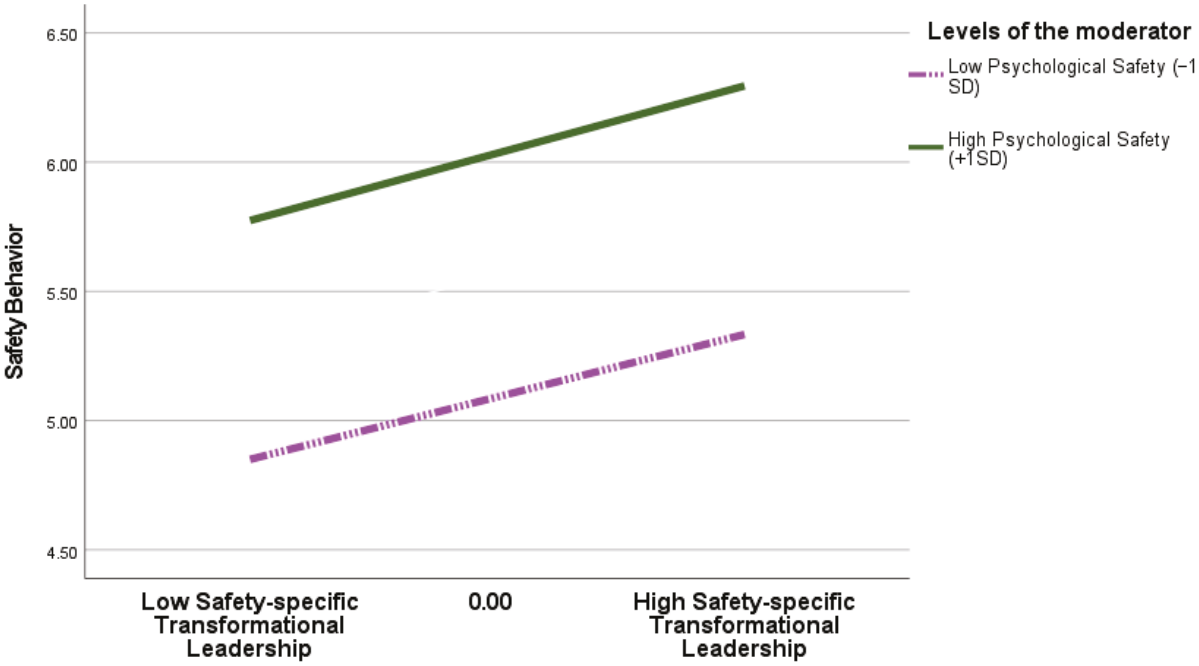

Figure 4. The indirect effect of SSTL on safety behavior through knowledge sharing at different levels of psychological safety.

5. Discussion

Grounded in the SET and positive organizational behavior perspectives, this study investigated the influence of SSTL on employee safety behavior in the construction sector in Turkiye. Moreover, this study aimed to demonstrate how SSTL influences safety behavior through knowledge sharing. Accordingly, we examined how SSTL influences safety behavior through the mediating role of knowledge sharing. The moderating role of psychological safety was also investigated.

The findings show that SSTL is positively associated with employee safety behavior. This result is consistent with prior research findings in the aviation sector [14]. One possible explanation for the consistency in these results is that safety-specific transformational leaders prioritize safety concerns. They motivate and inspire workers to establish areas for safety improvement. Such leaders can swiftly gain workers' trust by providing support and genuine care [26,64]. Thus, employees under this leadership approach reciprocate such support by adhering to safety measures to improve safety behavior. Cultural factors influence safety perceptions in Türkiye, particularly impacting how individuals assess and respond to risks in various settings. These factors include a strong sense of community and social responsibility, a hierarchical structure in social and professional settings, and a cultural emphasis on fate and trust in divine intervention, which can sometimes affect risk assessment and mitigation behaviors. Turkish culture often emphasizes close-knit

communities and strong social bonds [91]. This can lead to a heightened awareness of the safety of others within the community, fostering a sense of collective responsibility for ensuring safety. Turkish society has hierarchical structures that can influence safety perceptions. A cultural emphasis on fate and the belief that events are predetermined can sometimes influence how individuals perceive and respond to risk. Some may be more likely to accept risks as inevitable, potentially leading to a lower prioritization of preventative safety measures or a delayed response to potential hazards.

The findings show that SSTL is positively associated with employee safety behavior, consistent with prior research in the aviation sector [14]. Safety-specific transformational leaders prioritize safety concerns and inspire workers to improve safety practices. By providing genuine care and support, they gain employees' trust [26,64], which in turn motivates workers to adhere to safety measures and strengthen safety behavior. SSTL was positively associated with safety knowledge. This finding complements extant research on leadership and knowledge sharing. Though previous studies have established a positive link between broader transformational leadership and knowledge sharing [21,40,92], none of these studies considered the SSTL. Moreover, this finding supports the SET. This result implies that safety-specific transformational leadership facilitates reciprocity in safety-related knowledge-sharing practices. As individuals observe leaders' constant efforts and dedication to modeling safe behaviors, they feel inspired and motivated to reciprocate by offering their knowledge and insights. This reciprocal exchange is critical because it develops an environment in which workers understand the general organizational value of safety-related knowledge sharing.

Knowledge sharing is positively associated with safety behaviors. This finding offers empirical support for Edmondson [45] and Scarbrough [43] in that collective learning in the workplace promotes individuals' safety knowledge and prevents the repetition of mistakes and accidents. An earlier study confirmed that knowledge sharing is crucial because it can curb meaningless learning processes within organizations [43]. It has also been demonstrated that the most prevalent cause of errors and wrongdoings is a lack of experience and knowledge [44]. Based on this, Edmondson [45] argued that appropriate knowledge management encourages learning and work settings that boost employees' safety knowledge and circumvent the repetition of accidents and mistakes. When individuals proactively engage in knowledge sharing, specifically in relation to safety practices, lessons are learned to improve their safety behavior.

It was discovered that knowledge sharing mediates the relationship between SSTL and employee safety behavior. This finding is consistent with prior studies' findings that learning and safety knowledge serve as mechanisms between leadership and employee safety outcomes [2,18]. The explanation for this result is that safety-focused leadership, such as safety-specific transformational leadership, encourages greater effort among construction workers to share safety-related knowledge and motivate them to improve their safety practices. Such improvements in motivation and collective learning/knowledge sharing are transformed into practices manifested in safety behavior. Safety-specific transformational leaders cultivate and promote knowledge-sharing among employees. This not only develops a better-informed workplace but also one that is equipped to recognize the risk of safety breaches to improve safety behavior. Furthermore, we found that for construction workers with high psychological safety, the relationship between SSTL and knowledge sharing is stronger than that for workers with low psychological safety. Moreover, the indirect positive influence of SSTL on safety behavior through knowledge sharing is more pronounced at a high level of psychological safety than at a low level.

Construction leaders can foster a strong safety culture by embracing safety-specific transformational leadership (SSTL) and psychological safety. Some examples are as follows:

leaders should be actively present on-site, visibly demonstrating safety behaviors and participating in safety discussions. Leaders should articulate a clear and compelling safety vision, highlighting the importance of safety for both individual well-being and project success. Leaders should encourage workers to take ownership of safety by actively soliciting their input, encouraging them to identify hazards, and empowering them to stop unsafe work. Leaders should acknowledge and reward positive safety behaviors and accomplishments, reinforcing the importance of safety culture. Leaders should create a culture of open communication where workers feel comfortable raising safety concerns without fear of punishment.

6. Conclusions

This study enhances safety behavior among construction workers through the mediating role of knowledge sharing and the moderating role of psychological safety. Specifically, leaders who actively inspire and motivate their teams towards safety, coupled with encouraging a culture of open communication and trust (psychological safety), promote increased knowledge sharing about safety practices. This leads to workers adopting safer behaviors on the job.

Leaders who exhibit this style emphasize safety as a core value, set clear safety expectations, and actively participate in safety initiatives. When psychological safety is high, workers are more likely to share their knowledge and experiences related to safety, creating a collective learning environment. A sense of psychological safety, where individuals feel comfortable speaking up about safety concerns without fear of punishment, is crucial for promoting open communication and knowledge sharing. The study suggests that by facilitating a safe and open environment, leaders can significantly improve workers' safety behavior, potentially reducing accidents and injuries.

6.1. Theoretical Contribution

Theoretically, this study enriches the literature on leadership and safety management in several ways. First, the safety-focused leadership approach and safety behavior are crucial topics in the construction sector because the former concerns how to lead construction workers and the latter focuses on their job outcomes. However, there is a lack of empirical studies investigating the relationship between SSTL and safety behavior in the construction industry. Using a sample collected from the Turkish construction industry, we fill this void in the literature by offering empirical evidence that SSTL is a significant predictor of employee safety behavior. Based on this, this study responds to several research calls [14,26] for more specificity in leadership studies, urging researchers to move beyond broad categorization and develop more contextually driven frameworks. By doing this, this study establishes the foundation for future empirical investigation and extends SSTL into the construction context. In addition, the discovery of a positive relationship between SSTL and safety behavior demonstrates that this specific relationship is not limited to the aviation context.

Second, this study extends research streams that draw on SET as a theoretical framework in the literature on leadership and safety behavior [14,93]. Our findings extend the literature on the social interaction process through which safety-specific transformational leadership improves employee safety behavior. In the extant literature, while emerging research by Wu et al. [14] demonstrated that SSTL influences employee safety behavior, the exact link between safety-specific transformational leadership and knowledge remains unclear. However, the extant literature has not provided insights into how safety-specific transformational leadership influences knowledge sharing. Thus, by linking SSTL with knowledge sharing and investigating knowledge sharing as a mediating mechanism, this

study broadens the understanding of the link between SSTL, knowledge sharing, and safety behavior in the construction industry. Accordingly, we significantly extend the literature on leadership and positive social interaction. Hence, we fill the research void that Wu et al. [14] identified by demonstrating that knowledge sharing is a new mechanism in addition to the previously researched mechanisms of the leadership–safety behavior relationship [2,14].

Third, this study demonstrates that an individual's psychological state (i.e., psychological safety) is a contextual condition underlying the impact of SSTL on knowledge sharing. As an initial study to draw on and extend the positive organizational behavior perspective [24,94] in the context of SSTL in the construction sector, this research offers a unique insight to explain the conditions under which SSTL (positive leadership) can make employees more capable of engaging in knowledge. We found that psychological safety augmented the positive impact of SSTL on knowledge sharing. This finding suggests that psychological safety is a dynamic individual state that can either hinder or promote the diffusion of safety-related knowledge sharing among employees. By uncovering psychological safety as an individual psychological condition, this study bridges the safety-focused leadership and knowledge management literature, demonstrating how internal barriers, such as self-doubt or fear of reprisal, can impede the effectiveness of positive leadership (i.e., safety-focused transformational leadership). However, a secure psychological state can optimize the full potential of safety-related knowledge sharing. Thus, this study redefines psychological safety as not only a contextual facilitator but also an individual filter under which the safety leadership impact is processed, providing a new perspective for understanding safety-related knowledge sharing in the construction context.

Finally, the moderated mediation model contributes to our understanding of how the mechanism transmitting the influence of context-specific safety leadership (i.e., SSTL) to individual safety outcomes (i.e., safety behavior) is conditional on employees' psychological state (i.e., psychological safety). The findings of this study indicate that the interaction effect of safety-specific transformational leadership and psychological safety on knowledge sharing can be further extended to employee safety behavior, and the degree to which knowledge sharing mediates the influence of SSTL is highly contingent on employees' positive psychological states (i.e., the ability to speak up and report unsafe behaviors). Hence, in a secure psychological environment, it is critical for construction firms to seek to improve their workers' safety behavior by stimulating safety-related knowledge sharing [95].

6.2. Practical Implication

The findings of this study offer critical practical implications for management and employees in the construction sector. This research demonstrates that safety-specific transformational leadership directly impacts the safety behavior of construction workers. For construction leaders, safety-specific transformational leadership represents the most suitable form of leadership, yielding efficient and successful safety management. The management of construction firms should promote awareness of integrating the principles of SSTL into everyday management practices and fully leverage the benefits of SSTL to improve construction workers' safety behavior. Construction firms' leaders should prioritize professional and psychological well-being, actively listen to workers' concerns, and show genuine care for them, rather than solely enforcing punishment for less-than-ideal performance. Further, the management of construction firms should consider hiring professional human resource advisory firms to conduct training sessions and empower leaders in the application of SSTL. At the conclusion of each training session, an assessment can also be given to evaluate the leaders' understanding of SSTL.

For leaders in the construction industry, this research demonstrates that it is essential to establish an environment in which knowledge sharing is constantly encouraged and

woven into everyday construction activities. This can be accomplished by safety-specific transformational leaders by establishing well-structured avenues for employees to share safety-related information, such as peer-to-peer learning meetings, pre-shift safety briefings, or electronic channels for voicing near misses and solutions. For instance, leaders could inspire and motivate employees by sharing a personal account of learned safety lessons and then encourage employees to share their own experiences, thus creating a shared repository of safety knowledge. Such a process will not only reinforce leaders' safety messages but can also empower workers to turn such motivation into practical safety behavior.

A key consideration for leaders in the construction industry is the importance of fostering psychological safety as a fundamental aspect of safety-specific transformational leadership strategies. Leaders can achieve this by practicing behaviors that alleviate fear of reprisals and building trust, such as regularly listening to employees' safety concerns, recognizing contributions without condemnation, and addressing reported issues in a constructive manner. For instance, leaders should promote the sharing of near-miss experiences during safety meetings, express gratitude for their contributions, and use the information gained to strengthen safety practices. This creates an environment of psychological safety that allows employees to freely express their ideas or concerns. By prioritizing this approach (i.e., mechanism), leaders can facilitate the seamless dissemination of crucial safety knowledge, such as improved risk control measures, and ensure that lessons learned from prior events flow freely in the workplace, consequently improving safety behavior.

6.3. Limitations and Future Studies

While this research offers new insights and contributions to the leadership and construction safety management literature, it has certain limitations that open research opportunities for future studies. This study employed a cross-sectional design, which restricts causal inferences. Future studies could adopt a longitudinal approach to assess whether safety-specific transformational leadership can predict employee safety behavior over an extended timeframe. Furthermore, the sample used in this study is limited to the construction industry; future studies can replicate the research framework in other industries or conduct a cross-national study to deepen its applicability. Furthermore, there could be other mechanisms (i.e., mediators) that can bridge the SSTL–safety behavior relationship. For example, safety accountability [96], safety identification [14], and role definition [97] can be investigated as potential mediating mechanisms. Finally, although safety-specific transformational leaders motivate and inspire through their safety vision and intellectual stimulation with safety goals [12], the current study demonstrates that such efforts may fall short if individuals lack the psychological safety necessary to act on such motivation. Thus, other contextual individual psychological factors could also be examined in future studies [98].

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References

1. Liang, H.; Shi, X.; Yang, D.; Liu, K. Impact of mindfulness on construction workers' safety performance: The mediating roles of psychological contract and coping behaviors. *Saf. Sci.* **2022**, *146*, 105534. [CrossRef]
2. Ayouz, H.; Alzubi, A.; Iyiola, K. Using benevolent leadership to improve safety behaviour in the construction industry: A moderated mediation model of safety knowledge and safety training and education. *Int. J. Occup. Saf. Ergon.* **2025**, *31*, 167–180. [CrossRef]
3. Slil, E.; Iyiola, K.; Alzubi, A.; Aljuhmani, H.Y. Impact of Safety Leadership and Employee Morale on Safety Performance: The Moderating Role of Harmonious Safety Passion. *Buildings* **2025**, *15*, 186. [CrossRef]
4. Rafindadi, A.D.; Napiah, M.; Othman, I.; Mikić, M.; Haruna, A.; Alarifi, H.; Al-Ashmori, Y.Y. Analysis of the Causes and Preventive Measures of Fatal Fall-Related Accidents in the Construction Industry. *Ain Shams Eng. J.* **2022**, *13*, 101712. [CrossRef]
5. Al-Naser, N.K.; Al-Tabtabai, H. The Impact of Safety Violations on Construction Project Performance: A Case Study of the ADFA Project. *J. Eng. Res.* **2024**. [CrossRef]
6. AlShemeili, H.; Davidson, R.; Khalid, K. Impact of empowering leadership on safety behavior and safety climate: Mediating and moderating role of safety monitoring. *J. Eng. Des. Technol.* **2022**, *22*, 1282–1305. [CrossRef]
7. Amponsah-Tawaih, K.; Adu, M.A. Work Pressure and Safety Behaviors among Health Workers in Ghana: The Moderating Role of Management Commitment to Safety. *Saf. Health Work.* **2016**, *7*, 340–346. [CrossRef] [PubMed]
8. Wang, D.; Sun, Z.; Zong, Z.; Mao, W.; Wang, L.; Sun, Y.; Zhang, J.; Maguire, P.; Hu, Y. The effect of benevolent leadership on safety behavior: A moderated mediation model. *J. Saf. Res.* **2023**, *85*, 31–41. [CrossRef]
9. Clarke, S. Safety leadership: A meta-analytic review of transformational and transactional leadership styles as antecedents of safety behaviours. *J. Occup. Organ. Psychol.* **2013**, *86*, 22–49. [CrossRef]
10. Hoffmeister, K.; Gibbons, A.M.; Johnson, S.K.; Cigularov, K.P.; Chen, P.Y.; Rosecrance, J.C. The differential effects of transformational leadership facets on employee safety. *Saf. Sci.* **2014**, *62*, 68–78. [CrossRef]
11. Shen, Y.; Ju, C.; Koh, T.Y.; Rowlinson, S.; Bridge, A.J. The Impact of Transformational Leadership on Safety Climate and Individual Safety Behavior on Construction Sites. *Int. J. Environ. Res. Public Health* **2017**, *14*, 45. [CrossRef] [PubMed]
12. Barling, J.; Loughlin, C.; Kelloway, E.K. Development and test of a model linking safety-specific transformational leadership and occupational safety. *J. Appl. Psychol.* **2002**, *87*, 488–496. [CrossRef] [PubMed]
13. Lu, H.; Wu, T.; Shao, Y.; Liu, Y.; Wang, X. Safety-Specific Leadership, Goal Orientation, and Near-Miss Recognition: The Cross-Level Moderating Effects of Safety Climate. *Front. Psychol* **2019**, *10*, 1136. [CrossRef]
14. Wu, Y.; Xu, Q.; Jiang, J.; Li, Y.; Ji, M.; You, X. The influence of safety-specific transformational leadership on safety behavior among Chinese airline pilots: The role of harmonious safety passion and organizational identification. *Saf. Sci.* **2023**, *166*, 106254. [CrossRef]
15. Bai, Y.; Lin, L.; Li, P.P. How to enable employee creativity in a team context: A cross-level mediating process of transformational leadership. *J. Bus. Res.* **2016**, *69*, 3240–3250. [CrossRef]
16. Lee, P.; Gillespie, N.; Mann, L.; Wearing, A. Leadership and trust: Their effect on knowledge sharing and team performance. *Manag. Learn.* **2010**, *41*, 473–491. [CrossRef]
17. Park, S.; Kim, E.-J. Fostering organizational learning through leadership and knowledge sharing. *J. Knowl. Manag.* **2018**, *22*, 1408–1423. [CrossRef]
18. Lee, Y.-H.; Lu, T.-E.; Yang, C.C.; Chang, G. A multilevel approach on empowering leadership and safety behavior in the medical industry: The mediating effects of knowledge sharing and safety climate. *Saf. Sci.* **2019**, *117*, 1–9. [CrossRef]
19. Agarwal, U.A.; Anantatmula, V. Psychological Safety Effects on Knowledge Sharing in Project Teams. *IEEE Trans. Eng. Manag.* **2023**, *70*, 3876–3886. [CrossRef]
20. Siemsen, E.; Roth, A.V.; Balasubramanian, S.; Anand, G. The Influence of Psychological Safety and Confidence in Knowledge on Employee Knowledge Sharing. *Manuf. Serv. Oper. Manag.* **2009**, *11*, 429–447. [CrossRef]
21. Yin, J.; Ma, Z.; Yu, H.; Jia, M.; Liao, G. Transformational leadership and employee knowledge sharing: Explore the mediating roles of psychological safety and team efficacy. *J. Knowl. Manag.* **2019**, *24*, 150–171. [CrossRef]
22. Edmondson, A. Psychological Safety and Learning Behavior in Work Teams. *Adm. Sci. Q.* **1999**, *44*, 350–383. [CrossRef]
23. Blau, P. *Exchange and Power in Social Life*; John Wiley & Sons: New York, NY, USA, 1964.
24. Luthans, F. Positive organizational behavior: Developing and managing psychological strengths. *Acad. Manag. Perspect.* **2002**, *16*, 57–72. [CrossRef]

25. Wu, W.-L.; Lee, Y.-C. Empowering group leaders encourages knowledge sharing: Integrating the social exchange theory and positive organizational behavior perspective. *J. Knowl. Manag.* **2017**, *21*, 474–491. [CrossRef]
26. Molm, L.D. Theoretical Comparisons of Forms of Exchange. *Sociol. Theory* **2003**, *21*, 1–17. [CrossRef]
27. Elkhweildi, M.; Vetbuje, B.; Alzubi, A.B.; Aljuhmani, H.Y. Leading with Green Ethics: How Environmentally Specific Ethical Leadership Enhances Employee Job Performance Through Communication and Engagement. *Sustainability* **2025**, *17*, 7923. [CrossRef]
28. Nguyen, V.Q.; Turner, N.; Barling, J.; Axtell, C.M.; Davies, S. Reconciling general transformational leadership and safety-specific transformational leadership: A paradox perspective. *J. Saf. Res.* **2023**, *84*, 435–447. [CrossRef]
29. Wright, T.A.; Quick, J.C. The emerging positive agenda in organizations: Greater than a trickle, but not yet a deluge. *J. Organ. Behav.* **2009**, *30*, 147–159. [CrossRef]
30. Mazlina Zaira, M.; Hadikusumo, B.H.W. Structural equation model of integrated safety intervention practices affecting the safety behaviour of workers in the construction industry. *Saf. Sci.* **2017**, *98*, 124–135. [CrossRef]
31. Christian, M.S.; Bradley, J.C.; Wallace, J.C.; Burke, M.J. Workplace safety: A meta-analysis of the roles of person and situation factors. *J. Appl. Psychol.* **2009**, *94*, 1103–1127. [CrossRef]
32. Feng, J.; Chang, Y. Relationship between perception of patient safety climate, work pressure and safety behaviour. *Cheng Ching Med. J.* **2018**, *29*, 190–198.
33. Irshad, M.; Majeed, M.; Khattak, S.A. The Combined Effect of Safety Specific Transformational Leadership and Safety Consciousness on Psychological Well-Being of Healthcare Workers. *Front. Psychol.* **2021**, *12*, 688463. [CrossRef]
34. Smith, T.D.; DeJoy, D.M.; Dyal, M.-A. Safety specific transformational leadership, safety motivation and personal protective equipment use among firefighters. *Saf. Sci.* **2020**, *131*, 104930. [CrossRef]
35. Yasin, R.; Yang, S.; Huseynova, A.; Atif, M. Spiritual leadership and intellectual capital: Mediating role of psychological safety and knowledge sharing. *J. Intellect. Cap.* **2022**, *24*, 1025–1046. [CrossRef]
36. Mittal, S.; Dhar, R.L. Transformational leadership and employee creativity: Mediating role of creative self-efficacy and moderating role of knowledge sharing. *Manag. Decis.* **2015**, *53*, 894–910. [CrossRef]
37. Boer, N.-I.; Berends, H.; van Baalen, P. Relational models for knowledge sharing behavior. *Eur. Manag. J.* **2011**, *29*, 85–97. [CrossRef]
38. Ma, Z.; Huang, Y.; Wu, J.; Dong, W.; Qi, L. What matters for knowledge sharing in collectivistic cultures? Empirical evidence from China. *J. Knowl. Manag.* **2014**, *18*, 1004–1019. [CrossRef]
39. Li, G.; Shang, Y.; Liu, H.; Xi, Y. Differentiated transformational leadership and knowledge sharing: A cross-level investigation. *Eur. Manag. J.* **2014**, *32*, 554–563. [CrossRef]
40. Le, P.; Lei, H. Determinants of innovation capability: The roles of transformational leadership, knowledge sharing and perceived organizational support. *J. Knowl. Manag.* **2019**, *23*, 527–547. [CrossRef]
41. Lu, C.-S.; Yang, C.-S. Safety leadership and safety behavior in container terminal operations. *Saf. Sci.* **2010**, *48*, 123–134. [CrossRef]
42. Al'Ararah, K.; Çağlar, D.; Aljuhmani, H.Y. Mitigating Job Burnout in Jordanian Public Healthcare: The Interplay between Ethical Leadership, Organizational Climate, and Role Overload. *Behav. Sci.* **2024**, *14*, 490. [CrossRef]
43. Scarbrough, H. Knowledge management, HRM and the innovation process. *Int. J. Manpow.* **2003**, *24*, 501–516. [CrossRef]
44. Meurier, C.E.; Vincent, C.A.; Parmar, D.G. Learning from errors in nursing practice. *J. Adv. Nurs.* **1997**, *26*, 111–119. [CrossRef]
45. Edmondson, A.C. Learning from failure in health care: Frequent opportunities, pervasive barriers. *BMJ Qual. Saf.* **2004**, *13* (Suppl. 2), ii3–ii9. [CrossRef]
46. Neal, A.; Griffin, M.A.; Hart, P.M. The impact of organizational climate on safety climate and individual behavior. *Saf. Sci.* **2000**, *34*, 99–109. [CrossRef]
47. Le, Q.T.; Lee, D.Y.; Park, C.S. A social network system for sharing construction safety and health knowledge. *Autom. Constr.* **2014**, *46*, 30–37. [CrossRef]
48. Shin, D.-P.; Gwak, H.S.; Lee, D.E. Modeling the predictors of safety behavior in construction workers. *Int. J. Occup. Saf. Ergon.* **2015**, *21*, 298–311. [CrossRef]
49. Nesheim, T.; Gressgård, L.J. Knowledge sharing in a complex organization: Antecedents and safety effects. *Saf. Sci.* **2014**, *62*, 28–36. [CrossRef]
50. Hussain, S.T.; Abbas, J.; Lei, S.; Haider, M.J.; Akram, T. Transactional leadership and organizational creativity: Examining the mediating role of knowledge sharing behavior. *Cogent Bus. Manag.* **2017**, *4*, 1361663. [CrossRef]
51. Reason, J.T. *Managing the Risks of Organizational Accidents*; Routledge, Taylor & Francis Group: London, UK, 2016.
52. HSE. Health and Safety Statistics: 2023 to 2024 Annual Release. GOV.UK. 2024. Available online: https://www.gov.uk/government/statistics/health-and-safety-statistics-2023-to-2024-annual-release (accessed on 9 April 2025).
53. Loosemore, M.; Malouf, N. Safety training and positive safety attitude formation in the Australian construction industry. *Saf. Sci.* **2019**, *113*, 233–243. [CrossRef]

54. SWA. Notifiable Fatalities: December 2015 Monthly Report. 2015. Available online: https://www.safeworkaustralia.gov.au/system/files/documents/1702/notifiable-fatalities-report-december-2015.pdf (accessed on 4 January 2025).
55. Li, H.; Lu, M.; Hsu, S.-C.; Gray, M.; Huang, T. Proactive behavior-based safety management for construction safety improvement. *Saf. Sci.* **2015**, *75*, 107–117. [CrossRef]
56. Guo, B.H.W.; Goh, Y.M.; Wong, K.L.X. A system dynamics view of a behavior-based safety program in the construction industry. *Saf. Sci.* **2018**, *104*, 202–215. [CrossRef]
57. Demirkesen, S.; Sadikoglu, E.; Jayamanne, E. Assessing psychological safety in lean construction projects in the United States. *Constr. Econ. Build.* **2021**, *21*, 159–175. [CrossRef]
58. Gomez, S.; Ballard, G.; Arroyo, P.; Hackler, C.; Spencley, R.; Tommelein, I.D. Lean, Psychological Safety, and Behavior-Based Quality: A Focus on People and Value Delivery. *Director* **2020**, *2*, 97–108.
59. Walumbwa, F.O.; Peterson, S.J.; Avolio, B.J.; Hartnell, C.A. An investigation of the relationships among leader and follower psychological capital, service climate, and job performance. *Pers. Psychol.* **2010**, *63*, 937–963. [CrossRef]
60. Aljuhmani, H.Y.; Emeagwali, O.L.; Ababneh, B. The relationships between CEOs' psychological attributes, top management team behavioral integration and firm performance. *Int. J. Organ. Theory Behav.* **2021**, *24*, 126–145. [CrossRef]
61. Eva Dodoo, J.; Surienty, L.; Zahidah, S. Safety citizenship behaviour of miners in Ghana: The effect of hardiness personality disposition and psychological safety. *Saf. Sci.* **2021**, *143*, 105404. [CrossRef]
62. Edmondson, A.C. *The Fearless Organization: Creating Psychological Safety in the Workplace for Learning, Innovation, and Growth*, 1st ed.; Wiley: Hoboken, NJ, USA, 2018.
63. Liu, Y.; Ye, L.; Guo, M. The influence of occupational calling on safety performance among train drivers: The role of work engagement and perceived organizational support. *Saf. Sci.* **2019**, *120*, 374–382. [CrossRef]
64. Quansah, P.E.; Zhu, Y.; Guo, M. Assessing the effects of safety leadership, employee engagement, and psychological safety on safety performance. *J. Saf. Res.* **2023**, *86*, 226–244. [CrossRef]
65. Alsafadi, Y.; Aljuhmani, H.Y. The influence of entrepreneurial innovations in building competitive advantage: The mediating role of entrepreneurial thinking. *Kybernetes* **2023**, *53*, 4051–4073. [CrossRef]
66. Enbaia, E.; Alzubi, A.; Iyiola, K.; Aljuhmani, H.Y. The Interplay Between Environmental Ethics and Sustainable Performance: Does Organizational Green Culture and Green Innovation Really Matter? *Sustainability* **2024**, *16*, 10230. [CrossRef]
67. He, C.; McCabe, B.; Jia, G.; Sun, J. Effects of Safety Climate and Safety Behavior on Safety Outcomes between Supervisors and Construction Workers. *J. Constr. Eng. Manag.* **2020**, *146*, 04019092. [CrossRef]
68. Dillman, D.A.; Smyth, J.D.; Christian, L.M. *Internet, Mail, and Mixed-Mode Surveys: The Tailored Design Method*, 3rd ed.; John Wiley & Sons Inc.: Hoboken, NJ, USA, 2008.
69. Brislin, R.W. Translation and content analysis of oral and written materials. *Methodology* **1980**, 389–444.
70. Kelloway, E.K.; Mullen, J.; Francis, L. Divergent effects of transformational and passive leadership on employee safety. *J. Occup. Health Psychol.* **2006**, *11*, 76–86. [CrossRef]
71. Ni, G.; Zhu, Y.; Zhang, Z.; Qiao, Y.; Li, H.; Xu, N.; Deng, Y.; Yuan, Z.; Wang, W. Influencing Mechanism of Job Satisfaction on Safety Behavior of New Generation of Construction Workers Based on Chinese Context: The Mediating Roles of Work Engagement and Safety Knowledge Sharing. *Int. J. Environ. Res. Public Health* **2020**, *17*, 8361. [CrossRef]
72. Neal, A.; Griffin, M.A. A study of the lagged relationships among safety climate, safety motivation, safety behavior, and accidents at the individual and group levels. *J. Appl. Psychol.* **2006**, *91*, 946–953. [CrossRef]
73. Ye, X.F.; Li, X.C.; Wang, Z.N. Safety climate, work pressure and safety behavior. *J. Tech. Econ. Manag.* **2014**, *10*, 44–50.
74. Nasr, E.; Emeagwali, O.L.; Aljuhmani, H.Y.; Al-Geitany, S. Destination Social Responsibility and Residents' Environmentally Responsible Behavior: Assessing the Mediating Role of Community Attachment and Involvement. *Sustainability* **2022**, *14*, 14153. [CrossRef]
75. Alashiq, S.; Aljuhmani, H.Y. From Sustainable Tourism to Social Engagement: A Value-Belief-Norm Approach to the Roles of Environmental Knowledge, Eco-Destination Image, and Biospheric Value. *Sustainability* **2025**, *17*, 4353. [CrossRef]
76. Hayes, A.F. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, 3rd ed.; The Guilford Press: New York, NY, USA, 2022.
77. Fowler, F.J. *Survey Research Methods*, 2nd ed.; SAGE Publications, Inc.: Thousand Oaks, CA, USA, 1993.
78. Cote, J.A.; Buckley, M.R. Estimating Trait, Method, and Error Variance: Generalizing across 70 Construct Validation Studies. *J. Mark. Res.* **1987**, *24*, 315–318. [CrossRef]
79. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef]
80. Awwad, R.I.; Aljuhmani, H.Y.; Hamdan, S. Examining the Relationships Between Frontline Bank Employees' Job Demands and Job Satisfaction: A Mediated Moderation Model. *Sage Open* **2022**, *12*, 21582440221079880. [CrossRef]
81. Lindell, M.K.; Whitney, D.J. Accounting for common method variance in cross-sectional research designs. *J. Appl. Psychol.* **2001**, *86*, 114–121. [CrossRef]

82. Aljuhmani, H.Y.; Ababneh, B.; Emeagwali, L.; Elrehail, H. Strategic Stances and Organizational Performance: Are Strategic Performance Measurement Systems the Missing Link? *Asia-Pac. J. Bus. Adm.* **2022**, *16*, 282–306. [CrossRef]
83. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E. *Multivariate Data Analysis*; Pearson Education Limited: London, UK, 2013.
84. Fornell, C.; Larcker, D.F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
85. Bagozzi, R.P.; Yi, Y. On the evaluation of structural equation models. *J. Acad. Mark. Sci.* **1988**, *16*, 74–94. [CrossRef]
86. Hu, L.; Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Model. A Multidiscip. J.* **1999**, *6*, 1–55. [CrossRef]
87. Collier, J. *Applied Structural Equation Modeling Using AMOS: Basic to Advanced Techniques*, 1st ed.; Routledge: London, UK, 2020.
88. Iyiola, K.; Alzubi, A.; Dappa, K. The influence of learning orientation on entrepreneurial performance: The role of business model innovation and risk-taking propensity. *J. Open Innov. Technol. Mark. Complex.* **2023**, *9*, 100133. [CrossRef]
89. Krara, W.; Alzubi, A.; Khadem, A.; Iyiola, K. The Nexus of Sustainability Innovation, Knowledge Application, and Entrepreneurial Success: Exploring the Role of Environmental Awareness. *Sustainability* **2025**, *17*, 716. [CrossRef]
90. Abuseta, H.; Iyiola, K.; Aljuhmani, H.Y. Digital Technologies and Business Model Innovation in Turbulent Markets: Unlocking the Power of Agility and Absorptive Capacity. *Sustainability* **2025**, *17*, 5296. [CrossRef]
91. Alkish, I.; Iyiola, K.; Alzubi, A.B.; Aljuhmani, H.Y. Does Digitization Lead to Sustainable Economic Behavior? Investigating the Roles of Employee Well-Being and Learning Orientation. *Sustainability* **2025**, *17*, 4365. [CrossRef]
92. García-Morales, V.J.; Lloréns-Montes, F.J.; Verdú-Jover, A.J. The Effects of Transformational Leadership on Organizational Performance through Knowledge and Innovation. *Br. J Manag.* **2008**, *19*, 299–319. [CrossRef]
93. He, C.; McCabe, B.; Jia, G. Effect of leader-member exchange on construction worker safety behavior: Safety climate and psychological capital as the mediators. *Saf. Sci.* **2021**, *142*, 105401. [CrossRef]
94. Inness, M.; Turner, N.; Barling, J.; Stride, C.B. Transformational leadership and employee safety performance: A within-person, between-jobs design. *J. Occup. Health Psychol.* **2010**, *15*, 279–290. [CrossRef]
95. MG, S.P.; KS, A.; Rajendran, S.; Sen, K.N. The role of psychological contract in enhancing safety climate and safety behavior in the construction industry. *J. Eng. Des. Technol.* **2024**, *23*, 1189–1210. [CrossRef]
96. Sha, Y.; Zhang, Y.; Zhang, Y. How safety accountability impacts the safety performance of safety managers: A moderated mediating model. *J. Saf. Res.* **2024**, *89*, 160–171. [CrossRef]
97. Clark, O.L.; Zickar, M.J.; Jex, S.M. Role Definition as a Moderator of the Relationship Between Safety Climate and Organizational Citizenship Behavior Among Hospital Nurses. *J. Bus. Psychol.* **2014**, *29*, 101–110. [CrossRef]
98. Ghasemi, F.; Mahdinia, M.; Doosti-Irani, A. Safety-Specific Transformational Leadership and Safety Outcomes at Workplaces: A Scoping Review Study. *BMC Public Health* **2025**, *25*, 2723. [CrossRef] [PubMed]

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A High-Performance Hybrid Transformer–LSTM–XGBoost Model for sEMG-Based Fatigue Detection in Simulated Roofing Postures

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Abstract

Within the hazardous construction industry, roofers represent one of the most at-risk workforces, with high fatalities and injury rates largely driven by Work-Related Musculoskeletal Disorders (WMSDs). The primary precursor to these disorders is muscle fatigue, yet its objective assessment remains a significant challenge for implementing proactive safety management. To address this gap, this study details the implementation and validation of an AI-driven predictive analytics framework for automated fatigue detection using surface electromyography (sEMG) signals. Data was collected as participants (novice roofers) performed strenuous, simulated roofing tasks involving sustained standing, stooping, and kneeling postures. A key innovation is a data-driven labeling methodology using Weak Monotonicity (WM) trend analysis to automate the generation of objective labels. After a feature selection process yielded seven significant features, an evaluation of standard models confirmed that their classification performance was highly posture-dependent, motivating a more robust, hybrid solution. The framework culminates in a high-performance hybrid machine learning model. This architecture synergistically combines a Transformer–LSTM network for deep feature extraction with an XGBoost classifier. The model outperformed all standalone approaches, achieving over 82% accuracy across all postures with consistently strong fatigue F1-scores (0.77–0.78). The entire framework was validated using a stringent Leave-One-Subject-Out (LOSO) cross-validation protocol to ensure subject-independent generalizability. This research provides a validated component for AI-enhanced safety management systems. Future work should prioritize field validation with professional workers to translate this framework into practical, real-world ergonomic monitoring systems.

Keywords: muscle fatigue; surface electromyography (sEMG); machine learning; construction safety; hybrid model; wearable sensors; ergonomics

1. Introduction

The construction industry, a vital pillar of economic development, consistently ranks among the most hazardous sectors for its workforce in the United States [1]. This sector was responsible for approximately one in every five workplace deaths in private industry in 2023, recording 1075 fatal injuries, the highest number in over a decade [2]. Within this hazardous landscape, roofing stands out as an exceptionally high-risk occupation [3]. Roofing work is characterized by physically strenuous tasks, repetitive motions, and awkward

postures. These ergonomic hazards are the primary contributors to Work-Related Musculoskeletal Disorders (WMSDs), which are defined as injuries and disorders affecting the body's movement system and are caused or exacerbated by physical exertion [4]. The ergonomic burdens of roofing, such as spending up to 75% of working time in non-neutral positions like kneeling or stooping, lead to cumulative overloading and predispose workers to these debilitating conditions [5,6].

These WMSDs, which often arise specifically from overexertion and bodily reactions, represent a significant portion of the economic and human toll, costing U.S. businesses over USD 16 billion annually in direct costs alone [7]. The direct physiological driver of this overexertion is muscle fatigue, defined as a decline in a muscle's force-generating capacity from prolonged or repetitive activity [8]. As muscles tire, performance degrades, increasing the likelihood of biomechanical errors. Detecting this state is therefore critical to preventing overexertion that leads to injury.

Despite this clear causal link, its assessment in the field has been traditionally problematic. A significant body of research has relied on subjective methods where workers rate their perceived exertion. While useful, these methods capture a perception rather than the objective physiological state of the muscle tissue, and they are prone to individual bias and interpretation. To truly prevent WMSDs, there is a critical need for proactive interventions built on objective, physiological measurement. Wearable sensor technology offers a transformative paradigm, and for localized fatigue, surface electromyography (sEMG) is an ideal tool. sEMG is a non-invasive technique that measures the electrical potential generated by muscle cells, providing a time-varying representation of the underlying muscle activity [9,10].

The raw sEMG signal is a complex time series from which numerous features can be extracted to track fatigue. These include amplitude-domain features like Root Mean Square (RMS) and frequency-domain features such as Median Frequency (MDF), which are considered classic and reliable indicators [9,11]. While these features are established, their relative effectiveness for identifying fatigue during the specific, physically demanding, and varied postures of roofing work is not well understood. This ambiguity necessitates a systematic investigation to determine which sEMG features are most effective at identifying muscle fatigue during roofing tasks.

The true potential of these features is unlocked through sophisticated machine learning (ML) algorithms [12]. Previous studies have explored various ML techniques, employing classical ensemble methods like Extreme Gradient Boosting (XGBoost) and deep learning models such as BiLSTM and CNN-LSTM to analyze sEMG signals [13–15]. While previous studies have demonstrated the potential of ML for fatigue detection, a critical review reveals that the translation of this research into practical, real-world safety systems has been stalled by two fundamental barriers.

The first is the critical barrier of subject-dependency, a multifaceted challenge that has severely limited the translation of research into practice. At a fundamental physiological level, comparing raw sEMG signals between individuals is inherently problematic due to vast differences in muscle size, skin impedance, and electrode placement, factors that create significant inter-individual variability [10]. Without robust signal processing, particularly normalization to a subject's Maximum Voluntary Contraction (%MVC), any model is built on a foundation of uncalibrated, inconsistent data, rendering inter-subject comparisons unreliable [16,17]. Compounding this physiological challenge is a widespread methodological flaw in model validation. Many published findings rely on protocols that fail to test for inter-subject generalizability, instead opting for less stringent methods that lead to artificially inflated performance metrics. The failure to adopt rigorous validation, particularly Leave-One-Subject-Out (LOSO) cross-validation, means that many reported models,

while accurate for the individuals they were trained on, are fundamentally unreliable when applied to new workers. Together, the neglect of proper normalization and rigorous validation has populated the literature with solutions that are ultimately impractical for deployment, creating a false sense of progress and hindering the development of truly universal systems.

The second is the critical barrier of subjective and unscalable data labeling. The development of modern supervised machine learning is contingent on large, accurately labeled datasets, a need that presents a critical bottleneck as generating such data is often expensive and time-consuming [18]. To circumvent this, the field has frequently relied on creating ground-truth labels from subjective, self-reported measures [12]. However, this reliance on subjective perception is not merely a minor inconvenience; it is a fundamental obstacle that introduces ambiguity and noise into the very ground-truth data used for model training. Human judgment of internal states is essentially ordinal and can be matched to interval scales only with difficulty, and single ratings are often tainted with measurement errors [19]. This compromises the reliability of the resulting models and prevents the development of the large-scale, objectively labeled datasets required to train truly robust and generalizable AI systems.

Finally, while hybrid ML models exist, the potential synergy between different modeling paradigms has not been fully exploited. The performance of advanced multi-stage hybrid architectures, for instance, a model that uses a deep learning network like a Transformer–LSTM for automated feature representation before feeding these features into a powerful classical classifier like XGBoost, is an underexplored area. Such an approach could offer the combined benefits of both paradigms, but its efficacy for fatigue detection has not been systematically evaluated. This points to a clear need to investigate whether advanced hybrid models perform better than traditional machine learning and deep learning models.

To dismantle these barriers and build a foundational component for a truly practical AI-enhanced safety management system, this study implements a framework designed to directly confront these challenges. Therefore, our research is guided by the following questions:

1. Which sEMG features are most effective at identifying muscle fatigue during roofing tasks?
2. Which machine learning models have the best performance in predicting muscle fatigue using the sEMG data?
3. Do advanced hybrid models perform better than traditional machine learning and deep learning models?

2. Methodology

The methodology of this research details the implementation of a multi-stage AI-driven predictive analytics framework designed to systematically classify localized muscle fatigue through the analysis of sEMG data. The workflow, depicted in Figure 1, begins with the collection of experimental data and proceeds through signal processing, feature engineering, and the implementation and evaluation of various machine learning models. This chapter provides a detailed step-by-step description of this process to ensure replicability.

2.1. Experimental Protocol and Data Collection

The foundational stage of this research involved a meticulous data acquisition protocol designed to generate high-quality physiological data from participants performing simulated occupational tasks. All procedures were reviewed and approved by the Institutional

Review Board of Texas State University (IRB) under protocol #9649, ensuring the adherence to ethical guidelines for human subject research.

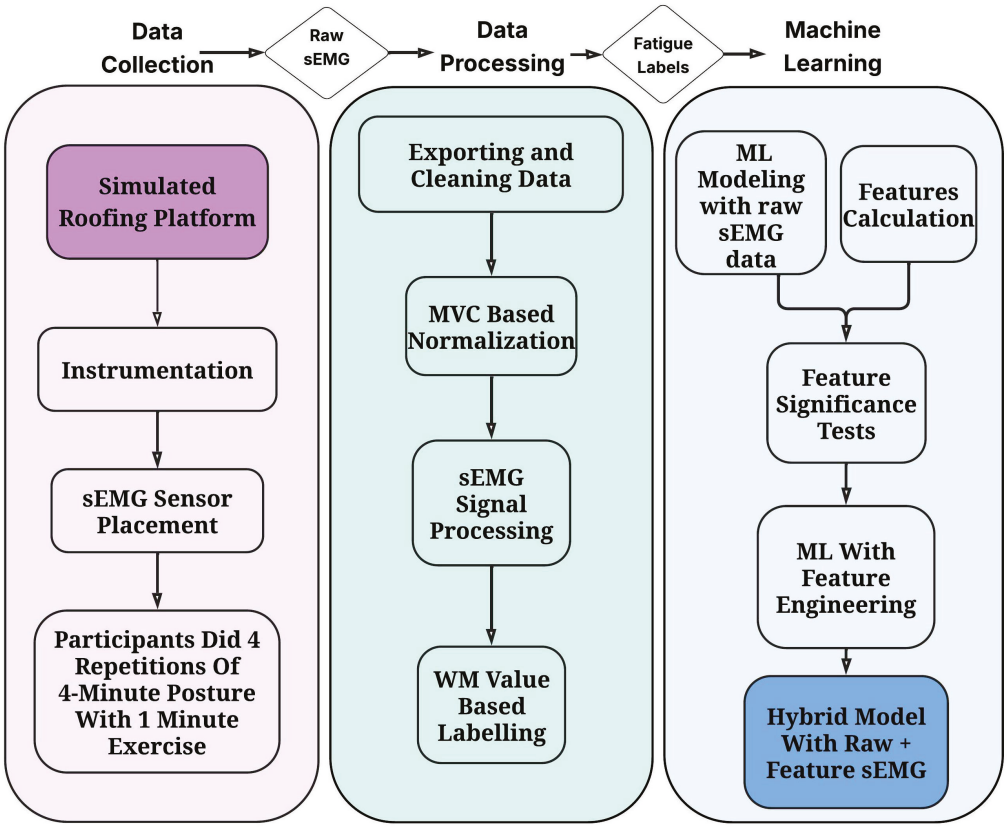

Figure 1. Research methodology flowchart.

The experiment was carried out on a custom-built simulated roofing platform set on a 30-degree slope. Upon arrival at the laboratory, each participant was first informed of the experimental protocol and their consent to the experiment was given. Then, they were outfitted with wearable sensors for instrumentation. Twelve wireless sEMG sensors (Cometa sEMG sensors) were used to measure the electrical activity of key muscle groups. For this study, we recruited only novice participants (referred to as novice roofers). This was a deliberate choice to first test our model on a controlled, consistent group before including the wide variations seen in experienced workers. Although participants were novice, the experiment setup and postures involved in the roofing task were verified by experts and the novice participants replicated the postures as instructed. This study serves as the first phase of a larger research program that will include experienced roofers in the next study.

2.1.1. sEMG Sensor Placement

For sEMG sensor placement, the sensors were placed bilaterally on six muscle groups (shown in Figures 2 and 3) critical for posture and movement during the selected tasks: erector spinae (lower back), rectus femoris (quadriceps), rectus abdominis (abdominals), biceps femoris (hamstrings), tibialis anterior (shin), and gastrocnemius (calf). The placement followed the standardized SENIAM (Surface EMG for Non-Invasive Assessment of Muscles) guidelines to ensure high signal quality, minimize crosstalk, and maintain replicability [20]. Prior to sensor placement, the skin at each location was prepared by wiping with alcohol to reduce skin impedance and improve signal conductivity.

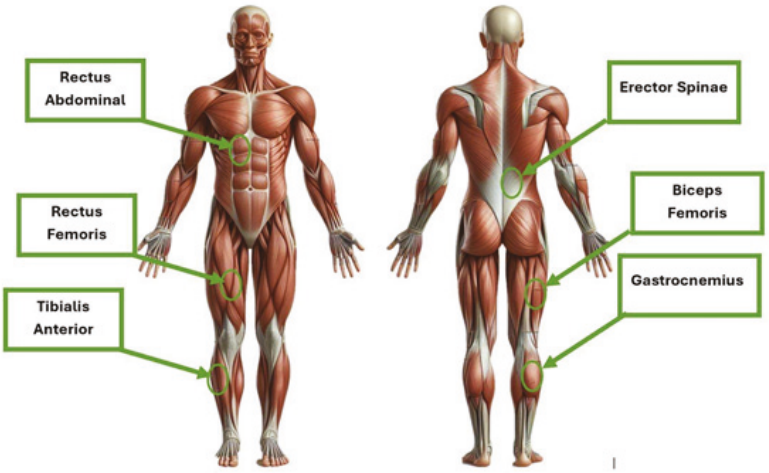

Figure 2. Surface electromyography (sEMG) sensors placement muscle groups.



Figure 3. Illustration of sEMG sensors worn on the 12 muscle groups. (**a**) View from front, (**b**) view from back.

Before the main experimental task, the MVC of each participant was determined for each of the 12 muscles. This involved performing three repetitions of muscle-specific isometric exercises [16,20]. Specific MVC tasks included the following:

- Erector Spinae: Lumbar extension.
- Rectus Abdominis: Sit-ups.
- Rectus Femoris: Isometric knee extension at 90° flexion.
- Biceps Femoris: Isometric prone leg curl.
- Tibialis Anterior: Foot dorsiflexion against resistance.
- Gastrocnemius: Plantar flexion of the foot while standing on one leg.

In addition, a resting period was recorded to establish a baseline sEMG value for each muscle, which is essential for the two-point normalization process used to negate the effects of hyperactive muscles.

2.1.2. Experiment

After a sufficient rest period to prevent premature fatigue, participants proceeded to the main experimental tasks. These tasks were performed on a custom-built sloped platform set at a 30-degree incline with a maximum height of 6 feet, designed to simulate a roofing environment. The core experimental tasks required participants to maintain three

quasi-static postures. These specific postures and the experimental setup were selected and validated through expert consultation. Figure 4 illustrates participants performing these tasks. This study defines the specific postures as follows:

- Standing: The participant maintains balance by exerting pressure on their legs, positioning one foot slightly in front of the other (Figure 4b).
- Kneeling: The participant places both knees on the sloped surface, supported by 2-inch foam padding to minimize discomfort, and exerts pressure on them (Figure 4c).
- Stooping: The participant bends their upper body forward while flexing their legs and applying pressure on the lower limbs (Figure 4a).



Figure 4. Different simulated postures. (**a**) Stooping, (**b**) standing and (**c**) kneeling.

The experimental protocol varied by posture. For the stooping and kneeling tasks, each conducted on a separate day, the participants performed four repetitions of a cycle consisting of a four-minute static hold followed by a one-minute rest. The standing protocol involved alternating between left-foot-up and right-foot-up stances for a total of eight 4 min trials (four for each stance). Each trial was separated by a one-minute rest, with a single four-minute extended break provided after the first four trials. Throughout the tasks, continuous data collection was conducted using inertial measurement unit sensors to track movement, EMG sensors to measure muscle activity, and an O_2 meter to monitor oxygen levels and pulse rate. Gautam et al. [21] performed a preliminary study to find the most activated muscle groups using a subset of this dataset.

2.2. Data Processing and Analysis

Following the experiment, the collected sEMG data was systematically processed and analyzed. This phase involved exporting and cleaning the data, normalizing the signals, applying signal processing techniques, generating fatigue labels, and calculating a comprehensive set of features.

First, the raw data from the sensors were exported for processing. A two-point MVC-Based Normalization: This procedure scaled the filtered sEMG signals to a range of 0 to 1, where the baseline sEMG value of the resting period was set to 0 and the peak amplitude from the MVC test was set to 1. This is essential to reduce variability caused by differences in electrode placement, muscle size, or skin impedance [16,17].

The normalized signals then underwent further sEMG signal processing. The signals were first filtered using a bandpass filter with a frequency range of 20–450 Hz, a standard practice in sEMG research to isolate physiological signals while removing low-frequency motion artifacts and high-frequency noise. A 60 Hz notch filter was also applied to

specifically eliminate power line interference [20,22]. An outlier removal script was then run on the normalized signals; a 5 Standard Deviation (SD) threshold was set, and any data outside of this range were replaced by the 5SD value. Finally, the clean signals were segmented into overlapping windows using a sliding window technique with a window size of 2.5 s and a 90% overlap, preserving temporal information for subsequent modeling.

From the processed sEMG signal, two parallel paths were taken: one for labeling the data and one for feature engineering.

2.2.1. WM Value-Based Labeling

A key innovation of this study was a robust, two-stage process for the generation of high-confidence fatigue labels directly from sEMG data.

- Stage 1: WM-based label generation: This process was adapted from the Weak Monotonicity method proposed by [23]. Through an exploratory analysis of several established fatigue indicators, MDF was selected as the most consistent indicator for the labeling pipeline. Crucially, while MDF physiologically decreases with fatigue, this study deliberately tested for an increasing monotonic trend to standardize the procedure. Consequently, the interpretation of the WM score was inverted: a lack of a strong increasing trend (i.e., a flat or decreasing trend) was used as the indicator for the onset of fatigue. Based on this logic, a WM value below 0.52 was labeled 'fatigue', and a value above 0.58 was labeled 'non-fatigue'. The thresholds were selected based on our exploratory study. The criteria for the WM thresholds were data loss minimization and physiological consistency of the labeled groups. The threshold was selected because this retained the maximum number of samples in the minority class while also being statistically distinct in the pattern of change for physiologically recognized characteristics of fatigue.
- Stage 2: Data curation: To ensure the highest possible integrity of the labels, all data segments initially falling within the intermediate range (0.52 to 0.58) were labeled 'Uncertain' and were excluded from the final dataset used for model training. This conservative approach was adopted to minimize ambiguity and potential label noise.

This two-stage process represents a step towards automating the generation of objective ground-truth labels, moving beyond subjective reporting.

2.2.2. Feature Calculation and Significance Testing

In parallel, a Python script was used to extract a comprehensive set of physiologically relevant features from each 2.5 s sEMG window. These included the following:

- Time-Domain Features
  - Root Mean Square (RMS): Represents the square root of the average of squared sEMG signal amplitudes in a given window. Reflects the signal's power and is often correlated with muscle contraction force.
  - Integrated EMG (IEMG): The sum of absolute values of the sEMG signal over a window. Indicates total muscle activity.
  - Mean Absolute Value (MAV): The average of the absolute values of the sEMG signal amplitudes, representing overall signal intensity.
  - Willison Amplitude (WAMP): Counts the number of times the absolute difference between consecutive sEMG samples exceeds a predefined threshold. Provides information about the frequency of muscle activation changes.
  - Difference Absolute Standard Deviation Value (DASDV): A variation of RMS that measures the standard deviation of the differences between consecutive samples. Reflects signal variability.

  - Average Amplitude Change (AAC): The average absolute difference between consecutive signal samples, indicating how rapidly the signal changes.
- Frequency-Domain Features
  - Median Frequency (MDF): The frequency that divides the power spectrum into two regions with equal power. Commonly used to indicate muscle fatigue.
  - Mean Frequency (MNF): The average frequency weighted by the power spectrum. Reflects the frequency content of the signal.
  - Variance of Central Frequency (VCF): The variance around the mean frequency, providing insight into how spread out the frequency components are.
  - Power Spectrum Ratio (PSR): The ratio of power within a specific frequency band to the total power. Highlights dominant frequency regions.
- Nonlinear and Statistical Features
  - Sample Entropy (SampEn): A measure of the signal's complexity and regularity. Higher values indicate greater complexity.
  - Skewness (Skew): Describes the asymmetry of the amplitude distribution. Indicates signal bias or uneven activity.
  - Kurtosis: Measures the "peakedness" of the amplitude distribution. High values suggest the presence of outliers or burst activity.
  - Mean Power Ratio (MPR): Ratio of mean power within a specific frequency band to the total power. Emphasizes energy distribution in particular frequency regions.

To answer Research Question 1, Feature Significance Tests were conducted. A Kruskal–Wallis H-test, a non-parametric test robust to the non-Gaussian distributions typical of sEMG features, was applied to rank each engineered feature according to its ability to differentiate between the 'fatigue' and 'non-fatigue' classes [24]. This filter method provided an exploratory ranking to identify the most significant features for subsequent modeling.

2.3. Machine Learning Implementation and Evaluation

A comprehensive suite of machine learning models was implemented and systematically evaluated to address the research questions. The modeling process involved three distinct approaches as depicted in the flowchart.

2.3.1. Handling Class Imbalance

A critical aspect of the training process was addressing the class imbalance within the dataset. To mitigate the risk of models developing a bias towards the majority class, a class weighting strategy was uniformly applied across all trained models. For classifiers implemented with scikit-learn (Random Forest) and TensorFlow/Keras (deep learning models), the class weight = 'balanced' parameter was utilized. This automatically adjusts model penalties to give more importance to the minority class. For the XGBoost classifier, the equivalent scale_pos_weight parameter was calculated and set for each training fold. This ensured that the models were trained to value the correct classification of fatigue instances as highly as non-fatigue instances, leading to more robust performance.

2.3.2. Model Architectures and Hyperparameters

All models were developed in Python using the scikit-learn and TensorFlow libraries. Key architectural and training hyperparameters for each model are detailed below. All of the models were trained for 50 epochs with early stopping.

- Ensemble Models

  - Random Forest (RF): A Random Forest classifier was configured with 300 decision trees. The maximum depth of each tree was limited to 20, and a minimum of 5 samples was required to form a leaf node.
  - XGBoost (Standalone): An XGB classifier was configured with 500 boosting rounds (n_estimators), a learning rate of 0.001, and a max_depth of 6. Regularization was applied via a subsample ratio of 0.8 and a colsample_bytree of 0.8.
- Deep Learning Models
  All deep learning models were trained using the Adam optimizer and employed Early Stopping (monitoring validation loss with a patience of 10 epochs) and reduced learning rate on plateau callbacks.
  - 1D-CNN: The architecture consisted of three sequential 1D convolutional blocks (64, 128, and 256 filters), each with a kernel size of 5, followed by Batch Normalization and Max Pooling 1D. A Global Average Pooling 1D layer preceded the final dense classifier head. Key hyperparameters included a learning rate of 0.001, batch size of 128, and a dropout rate of 0.5.
  - Transformer: The model was composed of 4 stacked Transformer encoder blocks. Each block contained a Multi-Head Attention layer with 4 Attention heads and a head size of 256. Hyperparameters included a learning rate of 0.001, a batch size of 128, and dropout rates of 0.4 (Attention) and 0.5 (classifier).
  - CNN-LSTM with Attention: This model began with a Conv1D layer (64 filters, kernel size = 5), followed by an LSTM layer (64 units) and a custom Attention mechanism. The hyperparameter included a learning rate of 0.001, a batch size of 128, and a dropout rate of 0.5.
- Advanced Hybrid Model (Transformer–LSTM–XGBoost)
  This model utilizes a two-stage process.
  - Stage 1 (Feature Extractor): A Transformer–LSTM network processes three parallel input streams (raw signal, engineered features, muscle ID) to generate a 64-dimensional "deep features" latent vector. The architecture of the Transformer and LSTM paths mirrors the standalone models described above. The deep learning components were trained with a learning rate of 0.0001 and a batch size of 64.
  - Stage 2 (classifier): The final classification is performed by an XGBoost classifier which takes the 64-dimensional latent vector as input. This classifier was configured with hyperparameters identical to the standalone XGBoost model described previously.

2.3.3. Training and Validation Strategy

For all classification models, a Leave-One-Subject-Out (LOSO) cross-validation strategy was utilized. In LOSO, a model is trained on data from all participants except for one, which is held out as the complete test set. This process is repeated until every participant has served as the test set exactly once. The final performance is reported as the average across all folds. LOSO provides a much more realistic and robust estimate of how a model will generalize to new, unseen individuals.

2.3.4. Performance Evaluation Metrics

The performance of all machine learning models was assessed using a suite of standard quantitative classification metrics derived from the confusion matrix [25].

- Accuracy: (TP + TN)/(Total Samples);
- Precision: TP/(TP + FP);

- Recall: TP/(TP + FN);
- F1-score: 2 $*$ (Precision $*$ Recall)/(Precision + Recall).

where TP = true positive, TN = true negative, FP = false positive and FN = false negative.

High accuracy is critical for a reliable classification system, while the F1-score was considered particularly important as it provides the best overall picture of a model's balanced performance [26].

3. Results

This chapter presents the findings derived from the multi-stage sEMG data processing, feature extraction, and machine learning model training. The results are organized to sequentially address the research questions, detailing the data labeling process, the performance of various models on raw and engineered data, the identification of key sEMG features for fatigue detection, and finally, the evaluation of advanced hybrid model architecture. The analysis was conducted on data collected from a cohort of novice participants, whose demographic characteristics are summarized below.

The demographic characteristics of the participant cohort were analyzed per postural condition. The mean age for the standing, stooping, and kneeling postures was 27.88 (SD = 7.30), 26.57 (SD = 7.52), and 27.38 (SD = 7.12) years, respectively. Average height was similarly recorded as 172.88 cm (SD = 8.21), 173.14 cm (SD = 8.97), and 172.13 cm (SD = 8.07), while mean weight was 74.60 kg (SD = 11.83), 77.94 kg (SD = 13.23), and 73.24 kg (SD = 12.63) for the respective postures.

3.1. Data Labeling and Dataset Characteristics

This section details the outcomes of the sEMG data preprocessing and the two-stage fatigue labeling methodology. The objective here is to characterize the final dataset used for model training, ensuring transparency and validation in labels established for muscle fatigue prediction. The entire process was designed to create high-confidence, data-driven ground-truth labels for the subsequent supervised machine learning tasks.

The initial phase of establishing labels involved applying the WM trend analysis to the normalized sEMG data for all three postures. This method, adapted from [23] with thresholds refined for the current datasets, provided a preliminary labeling of fatigue states. The specific thresholds we used, which we obtained through exploratory study, were

- WM $<$ 0.52: **Fatigue**
- 0.52 $\leq$ WM $\leq$ 0.58: **Uncertain**
- WM $>$ 0.58: **Non-Fatigue**

The distribution of these initial labels across the 12 monitored muscles for the standing, stooping, and kneeling postures is detailed in Figure 5.

Figure 5 provides a detailed comparative analysis of muscle state distribution, utilizing a grouped stacked horizontal bar chart to facilitate a direct comparison across the three distinct postures. In this visualization, each of the twelve muscles, identified by an abbreviation on the y-axis, is represented by a cluster of three bars, where each bar corresponds to a specific posture (standing, stooping, or kneeling). This allows for an immediate assessment of how a single muscle's activation state changes with activity.

From the figures, we can see that the right and left upper rectus abdominis (R-URA and L-URA) consistently had the lowest percentages of fatigue among all the muscles for all postures. For example, R-URA registered fatigue in only 6%, 10%, and 12% of segments for standing, stooping, and kneeling, respectively. After these muscles, the least fatigued were the right and left rectus femoris. On the other hand, the muscles with the most instances of 'fatigue' were the right lumbar erector spinae and the right and left tibialis anterior.

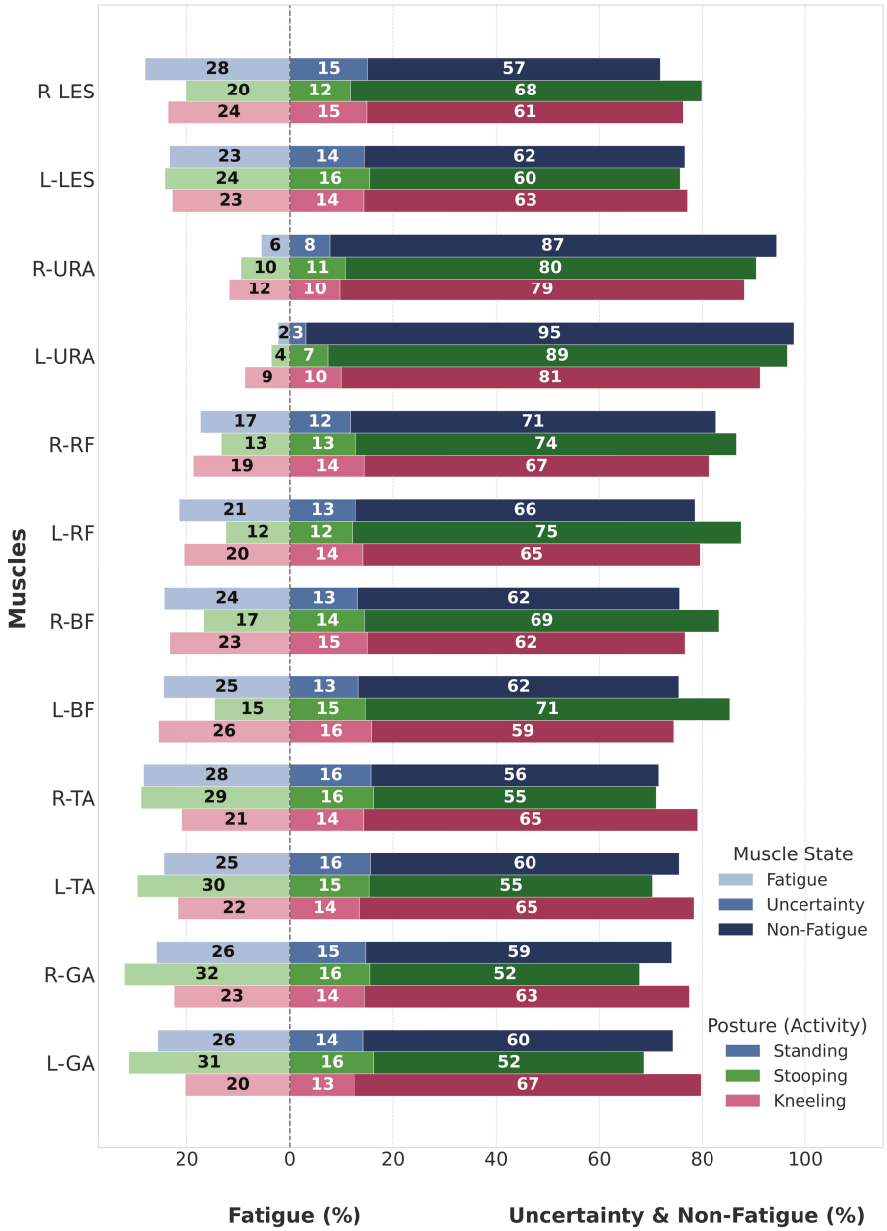

Figure 5. Distribution of labels across different muscles and postures. Note: Muscle abbreviation legend: L-BF = Left Biceps Femoris; R-BF = Right Biceps Femoris; L-GA = Left Gastrocnemius; R-GA = Right Gastrocnemius; L-LES = Left Lumbar Erector Spinae; R-LES = Right Lumbar Erector Spinae; L-URA = Left Upper Rectus Abdominis; R-URA = Right Upper Rectus Abdominis; L-RF = Left Rectus Femoris; R-RF = Right Rectus Femoris; L-TA = Left Tibialis Anterior; R-TA = Right Tibialis Anterior.

The results also reveal a critical insight into postural ergonomics: the impact of a given posture is highly muscle-specific. A notable disparity in fatigue was observed in the lower leg musculature. For example, the gastrocnemius (calf muscle) demonstrated substantial variation, with the stooping posture inducing the highest fatigue levels (31–32%), likely due to the increased demand for ankle plantarflexion to counteract the forward shift in the body's center of mass on the incline. Conversely, kneeling, which provides a larger and more stable base of support, reduced the load on the gastrocnemius, resulting in lower fatigue levels (20–23%).

To maintain the highest integrity and confidence in the ground-truth labels used for subsequent machine learning model development, a conservative approach was adopted for the data curation stage. The segments initially classified by the WM trend analysis as

'uncertain' ($0.52 \leq WM \leq 0.58$) represented ambiguous states that could not be definitively categorized. On average, 13.2% of the data was categorized as 'uncertain' and was flagged for exclusion. All segments falling into this 'uncertain' category were treated as Not a Number (NaN) and systematically excluded from the dataset used for training and evaluating the fatigue prediction models. This decision ensures that the models were trained exclusively on data segments with clear, high-confidence labels of either 'non-fatigue' or 'fatigue,' thereby minimizing potential noise and ambiguity in the learning process.

The final composition of the dataset used for modeling, after the exclusion of these uncertain segments, is presented in Table 1. As shown in the table, for all three postures, the final dataset available for modeling exhibited a notable class imbalance. Across the postures, approximately 76% of the total segments were categorized as 'non-fatigue,' while only 24% were categorized as 'fatigue'. This characteristic of the final dataset is an important consideration for the subsequent evaluation of model performance, particularly when interpreting metrics sensitive to class distribution like the F1-score.

Table 1. Final distribution of labeled sEMG data segments used for model training for posture.

Posture	Total Segments	Segments Excluded	Final Segments	Fatigue (%)	Non-Fatigue (%)
Standing	706,884	89,228	617,656	24%	76%
Stooping	352,380	47,695	352,380	23%	77%
Kneeling	348,360	47,427	300,933	23%	77%

3.2. Baseline Model Performance on Raw sEMG Data

Before undertaking comprehensive feature engineering, an initial exploration analysis was conducted to establish a performance baseline for muscle fatigue prediction using only the raw sEMG signals. This crucial step aimed to assess the inherent discriminative information present in the time-series data itself and to provide a benchmark against which the more complex, feature-based models could be compared. By evaluating models on the raw signal, we can quantify the precise value added by the subsequent feature engineering process.

For this baseline evaluation, three different machine learning models were selected: an LSTM network, an RF model, and an XGBoost model. These models were trained and tested directly on the normalized and outlier-removed raw sEMG time-series data. To investigate the potential for a universal model even at this raw data stage, signals from all twelve monitored muscles were pooled for each of the three distinct roofing postures: stooping, standing, and kneeling. The classification performance of these models on the raw data is summarized in Table 2.

As tabulated in Table 2, the results reveal a consistent pattern of model efficacy on the unprocessed time-series data. The LSTM network consistently outperformed the other two models, Random Forest and XGBoost, in all of the postures. This is a logical conclusion, as the LSTM model architecture was specifically built to understand and learn from temporal relationships, a characteristic that is crucial for extracting meaningful deep features from sequential raw signals.

A closer examination of the performance metrics reveals the following:

- For the standing posture, the LSTM achieved an accuracy of 55.34% and an F1-score of 59.01%. In contrast, the Random Forest model performed near the level of random chance with an accuracy of 48.13%, and the XGBoost model achieved 51.78% accuracy.
- For the stooping posture, all models showed a slight improvement. The LSTM model reached an accuracy of 58.2% and an F1-score of 62.33%, while the Random Forest

model achieved its best performance here with a 63.83% F1-score, despite a lower accuracy (55.23%).

- The best baseline performance was observed during the kneeling posture, where the LSTM model achieved an accuracy of 57.88% and a comparatively stronger F1-score of 66.76%. The relatively better performance during this posture might be attributed to the more static nature of the muscle contractions involved, leading to less signal non-stationarity compared to the more dynamic elements present in stooping or the subtle postural adjustments in standing.

Table 2. LSTM model performance on raw sEMG data.

Posture	Model	Accuracy (%)	F1 Score (%)
Standing	LSTM	55.34	59.01
	Random Forest	48.13	58.62
	XGBoost	51.78	59.95
Stooping	LSTM	58.20	62.33
	Random Forest	55.23	63.83
	XGBoost	53.64	59.23
Kneeling	LSTM	57.88	66.76
	Random Forest	48.23	54.38
	XGBoost	53.05	60.16

While these accuracy and F1-score values demonstrate that the raw sEMG signal contains some discernible patterns related to muscle fatigue, which is yielding results better than random chance, they also clearly highlight the limitations of relying solely on unprocessed time-series data for reliable fatigue classification. The performance, even for the best-performing LSTM model, does not meet the requirements for a practical and dependable application.

Overall, the baseline performance achieved with raw sEMG data was deemed insufficient for developing a robust fatigue prediction system. This outcome strongly motivated and justified the subsequent, more intensive approach of detailed feature engineering. The following sections will therefore focus on the performance of models trained using a comprehensive set of physiologically relevant sEMG features designed to enhance the discriminability between fatigued and non-fatigued states.

3.3. Significance of sEMG Features in Fatigue Detection

Having established that raw sEMG data alone provides limited predictive power, the subsequent analysis focused on a multi-step statistical process to identify the most important engineered features for fatigue detection. This section details the methodology and findings used to answer Research Question 1, "Which sEMG features are most effective at identifying muscle fatigue during roofing tasks?", by identifying and ranking the most discriminative features.

The first step was to determine the appropriate statistical test for comparing feature distributions between 'fatigue' and 'non-fatigue' states. A Shapiro–Wilk test for normality was performed on the distributions of each engineered sEMG feature for each muscle group across all participant data.

As illustrated by the representative Q-Q plots in Figure 6, the data consistently and significantly deviated from a normal distribution. The data points on the plots consistently diverge from the theoretical quantile line, a pattern that is statistically confirmed by the accompanying Shapiro–Wilk test results, which yielded a p-value < 0.001 for all tests. This finding rejected the null hypothesis of normality and confirmed our initial suspicion that

the sEMG data would not be normally distributed, particularly as the muscles become increasingly activated during the task. This step was crucial as it formally validated the decision to use a non-parametric statistical test for the subsequent analysis.

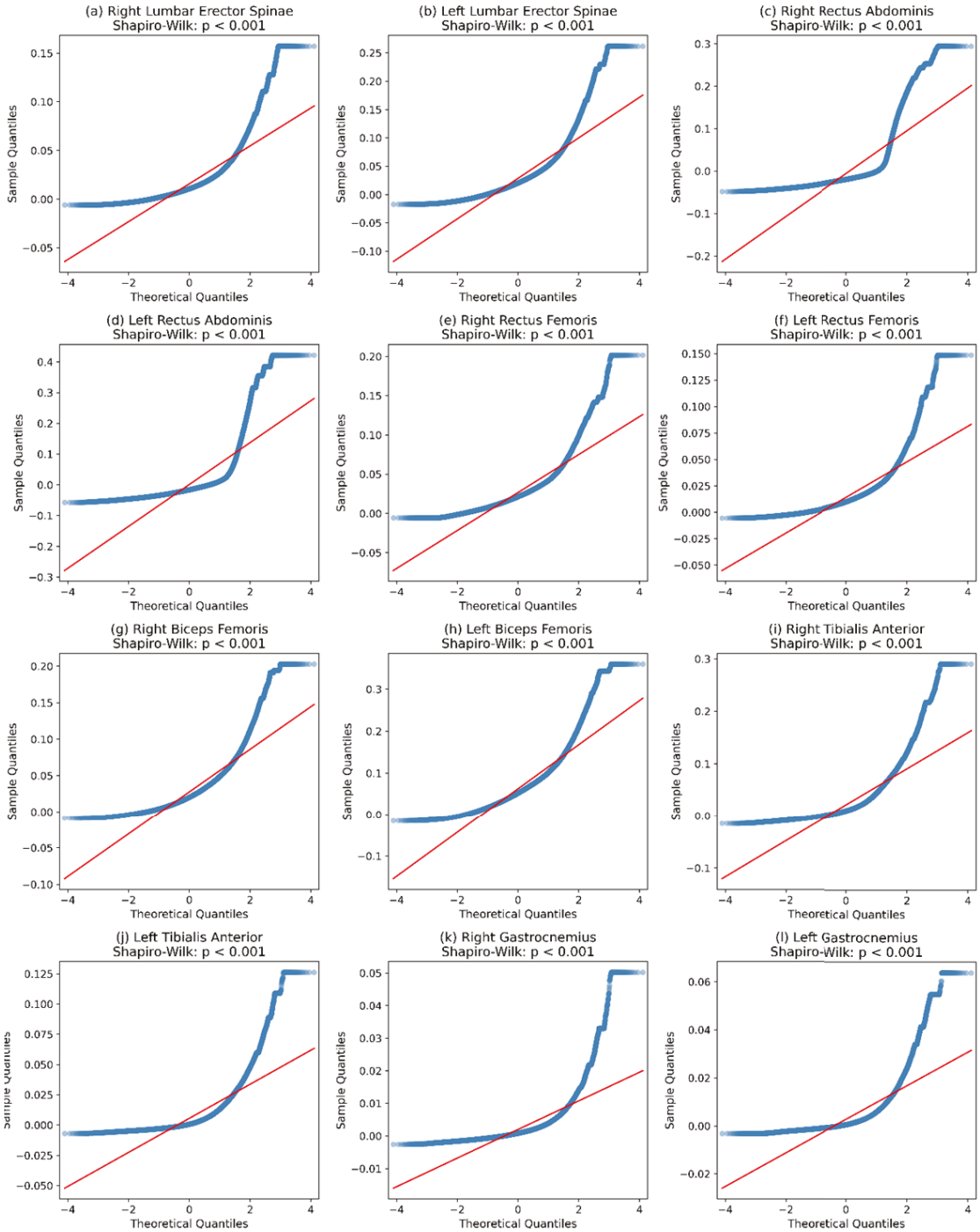

Figure 6. Representative normality Q-Q plots. The blue points represent the sample data quantiles, while the red line represents the theoretical quantiles of a normal distribution. The deviation of the blue points from the red line indicates a non-normal data distribution.

Based on the results of the normality testing, a non-parametric approach was required. To quantify the discriminative power of each feature, a one-way Kruskal–Wallis H-test was performed. The test was applied systematically to compare the distribution of each of the 26 engineered features between the 'fatigue' and 'non-fatigue' states. This process was

repeated for each of the 12 monitored muscles within every individual data file (32 total files from eight participants × four repetitions).

This granular analysis resulted in a large set of significance tests, assessing the ability of every feature to detect fatigue in every muscle for every experimental trial. To account for the large number of comparisons and control for the false discovery rate, a Benjamini–Hochberg False Discovery Rate (FDR) correction was applied with an alpha of 0.05. A feature was considered to have strong discriminative power for a given muscle in a given trial if the FDR-corrected p-value was less than 0.05.

To synthesize the granular statistical results into a high-level comparison of feature effectiveness, the outcomes were systematically aggregated. The process began by quantifying how frequently each feature detected a significant trend for each muscle within a given posture. For example, analysis of the MDF feature during the sustained kneeling task revealed it was a highly consistent indicator for the biceps femoris (showing a significant trend in 31–32 out of 32 experimental files) but was less consistent for the upper rectus abdominis (15–20 significant files). Summing out these instances for just the kneeling posture showed that the MDF feature successfully identified fatigue in 338 of the 384 possible muscle-trial combinations, yielding an overall consistency of 88%.

This aggregation method was then applied to all key sEMG features across all three postures (standing, stooping, and kneeling). For each feature and posture, the total count of significant instances was summed and divided by the total number of experimental files to calculate a final "consistency percentage." The complete results of this comprehensive analysis are presented in Table 3. As summarized in the table, the analysis reveals a clear hierarchy of feature effectiveness. The frequency-domain features, MDF and MNF, emerge as the most consistent, showing a significant change in an average of 88% of all datasets across all postures. Other metrics such as VCF, Skew, PSR, and SampEn also proved highly reliable, with average significance rates ranging from 76% to 81%. While the amplitude-based features RMS and MAV were also frequently significant, they demonstrated slightly lower consistency (73% and 72%, respectively).

Table 3. Consistency of feature differentiation between fatigue states.

Posture	MDF	MNF	RMS	MAV	SampEn	PSR	VCF	Skew
Standing	659	678	543	549	570	585	642	619
Percentage	86%	88%	71%	71%	74%	76%	84%	81%
Stooping	344	335	287	283	302	298	298	306
Percentage	89%	87%	75%	73%	78%	78%	78%	80%
Kneeling	338	342	278	272	296	304	289	299
Percentage	89%	89%	75%	71%	77%	79%	75%	78%
Average	88%	88%	73%	72%	76%	78%	79%	79%

Total number of muscle-specific datasets per posture: standing (8 participants × 8 repetitions × 12 muscles = 768); stooping and kneeling (8 participants × 4 repetitions × 12 muscles = 384).

These statistical findings are visually corroborated by main effect plots, which depict the general trends of these features. Figure 7 presents these main effects for the left rectus femoris muscle as a representative example, illustrating the characteristic physiological changes from a non-fatigued to a fatigued state. All features demonstrated a highly significant statistical difference between the two conditions (Kruskal–Wallis $p < 0.001$). A subset of features showed a clear increase with the onset of fatigue: RMS (a) rose substantially from a mean value of approximately 0.0047 to 0.0069, while Skew (e) increased from approximately 1.8 to 2.5. Conversely, the remaining features exhibited a significant

decrease, most notably the frequency-domain features MDF (b) and MNF (c), which showed pronounced drops from nearly 100–102 Hz down to 65–81 Hz.

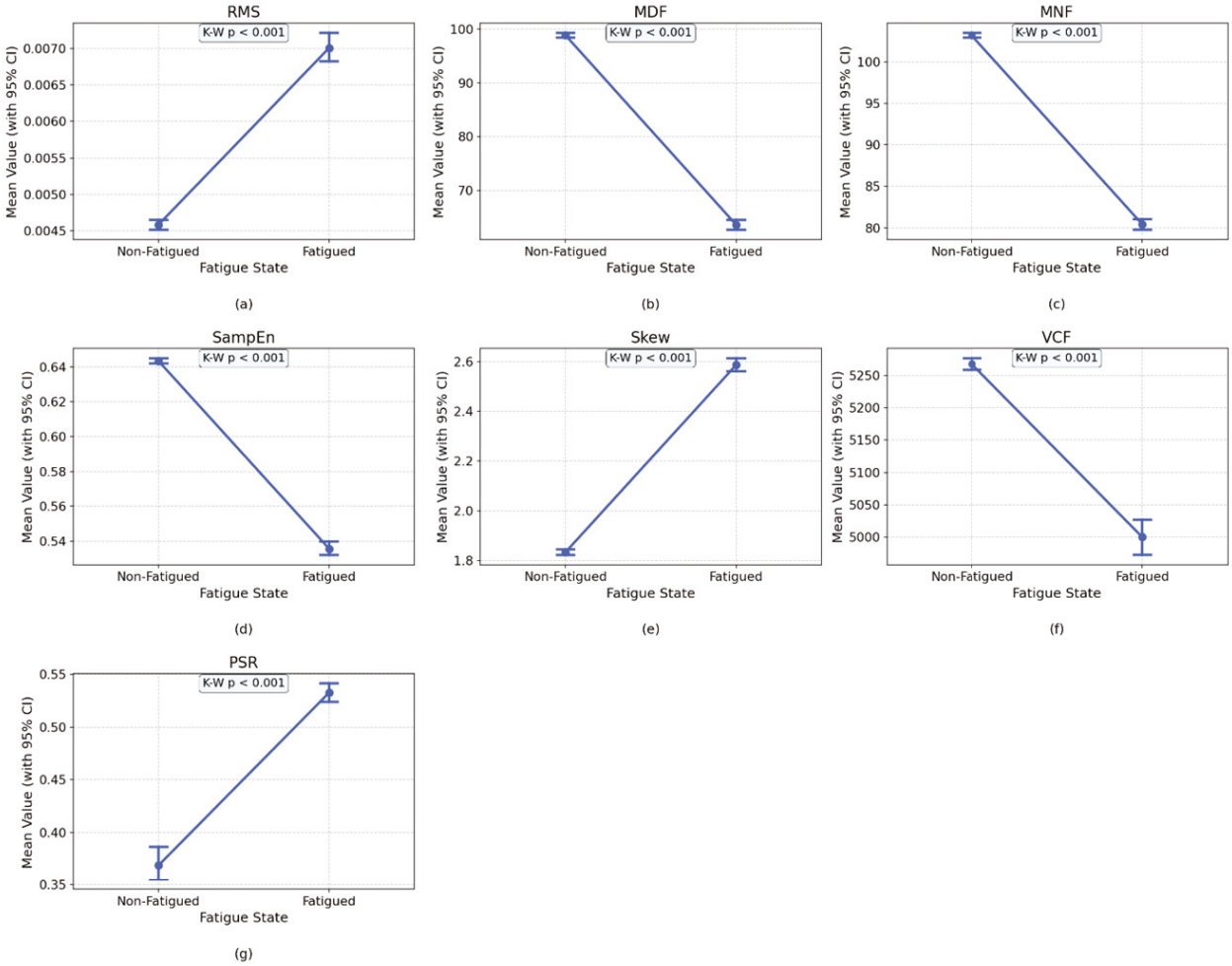

Figure 7. Main effect of fatigue state on sEMG features for the left rectus femoris muscle. The subfigures show the significant change (Kruskal-Wallis, $p < 0.001$) between non-fatigued and fatigued states for: (**a**) Root Mean Square (RMS), (**b**) Median Frequency (MDF), (**c**) Mean Frequency (MNF), (**d**) Sample Entropy (SampEn), (**e**) Skewness (Skew), (**f**) Variance of Central Frequency (VCF), and (**g**) Power Spectrum Ratio (PSR).

To complement the statistical significance identified by the Kruskal–Wallis H-test, a Random Forest model was also trained using the full set of extracted features. The purpose of this approach was to evaluate the relative predictive power of each feature in distinguishing between non-fatigued and fatigued states. The model's built-in feature importance mechanism provides a quantitative ranking based on how much each feature contributes to classification accuracy, offering a practical perspective on feature utility beyond statistical significance. Figure 8 depicts the mean feature importance scores derived from this model across all participants and postures. The ranking provides strong corroboration for the findings from the statistical analysis, with the same group of features emerging as the most valuable. Frequency-domain metrics MNF, MDF, PSR, and VCF are again ranked as the most influential predictors, reinforcing their status as primary indicators of fatigue. Similarly, Skew, SampEn, and RMS also demonstrated substantial importance, confirming their value in a predictive context.

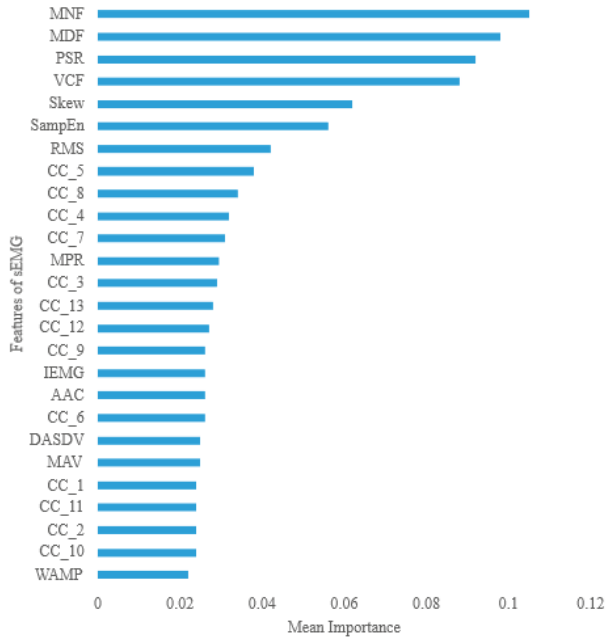

Figure 8. A bar chart representing the mean importance of features across all participants and postures.

Considering the converging evidence from both the statistical significance tests (Table 3) and the model-based importance ranking (Figure 8), a final set of seven features was chosen to definitively answer Research Question 1. Based on their superior and consistent performance in this dual analysis, MDF, MNF, RMS, VCF, PSR, Skew, and SampEn were selected for further investigation and for building the machine learning models in the subsequent sections.

3.4. Performance of Feature-Extracted sEMG Models

Building upon the feature selection process detailed in the previous section, this section presents a comparative evaluation of machine learning models to answer research question 2: "Which machine learning models have the best performance in predicting muscle fatigue using the sEMG data?"

A diverse set of models were selected to assess the performance on the engineered seven-feature set. This selection includes the following:

- Traditional Ensemble Models: Random Forest (RF) and XGBoost, which are well-established benchmarks renowned for their robustness on structured, tabular data.
- Deep Learning Architectures:
  - A one-dimensional Convolutional Neural Network (1D-CNN);
  - A hybrid CNN-LSTM with an Attention mechanism;
  - A Transformer-based model.

The classification performance metrics for models trained on sEMG features from the standing posture are presented in Table 4. The results for the standing posture indicate that the CNN-LSTM with Attention model yielded the best performance. It achieved the highest test accuracy (0.7830 ± 0.0120) and the best F1-score of 0.7135. The XGBoost model also performed competitively, positioning it as the clear second-best performer.

Conversely, the Transformer architecture underperformed significantly, with the lowest accuracy (0.6717) and F1-score (0.6120).

Table 4. Classification performance of sEMG-based models for standing posture.

Model	Test Accuracy	Non-Fatigue F1-Score	Fatigue F1-Score
XGB Boost	0.7694 ± 0.0094	0.8075 ± 0.0170	0.7099 ± 0.0160
CNN LSTM Attention	0.7830 ± 0.0120	0.8238 ± 0.0186	0.7135 ± 0.0198
Transformer	0.6717 ± 0.0152	0.7150 ± 0.0208	0.6120 ± 0.0153
1dCNN	0.7272 ± 0.0299	0.7570 ± 0.0618	0.6846 ± 0.0172
RF	0.7480 ± 0.0104	0.8010 ± 0.0136	0.6553 ± 0.0078

The superior classification capability of the leading models is further detailed in the confusion matrices presented in Figure 9.

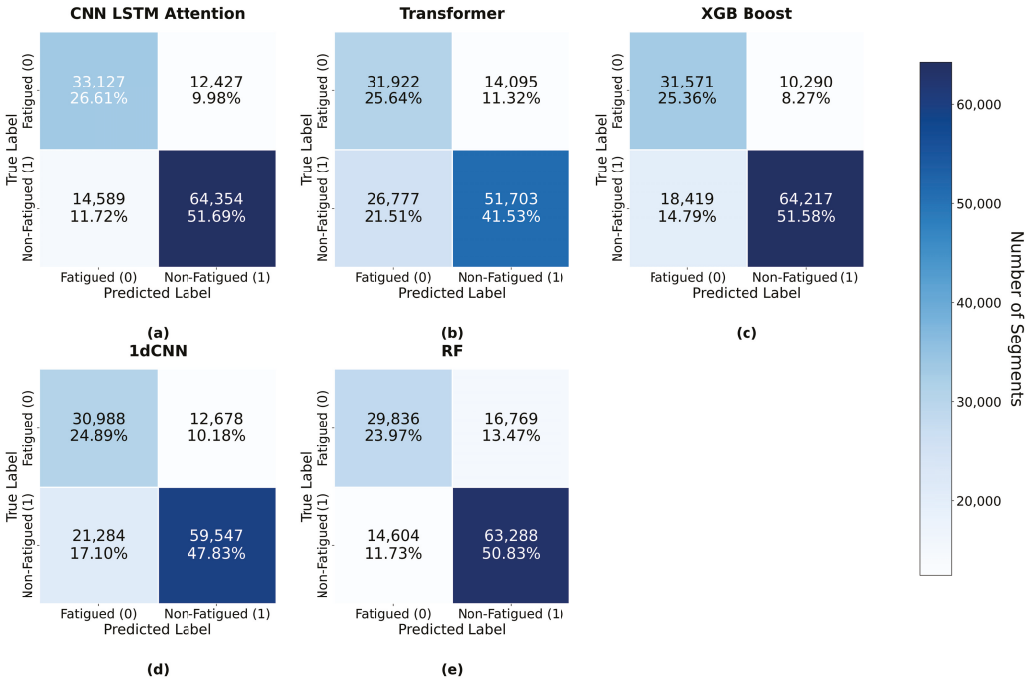

Figure 9. Confusion matrices illustrating the classification performance for the standing task for five different models: (**a**) CNN LSTM Attention, (**b**) Transformer, (**c**) XGBoost, (**d**) 1dCNN, and (**e**) Random Forest.

An analysis of the models in Figure 9 reveals their predictive capabilities.

- The CNN-LSTM with Attention model (a) correctly identified 33,127 fatigued segments (TP) and 64,354 non-fatigued segments (TN), demonstrating its balanced classification strength.
- The XGBoost model (c), while having slightly fewer TPs, notably committed the fewest false negative errors (10,290 instances). This is important as it indicates the lowest rate of missed fatigue cases among all models.
- The poor performance of the Transformer (b) is explained by its high number of FPs where it misclassified a high number of non-fatigued segments as fatigued, indicating a model bias that reduces its reliability.

This detailed breakdown confirms that for the standing posture, the CNN-LSTM and XGBoost models were better.

The stooping posture imposes a significant load on the lumbar and leg muscles, creating a different set of fatigue patterns. The performance of the models for this task is detailed in Table 5. An analysis of model performance for the stooping posture reveals a shift in the top-performing model. The XGBoost model demonstrated superior performance with the highest test accuracy (0.7809 ± 0.0109) and the highest F1-score (0.6943 ± 0.0120). This

suggests that the feature patterns indicative of fatigue while stooping are captured most effectively by the XGBoost model. The CNN-LSTM with Attention model followed closely with a test accuracy of 0.7753 and a F1-score of 0.6808. In contrast, RF, while achieving a reasonable accuracy (0.7599), showed a significant weakness in its F1-score (0.6163).

Table 5. Classification performance of sEMG-based models for stooping posture.

Model	Test Accuracy	Non-Fatigue F1-Score	Fatigue F1-Score
XGB Boost	0.7809 ± 0.0109	0.8289 ± 0.0123	0.6943 ± 0.0120
RF	0.7599 ± 0.0187	0.8245 ± 0.0199	0.6163 ± 0.0150
CNN LSTM Attention	0.7753 ± 0.0152	0.8254 ± 0.0177	0.6808 ± 0.0301
1dCNN	0.7534 ± 0.0270	0.7994 ± 0.0490	0.6709 ± 0.0330
Transformer	0.6942 ± 0.0182	0.7561 ± 0.0301	0.5832 ± 0.0260

A detailed examination of the classification behavior is provided by the confusion matrices in Figure 10.

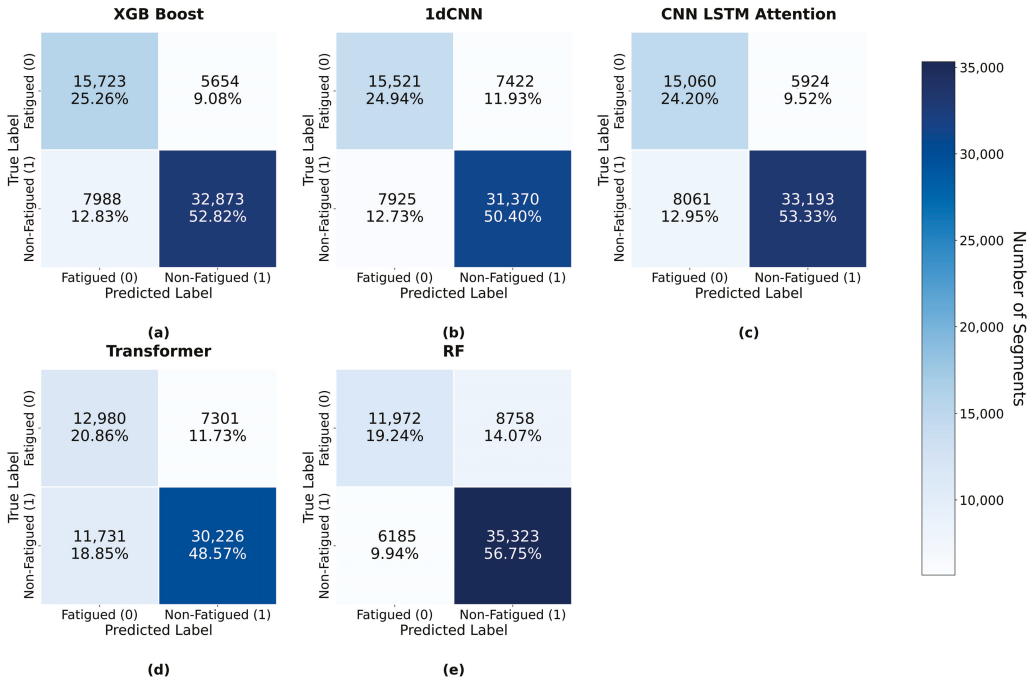

Figure 10. Confusion matrices illustrating the classification performance for the stooping posture. Each matrix displays the absolute number and percentage of test segments classified by: (**a**) XGBoost, (**b**) 1D-CNN, (**c**) CNN LSTM with Attention, (**d**) Transformer, and (**e**) Random Forest. The main diagonal represents correct classifications, while off-diagonal cells represent misclassifications.

The confusion matrices (Figure 10) confirm the strength of the XGBoost model (a), which minimized the critical False Negative errors, indicating high sensitivity to fatigue. In contrast, the Random Forest model (e) showed a significant weakness in fatigue detection, misclassifying a high number of fatigued segments as not fatigued.

This analysis confirms that for the stooping posture, the XGBoost model achieves high overall accuracy.

The kneeling posture introduces unique physiological demands. The performance of the models under this posture is detailed in Table 6.

The CNN-LSTM with Attention model emerged as the most balanced and effective classifier, achieving the highest overall test accuracy (0.7469 ± 0.0325) and the highest F1-score (0.6527 ± 0.0272). RF model attained the highest non-fatigue F1-score (0.8134),

suggesting a specialization in correctly identifying non-fatigued states, but this came at the expense of lower performance on the fatigue class (fatigue F1-score of 0.5904). The Transformer model continued its consistent underperformance.

The confusion matrices for kneeling (Figure 11) confirm the strong, balanced performance of the CNN-LSTM model (b), which correctly identified a high number of fatigued segments while maintaining a low rate of False Negatives. This analysis also highlights the specific trade-offs of other models, such as the high number of False Negatives for Random Forest (d) and the high number of False Positives for XGBoost (c).

Table 6. Classification performance of sEMG-Based Models for Kneeling Posture

Model	Test Accuracy	Non-Fatigue F1-Score	Fatigue F1-Score
XGB Boost	0.6989 ± 0.0189	0.7511 ± 0.0303	0.6123 ± 0.0346
RF	0.7450 ± 0.0222	0.8134 ± 0.0256	0.5904 ± 0.0222
CNN LSTM Attention	0.7469 ± 0.0325	0.7971 ± 0.0409	0.6527 ± 0.0272
Transformer	0.6602 ± 0.0419	0.7257 ± 0.0721	0.5128 ± 0.0969
1dCNN	0.7179 ± 0.0065	0.7799 ± 0.0116	0.6048 ± 0.0270

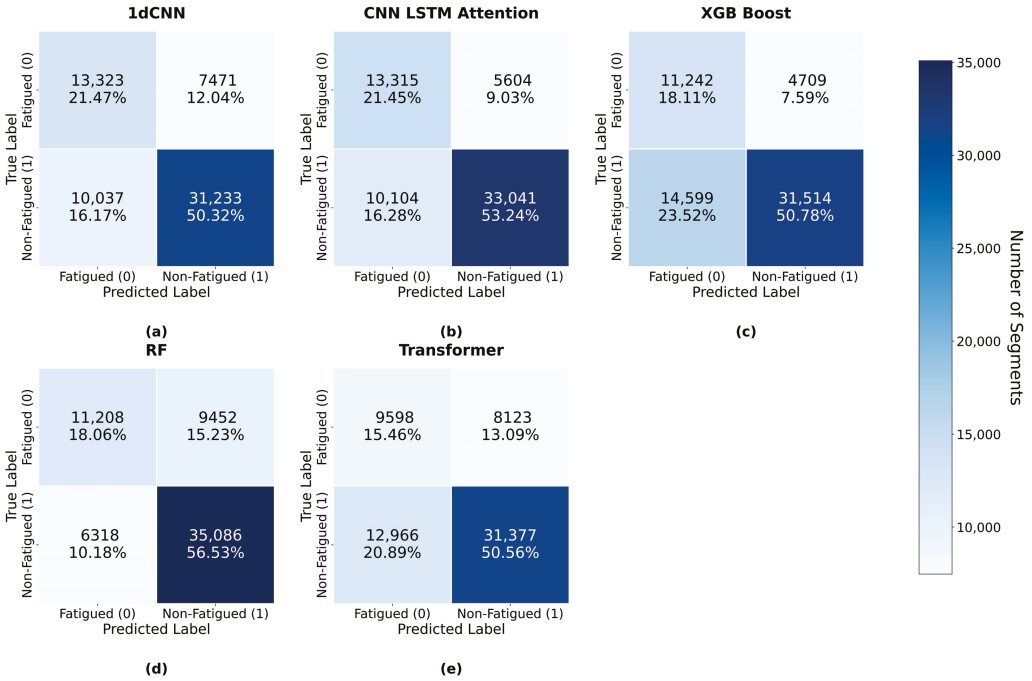

Figure 11. Confusion matrices illustrating the classification performance for the kneeling posture. Each matrix displays the absolute number and percentage of test segments classified by (**a**) 1D-CNN, (**b**) CNN LSTM with Attention, (**c**) XGBoost, (**d**) Random Forest, and (**e**) Transformer.

This detailed error analysis confirms that the CNN-LSTM with Attention provides the performance for the kneeling posture.

In direct response to Research Question 2, the comparative analysis across the three distinct postures confirms that classification performance was posture-dependent, with no single machine learning model demonstrating universal superiority. This result highlights the challenge of using standalone models for diverse ergonomic demands and motivated the development of a more robust, hybrid solution. The ensemble models, particularly XGBoost, showcased high efficacy in specific contexts, proving optimal for the biomechanically demanding stooping posture. However, the CNN-LSTM with Attention model emerged as the most consistently balanced performer overall. It achieved the highest performance in the standing and kneeling postures and remained highly competitive in stooping.

3.5. Performance of the Advanced Hybrid Model

The preceding analyses evaluated two distinct modeling philosophies: deep learning models trained on raw sEMG data and various machine learning models trained on a set of engineered features. The results demonstrated that while raw-signal models can automatically learn complex patterns, feature-based models excel by leveraging known physiological indicators of fatigue. This outcome naturally leads to the central research question for this final stage of analysis: Can an advanced hybrid model, which integrates both raw data and engineered features, outperform the standalone deep learning and traditional machine learning models?

To answer this question, and in direct response to Research Question 3, a hybrid architecture was developed. It was hypothesized to achieve synergistic performance by integrating the complementary strengths of these two data types. The model's design, illustrated in Figure 12, is a direct result of the preceding insights. It employs sophisticated, multi-stage architecture to make a final, decisive classification.

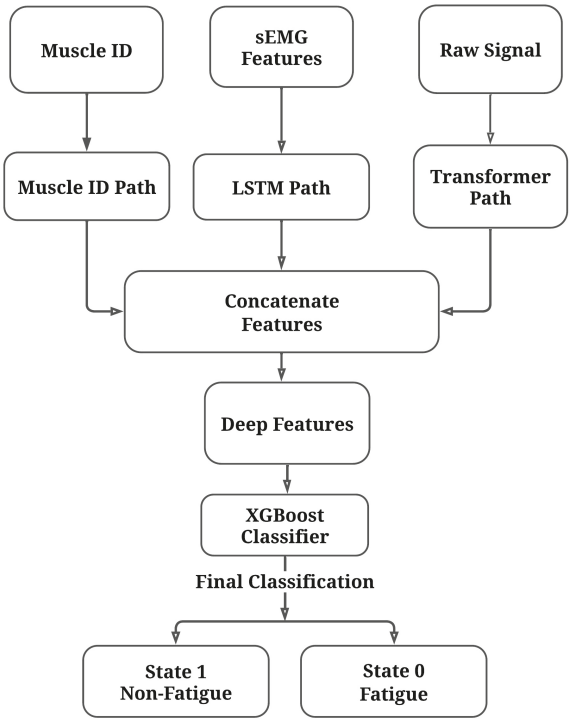

Figure 12. Hybrid transformer LSTM model with XGBoost classifier.

The architecture detailed in Figure 12 operates in two distinct stages.

- Stage 1 (Feature Extraction): This stage processes four parallel input streams to generate a rich, contextualized feature representation.
  - Raw sEMG Signal (Input A): A Transformer path autonomously extracts complex, hierarchical patterns directly from the raw sEMG waveform, capitalizing on its ability to discern intricate patterns that may not be captured by pre-defined features.
  - Engineered sEMG Features (Input B): An LSTM path processes the time series of the seven selected engineered features (MDF, MNF, RMS, etc.) to explicitly model the signal's evolution and learn its temporal dynamics.
  - Muscle ID (Input C): Separate dense layers learn embedding representations for these categorical variables, allowing the model to account for muscle-specific and subject-specific physiological variations.

The outputs from these paths are concatenated into a unified feature vector, which is passed through a final dense layer to produce a rich, 64-dimensional latent vector of deep features.

- Stage 2 (Final Classification): This stage then takes the learned latent feature vector as its sole input. An XGBoost classifier, selected for its robust performance in the preceding feature-based analyses, performs the final binary classification into fatigued (State 0) or non-fatigued (State 1).

The performance of this hybrid model, evaluated for each posture, is presented in Table 7. The performance of the hybrid model demonstrates a significant advancement over the single-paradigm models. It achieves not only high but also remarkably consistent performance across all three distinct postural conditions. The model's overall accuracy is clustered in a narrow and stable range, from 82.13% for standing to a peak of 82.66% for stooping. This indicates a strong capability to generalize its predictive power regardless of the specific biomechanical demands, a marked improvement over the posture-specific efficacy observed in the previous models.

Table 7. Performance of the hybrid Transformer–LSTM–XGBoost model.

Activity	Accuracy	Fatigue-F1 Score	Non-Fatigue F1 Score
Standing	0.8213	0.7772	0.8509
Stooping	0.8266	0.7688	0.8613
Kneeling	0.8238	0.7675	0.8582

A more granular, posture-by-posture analysis reveals the nuances of the model's superior behavior.

- For the Standing Posture: The model achieved an accuracy of 82.13% with a fatigue F1-score of 0.7772. A deeper dive into the constituent metrics for the fatigue class shows a precision of 0.7342 and a recall of 0.8257. This disparity, with recall significantly exceeding precision, indicates that the model is highly sensitive in detecting true instances of fatigue, a crucial attribute for ergonomic applications.
- For the Stooping Posture: In this more demanding posture, the model yielded its highest accuracy of 82.66%. The fatigue F1-score was 0.7688, derived from a precision of 0.7154 and the highest recall value observed across all tests at 0.8309. The precision for the non-fatigued class was also exceptionally high at 0.9017, signifying that when the model predicts a non-fatigued state during stooping, it does so with very high confidence.
- For the Kneeling Posture: The model maintained its robust performance with an accuracy of 82.38% and a fatigue F1-score of 0.7675. The precision–recall profile for the fatigue class (0.7249 and 0.8154, respectively) mirrored that of the other postures, again prioritizing the correct identification of fatigued states over precision.

To visually deconstruct these numerical results, the corresponding confusion matrices are presented in Figure 13. The confusion matrices offer a granular view of the hybrid model's classification behavior and visually confirm a critical performance characteristic. Across all three postures, the model demonstrates exceptionally high sensitivity (recall) for the fatigue class. For instance, in the standing posture (a), the model correctly identified 370,287 fatigued segments (TPs) while misclassifying only 78,165 (FNs). This pattern, where TPs for fatigue substantially outnumber FNs, holds for both stooping (b) and kneeling (c).

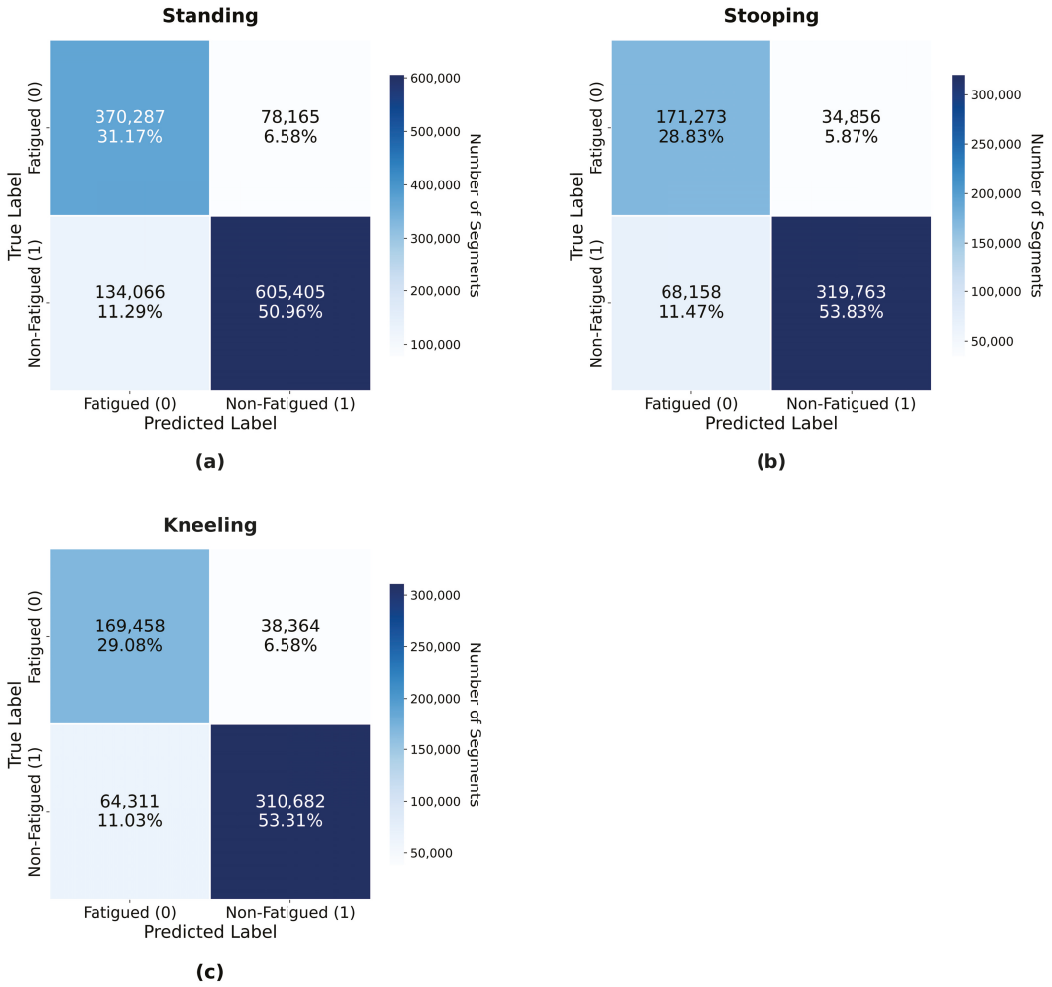

Figure 13. Comparative confusion matrices for the hybrid Transformer–LSTM–XGBoost model across different postures: (**a**) standing, (**b**) stooping, and (**c**) kneeling.

This performance profile is highly desirable for an ergonomic monitoring system. The high recall signifies a low false negative rate, meaning the model is adept at correctly identifying true instances of fatigue, thus minimizing the risk of overlooking a worker's fatigued state, the most critical error to avoid in a safety context. The trade-off for this high sensitivity is a slightly lower precision, evidenced by the number of FP (e.g., 134,066 for standing). This indicates the model may occasionally flag a non-fatigued state as fatigued. However, this is a far more acceptable error from a safety perspective than missing an actual case of fatigue.

In conclusion, and in direct answer to Research Question 3, this two-stage hybrid approach, by leveraging deep learning for feature representation and XGBoost for classification, has successfully created a robust model that not only performs with high accuracy but is also optimized for the most crucial requirement of an ergonomic tool: minimizing missed detections of fatigue. It clearly outperforms the standalone models evaluated previously.

4. Discussion

The preceding chapter detailed the results of a multi-faceted investigation into predicting muscle fatigue among novice roofers using wearable sensor technology and machine learning. This chapter provides an interpretation of these findings, contextualizing the performance of sEMG-based and hybrid modeling approaches within the existing literature and the specific demands of roofing tasks. The significance of the findings, method-

ological considerations, limitations of the study, and directions for future research are critically examined.

4.1. Recapitulation of Principal Findings

The comprehensive analysis of sEMG data yielded several key findings pertinent to the detection and assessment of muscle fatigue during simulated roofing tasks.

Firstly, the study established a robust two-stage sEMG labeling methodology, adapting the WM trend analysis and incorporating physiological markers to define 'fatigue' and 'non-fatigue' states, with 'uncertain' segments being conservatively excluded to ensure high-confidence ground-truth labels for model training.

Secondly, an initial baseline assessment revealed that models trained directly on raw sEMG data exhibited modest predictive performance across the standing, stooping, and kneeling postures (e.g., LSTM F1-scores ranging from approximately 59% to 67%). This underscored the necessity for subsequent feature engineering to enhance discriminability.

Thirdly, the analysis of engineered sEMG features identified MDF, MNF, RMS, Skew, VCF, PSR, and Sample Entropy as statistically significant and consistent indicators of fatigue. Frequency-domain features (MDF and MNF) showed the highest consistency (significant in 88% of datasets on average) in differentiating fatigue states across postures, aligning with known physiological responses to fatigue.

Fourthly, the performance of feature-based sEMG models in terms of overall test accuracy varied by posture. For the standing posture, the CNN LSTM Attention model achieved the highest accuracy (approximately 78.3%). In the stooping posture, the XGBoost model demonstrated the highest accuracy, reaching approximately 78.1%. These results highlighted that no single sEMG-only model universally achieved the highest accuracy across all specific tasks.

Fifthly, to explore the potential benefits of combining raw signal information with engineered features from sEMG, an advanced hybrid sEMG model was developed. This model utilized a Transformer–LSTM architecture to process both raw sEMG segments and the corresponding engineered sEMG features, with the extracted deep features then classified by an XGBoost classifier. This hybrid sEMG approach demonstrated strong and consistent performance across all three postures, achieving accuracies of approximately 82.1% for standing, 82.7% for stooping, and 82.4% for kneeling. The fatigue F1-scores were also robust, around 0.77–0.78 for all postures.

4.2. Discussion of sEMG-Based Fatigue Detection

This section critically evaluates the findings related to sEMG-based fatigue detection. It begins by interpreting the physiological significance of the observed feature behaviors, grounding them in established myoelectric principles. It then transitions to a comparative analysis of the machine learning model performances.

4.2.1. Significance and Physiological Interpretation of sEMG Feature Behavior

A foundational step in this research was to validate that the engineered sEMG features are physiologically meaningful indicators of muscle fatigue. The results presented in Section 3.3 confirm this unequivocally. The frequency-domain features, MDF and MNF, proved to be the most consistent indicators of fatigue. The characteristic downward trend of both MDF and MNF with developing fatigue is a classic hallmark of peripheral muscle fatigue and directly corroborates literature. This spectral compression is primarily attributed to a decrease in muscle fiber conduction velocity (MFCV) as metabolic byproducts accumulate and impair the efficiency of the sodium–potassium (Na+/K+) pump [15,27]. The high consistency of this finding across the varied biomechanical demands of standing,

stooping, and kneeling validates the study's labeling methodology and underscores the fundamental nature of this myoelectric signature of fatigue.

The time-domain feature RMS, which quantifies the amplitude or power of the sEMG signal, was also a powerful differentiator and exhibited a clear, marked increase with the onset of fatigue. This phenomenon reflects an augmented neural drive from the central nervous system. As individual muscle fibers begin to fatigue, the nervous system attempts to compensate by recruiting additional, often larger, motor units and/or by increasing the firing rate of already active units [28]. Finally, the nonlinear feature Sample Entropy (SampEn) also proved to be a strong indicator, showing a distinct decrease as fatigue progressed. A lower SampEn value indicates a loss of signal complexity and an increase in its regularity, which is consistent with literature suggesting that the nervous system may adopt a more synchronized firing pattern across motor units as a mechanism to maintain force output under duress [29].

4.2.2. Methodological Framework for Feature Selection

The answer to Research Question 1 rests on a methodological framework that warrants discussion. The process involved applying the Kruskal-Wallis H-test to features derived from overlapping time-series windows. While the use of overlapping windows is a standard practice in biosignal processing that increases dataset density and enhances feature stability [30], it introduces autocorrelation that violates the independence assumption of the test for formal inference. However, in this study, the test was not used for formal inference but was instead repurposed as a computationally efficient, non-parametric heuristic to score and rank features based on their class separability. This reframing of a statistical test as a feature ranking tool is a well-precedented, cross-disciplinary practice [24]. Therefore, the findings regarding feature importance are based on a sound engineering approach, where the statistical test was used as an exploratory tool and its findings were corroborated by a model-based feature importance analysis.

4.2.3. Performance of sEMG Machine Learning Models

The evaluation of various machine learning models revealed nuanced performance differences that depend heavily on the nature of the task. For posture-specific tasks, which represent a more constrained and homogeneous feature space, different models excelled under different conditions. Notably, for the highly demanding stooping posture, the XGBoost model achieved the highest accuracy (78.1%). XGBoost, a powerful tree-based gradient boosting ensemble, is exceptionally effective at discovering complex, non-linear decision boundaries within well-defined, structured feature sets like those derived from a single, consistent posture [31]. A particularly insightful, albeit counterintuitive, finding was the consistent underperformance of the Transformer model. This result provides a crucial lesson on the practical application of different deep learning architectures. Transformers, while state of the art in fields like natural language processing, are notoriously data-hungry and lack the strong inductive biases for the locality and sequentiality that are inherent to CNNs and RNNs, respectively [32]. The superior performance of the CNN-LSTM model strongly suggests that for this type of physiological data and at this data scale, architectures with built-in spatial and temporal priors are more effective.

Finally, the study explored an advanced hybrid sEMG model that used a Transformer–LSTM network as a sophisticated feature extractor, with an XGBoost classifier making the final prediction. This two-stage pipeline delivered the highest and most consistent accuracies in the posture-specific contexts, achieving over 82% accuracy for standing, stooping, and kneeling. This approach successfully leverages the strengths of both paradigms: deep learning's ability to learn rich, latent representations from both raw and engineered data,

and gradient boosting's exceptional power in classifying structured data. The success of the high-performance hybrid machine learning model is particularly noteworthy, confirming its potential as the core of a predictive analytics engine.

This architecture's superiority, as demonstrated in Figure 14, is attributable to this synergistic design, which allows it to consistently outperform standalone ensemble learning and deep learning alternatives across all postures. The ablation study (Section 4.2.4) further confirmed that each of these components is a critical contributor to the model's high performance.

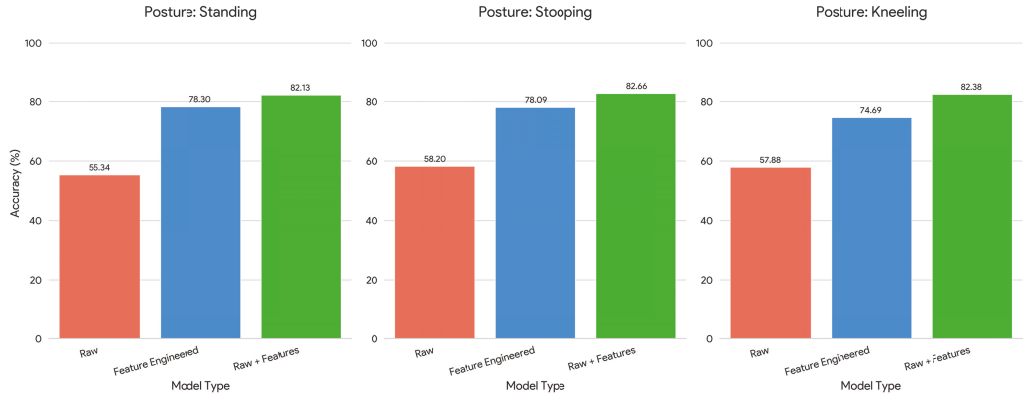

Figure 14. A comparative analysis of model accuracy for fatigue classification, segmented by posture and model complexity.

The figure illustrates the value of methodological progression. For every posture, standing, stooping, and kneeling, there is a distinct, stepwise improvement in accuracy. The baseline models using only raw data show modest performance, with accuracy ranging from 55.3% to 58.2%. The introduction of feature engineering provides a substantial boost, with the best feature-based models achieving accuracies between 74.7% and 78.3%. Finally, the advanced hybrid model, which integrates raw + features, demonstrates clear superiority, pushing the accuracy to over 82% for all three postures. This visual evidence provides a compelling answer to the research questions, confirming the necessity of feature engineering and the superior performance of advanced hybrid architecture.

4.2.4. Ablation Study of the Hybrid Architecture

To validate the design of the hybrid architecture, an ablation study was conducted to quantify the contribution of its individual components. The full Transformer–LSTM–XGBoost model served as the performance baseline. Three ablated versions were then evaluated.

- With the transformer path removed;
- With the LSTM path removed;
- With the final XGBoost classifier replaced by standard softmax layer.

The results for the kneeling posture are presented in Table 8. The results confirm that each component provides a critical contribution to the model's performance. The removal of the LSTM path, which processes the engineered features resulted in a catastrophic drop in F1 score. Similarly, removing either Transformer path or the XGBoost led to significant degradation in both accuracy and F1 score. This ablation study validates that performance of the hybrid model is because of the synergy between all of its components.

Table 8. Ablation study results for the hybrid model.

Models	Accuracy	F1 Fatigue
Hybrid Transformer–LSTM–XGBoost Model	0.8238	0.7675
No Transformer	0.7137	0.7594
No LSTM	0.7666	0.0251
XGBoost replaced by Softmax	0.7030	0.6911

4.3. Considerations for Real-Time Implementation and Deployment

The practical implementation of the proposed framework requires acknowledging both its reasoning delay and deployment hardware. The methodology's 2.5 s data acquisition window represents the minimum fixed latency. An analysis of the subsequent computational delay (end-to-end computational time that includes signal processing, seven selected feature calculations, deep feature extraction using LSTM and Transformer models, and final classification) was performed on a laptop (AMD Ryzen 9 CPU, NVIDIA RTX 4060 GPU, 16 GB RAM, and SSD with ∼3500 MBps read and write speed). The timing of each cross-validation fold was calculated as an average computational time of 100 iterations within that fold.

The results yielded an average end-to-end average inference time of 861.6 ms with a standard deviation of 11.8 (ranging from 836.78 ms to 876.32 ms) for all computational steps following data acquisition. When this computational delay is added to the 2.5 s acquisition delay, the total inference time from data capture to classification is approximately 3.4 s, which is feasible for a near-real-time monitoring system. For deployment, the study used an offline method to train and test the models. The intended future implementation involves wearable sensors streaming data to a local PC for processing.

4.4. Methodological Considerations and Limitations

Although this study provides valuable information on the application of wearable technology for fatigue detection, its findings must be interpreted within the context of several methodological limitations. The study was conducted in a controlled laboratory environment, which, while necessary for ensuring data quality and participant safety, does not fully replicate the complexities of a real-world roofing worksite. Factors such as environmental stressors like extreme heat and sun exposure, variable surface conditions, and the psychological stress associated with working at significant heights were not incorporated. Moreover, the scope of the physical tasks was limited to three specific quasi-static postures. Actual roofing involves a much wider range of dynamic movements, including carrying materials and using tools, so the findings from these sustained postures may not be directly generalizable to the more variable physical demands encountered in the field. The participant cohort consisted exclusively of novice individuals. Although this was a deliberate choice to ensure a homogeneous sample and establish a critical physiological baseline for this foundational proof-of-concept study, it is also a limitation. Experienced roofers are likely to exhibit more efficient motor patterns and different fatigue signatures developed through long-term adaptation. Consequently, the models developed here are not yet validated for a professional workforce and their real-world generalization is limited until they are validated with professional roofers. This underscores the importance of the next planned phase of this research with professional roofers, which is stated in our future directions. Finally, the sample size, while adequate for this exploratory investigation, is relatively small for the development of highly generalized deep learning models. Architectures like the Transformer and LSTM are known to be data-hungry, and their performance can be constrained by limited datasets.

5. Conclusions and Future Directions

This study presents a data-driven framework for classifying muscle fatigue in simulated roofing tasks using sEMG data and advanced machine learning. A dual-analysis approach identified a core set of effective features spanning spectral, amplitude, and complexity domains, confirming the necessity of feature engineering over raw signal analysis. Model evaluation showed that performance depends on task-specific biomechanical demands, with different algorithms excelling in different postures.

An advanced hybrid model, combining a Transformer–LSTM for deep feature extraction with an XGBoost classifier, consistently outperformed all alternatives. Supported by a stringent cross-validation protocol, the findings establish a subject-independent, high-performance fatigue classification approach. This work sets a new benchmark for ergonomic monitoring systems and offers a clear pathway toward practical, real-world deployment.

Future Directions

Building on this validated framework and acknowledging its limitations, several key avenues emerge for translating this research into a practical, real-world ergonomic monitoring system. The next step is to move from the laboratory to the field for field validation with professional roofers. In parallel with this, and as a direct extension of this study's findings, research will focus on a comparative analysis of novice and professional workers. This will quantify the effects of long-term adaptation on sEMG fatigue signatures and will be essential for developing models accurate for experienced workforce. Future work will aim to build a more holistic model of worker fatigue by integrating additional physiological data streams, such as heart rate variability (HRV), to assess autonomic nervous system response.

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References

1. Olimat, H.; Alwashah, Z.; Abudayyeh, O.; Liu, H. Data-Driven Analysis of Construction Safety Dynamics: Regulatory Frameworks, Evolutionary Patterns, and Technological Innovations. *Buildings* **2025**, *15*, 1680. [CrossRef]
2. U.S. Bureau of Labor Statistics. National Census of Fatal Occupational Injuries in 2023. Technical Report USDL-24-2564, U.S. Department of Labor. 2024. Available online: https://www.bls.gov/news.release/cfoi.nr0.htm (accessed on 10 July 2025).

3. Almaskati, D.; Kermanshachi, S.; Pamidimukkala, A.; Loganathan, K.; Yin, Z. A Review on Construction Safety: Hazards, Mitigation Strategies, and Impacted Sectors. *Buildings* **2024**, *14*, 526. [CrossRef]
4. Health and Safety Executive. The Health and Safety Executive Annual Report and Accounts 2023 to 2024. Technical Report HC 326, UK Government. 2024. Available online: https://www.gov.uk/government/publications/the-health-and-safety-executive-annual-report-and-accounts-2023-to-2024 (accessed on 12 July 2025).
5. Breloff, S.P.; Carey, R.E.; Dutta, A.; Sinsel, E.W.; Warren, C.M.; Dai, F.; Wu, J.Z. Kneeling trunk kinematics during simulated sloped roof shingle installation. *Int. J. Ind. Ergon.* **2020**, *77*, 102945. [CrossRef]
6. Dutta, A. An In-Depth Investigation of the Effects of Work-Related Factors on the Development of Knee Musculoskeletal Disorders among Construction Roofers. Ph.D. Dissertation, West Virginia University, Morgantown, WV, USA, 2020. [CrossRef]
7. Manning, C.; Jorgensen, M. The Price of Pain: Workers Compensation Costs for Musculoskeletal Claims in the State of Kansas, 2014–2022. *J. Occup. Environ. Med.* **2024**, *66*, 252–262. [CrossRef]
8. Ma, L.; Chablat, D.; Bennis, F.; Zhang, W.; Guillaume, F. A new muscle fatigue and recovery model and its ergonomics application in human simulation. *Virtual Phys. Prototyp.* **2010**, *5*, 123–137. [CrossRef]
9. De Luca, C.J. Myoelectrical manifestations of localized muscular fatigue in humans. *Crit. Rev. Biomed. Eng.* **1984**, *11*, 251–279.
10. Cifrek, M.; Medved, V.; Tonković, S.; Ostojić, S. Surface EMG based muscle fatigue evaluation in biomechanics. *Clin. Biomech.* **2009**, *24*, 327–340. [CrossRef] [PubMed]
11. Phinyomark, A.; Phukpattaranont, P.; Limsakul, C. Feature selection for sEMG signals based on the Mahalanobis distance. In Proceedings of the 2012 9th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, Phetchaburi, Thailand, 16–18 May 2012; pp. 1–4. [CrossRef]
12. Moshawrab, M.; Adda, M.; Bouzouane, A.; Ibrahim, H.; Raad, A. Smart Wearables for the Detection of Occupational Physical Fatigue: A Literature Review. *Sensors* **2022**, *22*, 7472. [CrossRef] [PubMed]
13. Bangaru, S.S.; Wang, C.; Aghazadeh, F.; Muley, S.; Willoughby, S. Oxygen Uptake Prediction for Timely Construction Worker Fatigue Monitoring Through Wearable Sensing Data Fusion. *Sensors* **2025**, *25*, 3204. [CrossRef] [PubMed]
14. Hwang, S.; Kwon, N.; Lee, D.; Kim, J.; Yang, S.; Youn, I.; Moon, H.J.; Sung, J.K.; Han, S. A Multimodal Fatigue Detection System Using sEMG and IMU Signals with a Hybrid CNN-LSTM-Attention Model. *Sensors* **2025**, *25*, 3309. [CrossRef]
15. Chen, S.W.; Liaw, J.W.; Chan, H.L.; Chang, Y.J.; Ku, C.H. A Real-Time Fatigue Monitoring and Analysis System for Lower Extremity Muscles with Cycling Movement. *Sensors* **2014**, *14*, 12410–12424. [CrossRef]
16. Burden, A. How should we normalize electromyograms obtained from healthy participants? What we have learned from over 25 years of research. *J. Electromyogr. Kinesiol.* **2010**, *20*, 1023–1035. [CrossRef]
17. Halaki, M.; Ginn, K. Normalization of EMG signals: To normalize or not to normalize and what to normalize to? In *Computational Intelligence in Electromyography Analysis—A Perspective on Current Applications and Future Challenges*; Naik, G.R., Ed.; InTech: Houston, TX, USA, 2012; pp. 175–194. [CrossRef]
18. Maheshwari, A.; Killamsetty, K.; Ramakrishnan, G.; Iyer, R. Learning to Robustly Aggregate Labeling Functions for Semi-supervised Data Programming. *arXiv* **2021**, arXiv:2109.11410. [CrossRef]
19. Annett, J. Subjective rating scales: Science or art? *Ergonomics* **2002**, *45*, 966–987. [CrossRef]
20. Hermens, H.J.; Freriks, B.; Disselhorst-Klug, C.; Rau, G. Development of recommendations for SEMG sensors and sensor placement procedures. *J. Electromyogr. Kinesiol.* **2000**, *10*, 361–374. [CrossRef]
21. Gautam, S.R.; Acharya, S.; Kayastha, R.; Mahmud, T.; Kisi, K. Muscle Activation Patterns in Stooping Posture on Sloped Roofing Surfaces. *Proc. Assoc. Sch. Con* **2025**, *6*, 816–825.
22. Guo, X.; Chen, Y.; Zhang, J. Automated detection of physical fatigue in transportation maintenance workers through physiological and motion data. *Theor. Issues Ergon. Sci.* **2025**, *26*, 158–177. [CrossRef]
23. Guo, X.; Lu, L.; Robinson, M.; Tan, Y.; Goonewardena, K.; Oetomo, D. A Weak Monotonicity Based Muscle Fatigue Detection Algorithm for a Short-Duration Poor Posture Using sEMG Measurements. In Proceedings of the 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Virtual, 1–5 November 2021. [CrossRef]
24. Abbaszadeh, A.; Teixeira, C.A.; Yagoub, M.C.E. Feature Selection Techniques for the Analysis of Discriminative Features in Temporal and Frontal Lobe Epilepsy: A Comparative Study. *Open Biomed. Eng. J.* **2021**, *15*, 1–30. [CrossRef]
25. Powers, D.M.W. Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness and Correlation. *arXiv* **2020**, arXiv:2010.16061. [CrossRef]
26. Sokolova, M.; Lapalme, G. A systematic analysis of performance measures for classification tasks. *Inf. Process. Manag.* **2009**, *45*, 427–437. [CrossRef]
27. Fitts, R.H. Cellular mechanisms of muscle fatigue. *Physiol. Rev.* **1994**, *74*, 49–94. [CrossRef] [PubMed]
28. Basmajian, J.V.; De Luca, C.J. *Muscles Alive: Their Functions Revealed by Electromyography*, 5th ed.; Williams & Wilkins: Baltimore, MD, USA, 1985.
29. Rampichini, S.; Vieira, T.M.; Castiglioni, P.; Merati, G. Complexity Analysis of Surface Electromyography for Assessing the Myoelectric Manifestation of Muscle Fatigue: A Review. *Entropy* **2020**, *22*, 529. [CrossRef]

30. Ashraf, H.; Waris, A.; Gilani, S.O.; Kashif, A.S.; Jamil, M.; Jochumsen, M.; Niazi, I.K. Evaluation of windowing techniques for intramuscular EMG-based diagnostic, rehabilitative and assistive devices. *J. Neural Eng.* **2021**, *18*, 016002. [CrossRef]
31. Velarde, G.; Weichert, M.; Deshmukh, A.; Deshmane, S.; Sudhir, A.; Sharma, K.; Joshi, V. Tree boosting methods for balanced and imbalanced classification and their robustness over time in risk assessment. *Intell. Syst. Appl.* **2025**, *22*, 200354. [CrossRef]
32. Turner, R.E. An Introduction to Transformers. *arXiv* **2024**, arXiv:2304.10557. [CrossRef]

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Prioritizing Critical Factors Affecting Occupational Safety in High-Rise Construction: A Hybrid EFA-AHP Approach

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Abstract

High-rise construction presents heightened safety risks due to vertical complexity, spatial constraints, and workforce variability. Conventional safety management often proves insufficient, especially in rapidly urbanizing or resource-limited settings. This study proposes a hybrid methodological framework to systematically identify and prioritize the critical factors influencing occupational safety in Vietnamese high-rise construction projects. Based on 181 valid survey responses from construction professionals, 23 observed variables were developed through extensive literature review and expert consultation. Exploratory Factor Analysis (EFA) was employed to empirically group 23 validated indicators into five key latent dimensions: (1) Safety Training and Inspection, (2) Employer's Knowledge and Responsibility, (3) Worker's Competence and Compliance, (4) Working Conditions and Environment, and (5) Safety Equipment and Signage. These dimensions were then structured into an Analytic Hierarchy Process (AHP) model, with pairwise comparisons conducted by industry experts to calculate consistency ratios and derive factor weights across three high-rise project case studies. The findings provide actionable insights for construction managers, safety professionals, and policymakers in developing and underdeveloped countries, supporting data-driven decision-making for safer and more sustainable urban development.

Keywords: occupational safety; high-rise construction; analytical hierarchy process (AHP); exploratory factor analysis (EFA); safety management

1. Introduction

The construction industry persists as one of the most hazardous occupational sectors globally, with high-rise construction presenting exceptionally complex safety challenges due to its inherent characteristics: extreme verticality creating severe fall hazards, confined working spaces intensifying worker proximity risks, intricate mechanical systems introducing multifaceted failure modes, and amplified environmental exposures to wind forces and lightning strikes [1–4]. This alarming reality manifests in sobering statistics worldwide, with South Korea's construction sector accounting for over half of all workplace fatalities [5]. The United States Bureau of Labor Statistics reports a 12-year peak of 1075 construction fatalities in 2023, with falls from heights constituting 39.2% of these incidents [6]. European construction sites mirror this concerning pattern through consistently higher-than-average nonfatal injury rates compared to other industries [7].

Studies show that safety frameworks designed for low- to mid-rise buildings are often inadequate for high-rise projects without major adjustments [8]. For instance, Ansari et al. [9] indicated that falling from heights was the most critical safety risk in high-rise construction, with safety training and monitoring being the most influential criteria, accounting for approximately 35% of the total weight in risk assessment. High-rise projects involve intricate logistics, including hoisting and lifting operations, which are prone to accidents due to their scale and complexity [10]. Given these heightened risks, there is a clear and urgent need to systematically prioritize the critical factors affecting occupational safety in high-rise construction. While existing research has effectively documented the severity of specific hazards, particularly fall-related incidents and mechanical failures, few studies have operationalized this knowledge into structured, decision-oriented frameworks that support practical intervention [11]. In particular, the field lacks integrative approaches that combine empirical identification of latent safety dimensions with expert-informed evaluation of their relative importance.

Methodological approaches to safety factor identification and prioritization have advanced considerably, with researchers increasingly employing sophisticated multivariate techniques to move beyond descriptive case studies toward empirically validated factor structures [12–14]. Contemporary safety research frequently utilizes latent variable modeling approaches, particularly Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM), to identify underlying constructs that explain patterns among observable safety indicators [15–17]. Mosly et al. [18] demonstrated EFA's effectiveness in construction safety research in Saudi Arabia by reducing 37 observable variables to 10 manageable latent factors, with minimal information loss. Bayesian networks have emerged as another powerful tool for modeling probabilistic relationships between identified safety factors, with Wang et al. [19] developing dynamic Bayesian networks that capture causal relationships between safety management practices and accident occurrence in high-rise construction. However, most existing studies either focus on general construction safety without considering the unique complexities of high-rise projects or examine high-rise safety challenges without providing systematic prioritization tools for resource allocation. Furthermore, there is limited research that translates identified safety factors into actionable, context-specific management recommendations for rapidly developing urban environments like those found in Southeast Asia.

This study addresses these research gaps through three specific, measurable objectives. First, it aims to empirically identify the latent factor structure underlying occupational safety in high-rise construction in Vietnam. The approach allows the factor structure to emerge naturally from the data, while the large and diverse sample strengthens its validity and generalizability. Second, the research seeks to determine the relative importance of identified factors. This systematic prioritization creates a hierarchical framework that quantifies the relative importance of each safety factor and facilitates evidence-based resource allocation decisions. Third, the study endeavors to develop specific, actionable recommendations for enhanced safety management practices tailored to high-rise construction in rapidly degrowing urban environments, emphasizing the highest-priority factors identified through the integrated EFA-AHP methodology. These objectives collectively address the identified research gaps by combining statistical rigor in factor identification with systematic prioritization and translational focus, potentially contributing to quantifiable reductions in occupational injuries and fatalities as vertical development continues to characterize urban growth throughout Southeast Asia and globally.

The remainder of this paper is organized as follows. Section 2 details the research methodology, describing the sequential integration of EFA and AHP to identify and prioritize critical safety factors. Section 3 presents the results of the empirical analyses, including

the extraction of latent safety dimensions and the hierarchical ranking of their relative importance across multiple high-rise construction projects. Section 4 discusses the key findings in the context of the existing literature, highlighting practical implications for safety management and outlining limitations and policy development in complex urban construction environments. Finally, Section 5 concludes the paper by summarizing the main contributions, and suggesting avenues for future research.

2. Method

This study employs a three-phase research framework to systematically identify, evaluate, and prioritize the critical factors influencing occupational safety in high-rise construction projects. The methodology integrates both data-driven statistical analysis and expert-based decision-making, combining EFA and the AHP within a sequential design, as illustrated in Figure 1.

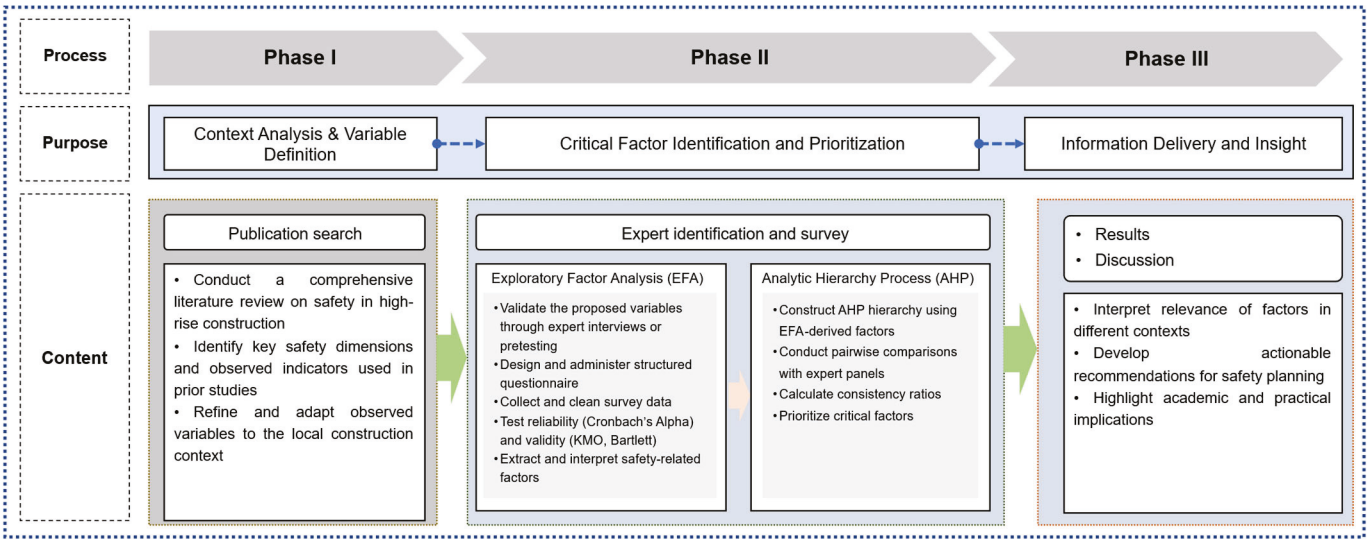

Figure 1. A hybrid EFA-AHP approach for prioritizing critical factors affecting occupational safety in high-rise construction.

Phase I focuses on context analysis and observed variable development. A comprehensive literature review was conducted to examine previous research on occupational safety in high-rise construction, with particular attention to accident causes, risk factors, and regulatory frameworks. This review facilitated the identification of key safety dimensions and observed indicators commonly used in international and local studies. These variables were then reviewed and refined through expert consultation to ensure their contextual relevance to construction practices in Vietnam. The resulting set of validated observed variables provided the foundation for the structured questionnaire used in Phase II.

Phase II comprises two sub-processes: factor extraction through EFA and factor prioritization using AHP. In the EFA sub-phase, survey data were collected from construction professionals with experience in managing on-site safety. The collected data underwent reliability assessment using Cronbach's Alpha and validity testing through the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity. Latent safety factors were extracted using Principal Axis Factoring with Varimax rotation. These factors represent underlying dimensions of occupational safety and were interpreted based on the pattern of factor loadings. Subsequently, in the AHP sub-phase, the extracted factors served as evaluation criteria in a hierarchical decision model. Expert panels from three high-rise construction projects were engaged to conduct pairwise comparisons, assessing the relative importance of each factor. Consistency ratios were calculated to verify the coherence of

expert judgments, and normalized weights were synthesized to produce a prioritized ranking of safety factors for each project.

Phase III centers on information delivery and practical insight generation. The results of the AHP analysis were compared across the three case study projects to identify both common and context-specific safety priorities. These findings were then interpreted to draw actionable implications for project managers, safety officers, and policymakers. Strategic recommendations are provided to support more targeted safety planning, resource allocation, and risk mitigation strategies in high-rise construction environments. By integrating empirical factor analysis with expert prioritization, this study offers a comprehensive framework for enhancing occupational safety management in complex urban construction settings.

2.1. Data Collection

The identification of observed variables in this study was conducted through a structured, multi-phase approach to ensure both theoretical rigor and contextual relevance to occupational safety in high-rise construction projects in Vietnam. Initially, 38 observed variables were compiled through a comprehensive review of 16 domestic and international studies on construction safety. This preliminary list was then evaluated by a panel of experienced professionals, including engineers, site supervisors, and safety managers, through targeted expert consultation sessions. Based on their feedback, eight variables were either redundant, unclear, or insufficiently relevant to the local construction context, and were therefore removed. At the same time, the experts proposed four additional variables that captured context-specific risks, such as limited working space and the use of stimulants during work. This refinement process resulted in a final set of 34 observed variables, which were then incorporated into the main questionnaire, as listed in Table 1.

Table 1. Observed variables after reviewing related studies.

No.	Code	Observed Variable Name	Reference
1	OV1	Lack of safety equipment and tools	[11,20–22]
2	OV2	Outdated or damaged safety equipment and tools	[20,22]
3	OV3	Improper use of equipment and tools	[20–22]
4	OV4	Presence of safety warning signs	[20,22]
5	OV5	Established safety regulations and guidelines	[23]
6	OV6	Hot or rainy weather conditions	[11,20–22]
7	OV7	Dust and noise	[11,20]
8	OV8	Lack of protective gear for workers	[22]
9	OV9	Heavy workload and overtime	[22]
10	OV10	Electrical leakage	[20,21]
11	OV11	Working space	Expert recommendation
12	OV12	Managers' knowledge of occupational safety	[11,22]
13	OV13	Work experience	[22]
14	OV14	Ability to plan reasonable construction site layout	[24]
15	OV15	Ability to schedule construction time reasonably	[25]
16	OV16	Ability to organize construction process reasonably	[24,26]
17	OV17	Ability to allocate tasks appropriately	[24]
18	OV18	Willingness to listen to subordinates' feedback and suggestions	[22]
19	OV19	Ability to communicate with subordinates	[22]
20	OV20	Low-skilled workers	[20,22]
21	OV21	Workers' compliance with safety rules on site	[21,27]
22	OV22	Workers lacking occupational safety certificates	[11]
23	OV23	Workers with poor health or underlying conditions	[22]
24	OV24	Workers using stimulants while working	Expert recommendation

Table 1. *Cont.*

No.	Code	Observed Variable Name	Reference
25	OV25	Monitoring the use of personal protective equipment by workers	[11,21,22]
26	OV26	Regular inspection of safety and risks on site	[11]
27	OV27	Commitment to safety management on site	[21]
28	OV28	Training/education	[11,22,28]
29	OV29	Periodic assessment of workers' safety knowledge	[11,20]
30	OV30	Ineffective safety training methods for workers	[29,30]
31	OV31	Periodic health check-ups for workers	[31]
32	OV32	Regular inspection and maintenance of equipment/machinery	[22]
33	OV33	Periodic labor management meetings	Expert recommendation
34	OV34	Inspections by related authorities on safety compliance	Expert recommendation

Based on the finalized list of 34 observed variables, a structured questionnaire was developed to evaluate the perceived impact of each factor on occupational safety in high-rise construction. A 5-point Likert scale was used, where respondents rated each item from 1 (very low impact) to 5 (very high impact). This scale allowed for the quantification of expert perceptions while maintaining clarity and consistency in responses. The questionnaire was distributed online via Google Forms and shared through professional networks, construction-related social media platforms, and organizational channels, to reach practitioners with relevant experience in high-rise projects in Vietnam.

2.2. Data Analysis

2.2.1. Exploratory Factor Analysis

To empirically identify the latent dimensions influencing occupational safety in high-rise construction, this study applied EFA to a dataset consisting of 23 observed variables. These variables were developed based on a comprehensive literature review and validated through expert consultation to ensure their contextual relevance to the construction industry in Vietnam. EFA was deemed appropriate to uncover latent constructs and organize the observed variables into coherent dimensions. This method is based on the assumption that correlations among observed variables are driven by a smaller number of unobserved latent factors that represent common sources of variance. Mathematically, the EFA model is expressed in matrix form as

$$\boldsymbol{X} = \boldsymbol{\Lambda F} + \varepsilon \tag{1}$$

where

- $\boldsymbol{X} = \left[\boldsymbol{X_1}, \boldsymbol{X_2}, \ldots \boldsymbol{X_p}\right]^\top$ is a $p \times 1$ vector of standardized observed variables,
- $\boldsymbol{F} = \left[\boldsymbol{F_1}, \boldsymbol{F_2}, \ldots \boldsymbol{F_m}\right]^\top$ is an $m \times 1$ vector of common (latent) factor,
- $\boldsymbol{\Lambda} = \left[\lambda_{ij}\right]$ is a $p \times m$ factor loading matrix, where each element λ_{ij} represents the degree to which factor F_j influences observed variable X_i,
- $\varepsilon = \left[\boldsymbol{\varepsilon_1}, \boldsymbol{\varepsilon_2}, \ldots \boldsymbol{\varepsilon_p}\right]^\top$ is a $p \times 1$ vector of unique variances or measurement errors.
- In this formulation, the subscript $i = 1, 2, \ldots, p$ indexes the observed variables, and $j = 1, 2, \ldots, m$ indexes the latent factors. Each observed variable X_i is modeled as a linear combination of the mmm underlying factors F_j, weighted by their corresponding loadings λ_{ij}, plus a unique error term ε_i. A large value of λ_{ij} implies a strong contribution of factor F_j to the variance of observed variable X_i, while the residual ε_i represents idiosyncratic variance, including measurement error.

The EFA procedure followed in this study consisted of five key steps. First, the adequacy of the dataset for factor analysis was evaluated using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity. A KMO value exceeding 0.6 and a significant Bartlett's test ($p < 0.05$) confirmed the dataset was suitable for EFA. Second,

internal consistency was assessed using Cronbach's Alpha, and items with corrected item-total correlations below 0.3 were considered for removal. Third, latent components were extracted using Principal Component Analysis (PCA), which aims to reduce dimensionality by transforming the original variables into a new set of orthogonal components that successively maximize explained variance. The number of factors to retain was determined using the Kaiser criterion (eigenvalues > 1) and validated by examining the scree plot. Fourth, to improve the clarity of the factor structure, a Varimax orthogonal rotation was applied, aiming to ensure each observed variable load, primarily on one factor. Items with factor loadings below 0.5 or with cross-loadings on multiple factors were subject to review and potential removal. Finally, the retained factors were labeled, based on thematic consistency among their associated observed variables. These extracted safety dimensions served as the structured input for the AHP conducted in the following phase of the study.

2.2.2. Analytic Hierarchy Process

In this study, AHP serves as a prioritization tool to quantify expert assessments regarding the significance of each factor previously extracted through EFA. This integration ensures that factor identification is data-driven, while the prioritization process captures context-specific expert insight, enhancing both the empirical grounding and practical relevance of the findings.

AHP structures decision problems into a hierarchical model that consists of three levels: (i) the overall goal at the top (i.e., prioritizing factors), (ii) the criteria layer composed of factors identified via EFA, and (iii) the alternatives or decision scenarios at the bottom (if applicable). The prioritization process begins by conducting pairwise comparisons of all criteria at the same level with respect to their contribution to the goal. Experts are asked to express their judgments using Saaty's fundamental 1–9 scale, where a score of 1 indicates equal importance, and a score of 9 reflects extreme preference of one factor over another.

The pairwise comparison matrix is denoted as $\boldsymbol{A} = [a_{kl}]$, where $k, l = 1, 2, \ldots, m$, and m is the number of criteria (i.e., factors extracted via EFA). Each entry $\boldsymbol{a_{k,l}}$ reflects the relative importance of criterion $\boldsymbol{C_k}$ over criterion $\boldsymbol{C_l}$ based on expert judgment. The matrix is reciprocal by definition, satisfying $a_{kl} = 1/a_{kl}$, and a $a_{kk} = 1$ for all k.

$$\boldsymbol{A} = \begin{bmatrix} 1 & \ldots & a_{1m} \\ \vdots & \ddots & \vdots \\ \frac{1}{a_{1m}} & \ldots & 1 \end{bmatrix} \tag{2}$$

The priority vector $\boldsymbol{w} = [\boldsymbol{w}_1, \boldsymbol{w}, \ldots \boldsymbol{w_m}]^\top$, which contains the normalized weights of each criterion, is obtained by solving the eigenvalue equation:

$$\boldsymbol{Aw} = \lambda_{max}\boldsymbol{w} \tag{3}$$

where λ_{max} is the maximum eigenvalue of matrix A. It is important to note that λ_{max} is conceptually distinct from the factor loadings λ_{ij} used in EFA. While λ_{ij} represents the strength of the relationship between observed variable i and latent factor j, λ_{max} in AHP is a scalar measure used solely to evaluate the internal consistency of expert judgments.

To determine the consistency of the pairwise comparisons, the Consistency Index (CI) and Consistency Ratio (CR) are calculated as follows:

$$CI = \frac{\lambda_{max} - m}{m - 1}, CR = \frac{CI}{RI} \tag{4}$$

where RI is the Random Index, a standard value depending on matrix size mmm. A $CR \leq 0.10$ is considered acceptable. If CR exceeds this threshold, expert judgments are subject to revision, for improved consistency.

Once consistency is verified, the normalized weights w_k are synthesized to yield a priority ranking of the safety factor groups. This process was independently applied to expert panels from three real-world high-rise construction projects in Vietnam, enabling a comparative analysis of safety priorities across project contexts. The integration of EFA and AHP provides a robust analytical foundation for identifying, structuring, and ranking the critical dimensions of occupational safety, ultimately supporting data-informed decision-making in construction safety management.

3. Results

The survey targeted individuals with practical experience in high-rise construction projects in Vietnam, including engineers, site supervisors, project managers, and contractor and investor organizations. A total of 186 responses were collected through the online questionnaire distribution. After applying data screening procedures, including removing incomplete entries, duplicate submissions, and responses with uniform scoring patterns, 181 valid responses were retained for analysis. As illustrated in Figure 2, most respondents were site supervisors and engineers with more than three years of professional experience, ensuring that the collected data reflected informed and practical insights from the field. A preliminary screening based on mean values was conducted to ensure the analytical validity of the dataset. Since the questionnaire used a 5-point Likert scale where a score of 3 represented neutrality, only variables with a mean score of 3 or higher were considered relevant and retained. As a result, 11 variables with mean values below three were excluded, leaving a refined set of 23 observed variables, as listed in Table 2. These variables were then analyzed using EFA to identify latent factor structures. The resulting factors formed a validated basis for the subsequent prioritization using the AHP.

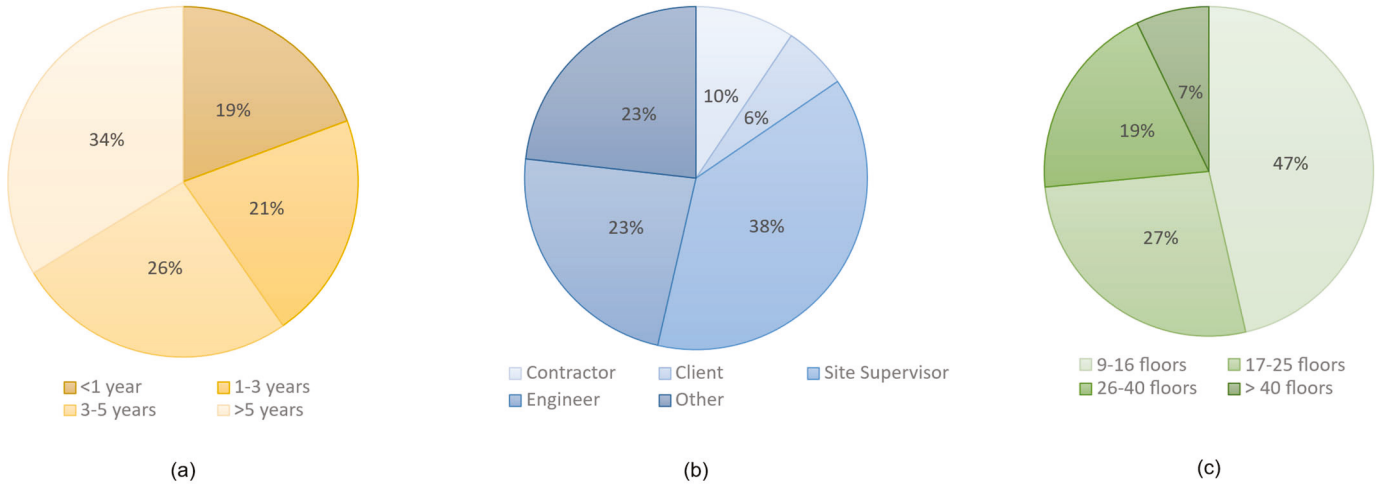

Figure 2. Distribution of the 181 collected survey responses by (**a**) work experience in the construction industry, (**b**) occupational role, and (**c**) number of floors of buildings worked on.

Table 2. Observed Variables for EFA.

No.	Code	Observed Variable Name	Mean
1	OV2	Outdated or damaged safety equipment and tools	4.1713
2	OV3	Improper use of equipment and tools	4.1105
3	OV5	Established safety regulations and guidelines	4.105
4	OV22	Workers lacking occupational safety certificates	4.0608
5	OV21	Workers' compliance with safety rules on site	4.0442
6	OV4	Presence of safety warning signs	4.0166
7	OV30	Ineffective safety training methods for workers	3.9448
8	OV31	Periodic health check-ups for workers	3.9392
9	OV32	Regular inspection and maintenance of equipment/machinery	3.9392
10	OV20	Low-skilled workers	3.9116
11	OV29	Periodic assessment of workers' safety knowledge	3.9116
12	OV28	Training/education	3.9006
13	OV9	Heavy workload and overtime	3.8398
14	OV1	Lack of safety equipment and tools	3.8287
15	OV7	Dust and noise	3.8122
16	OV14	Ability to plan reasonable construction site layout	3.8122
17	OV8	Lack of protective gear for workers	3.7735
18	OV15	Ability to schedule construction time reasonably	3.6906
19	OV16	Ability to organize construction process reasonably	3.6906
20	OV12	Managers' knowledge of occupational safety	3.6796
21	OV13	Work experience	3.6685
22	OV10	Electrical leakage	3.5801
23	OV27	Commitment to safety management on site	3.3702

3.1. EFA Results

Prior to factor extraction, the dataset's suitability for EFA was confirmed by the Kaiser–Meyer–Olkin (KMO) measure of 0.750 and a highly significant Bartlett's Test of Sphericity (Chi-square = 2261.683, df = 253, $p < 0.001$), demonstrating sampling adequacy and sufficient inter-variable correlation, as listed in Table 3.

Table 3. KMO and Bartlett's test of sphericity—analysis based on 23 observed variables.

KMO and Bartlett's Test		
Kaiser–Meyer–Olkin Measure of Sampling Adequacy.		0.750
Bartlett's Test of Sphericity	Approx. Chi-Square	2261.683
	df	253
	Sig.	0.000

In this study, EFA was performed using the Principal Component Analysis (PCA) method as the extraction technique. PCA assumes that observed variables share a common variance structure, and aims to explain the maximum variance through a reduced set of components. Components were retained based on the Kaiser criterion (eigenvalues > 1.0) and further supported by the scree plot. As shown Table 4, five factors were extracted, explaining a cumulative variance of 66.97%, which exceeds the conventional threshold of 50% for social and management sciences. The first factor accounted for 17.07% of the variance after rotation, while the second to fifth factors explained 14.60%, 13.52%, 13.01%, and 8.76%, respectively.

Table 4. Principal Component Analysis.

Total Variance Explained									
Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	4.182	18.183	18.183	4.182	18.183	18.183	3.926	17.071	17.071
2	3.524	15.323	33.506	3.524	15.323	33.506	3.358	14.601	31.673
3	3.114	13.540	47.046	3.114	13.540	47.046	3.111	13.525	45.197
4	2.626	11.419	58.465	2.626	11.419	58.465	2.992	13.010	58.207
5	1.955	8.502	66.967	1.955	8.502	66.967	2.015	8.760	66.967
6	0.977	4.246	71.213						
7	0.813	3.536	74.749						
8	0.750	3.260	78.009						
9	0.611	2.655	80.664						
10	0.588	2.557	83.222						
11	0.553	2.405	85.627						
12	0.481	2.093	87.720						
13	0.445	1.933	89.653						
14	0.394	1.713	91.366						
15	0.332	1.445	92.811						
16	0.315	1.371	94.182						
17	0.277	1.202	95.384						
18	0.214	0.932	96.317						
19	0.213	0.927	97.244						
20	0.191	0.832	98.076						
21	0.168	0.729	98.805						
22	0.150	0.651	99.457						
23	0.125	0.543	100.000						

Extraction Method: Principal Component Analysis.

To enhance interpretability, the extracted factors were rotated using the Varimax orthogonal rotation method. This approach aims to simplify the factor structure by maximizing the variance of squared loadings across variables, thereby ensuring each variable loads highly on only one factor. As presented in Table 5, 23 observed variables had factor loadings greater than 0.5 on their respective components, indicating statistically significant contributions to the extracted structure.

Table 5. Varimax orthogonal rotation.

Rotated Component Matrix [a]					
	Component				
	1	**2**	**3**	**4**	**5**
OV28	0.847				
OV30	0.834				
OV29	0.829				
OV31	0.826				
OV32	0.821				
OV27	0.632				
OV15		0.851			
OV14		0.822			
OV13		0.802			
OV12		0.796			
OV16		0.793			
OV9			0.915		
OV7			0.883		
OV8			0.872		
OV10			0.783		
OV4				0.862	

Table 5. *Cont.*

Rotated Component Matrix [a]					
	Component				
	1	2	3	4	5
OV5				0.828	
OV2				0.816	
OV3				0.758	
OV1				0.511	
OV21					0.887
OV20					0.759
OV22					0.753

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. [a] Rotation converged in five iterations.

Based on the pattern of loadings and conceptual coherence, the five factors were interpreted and labeled as follows:

- Factor 1 (TB): Safety Equipment, Tools, and Signage (OV1, OV2, OV3, OV4, OV5).
- Factor 2 (MTLV): Working Conditions and Environment (OV7, OV9, OV10, OV8).
- Factor 3 (NSDLD): Employer's Knowledge, Skills, and Responsibility (OV12, OV13, OV14, OV15, OV16).
- Factor 4 (KTNLD): Worker's Skills and Compliance (OV20, OV21, OV22).
- Factor 5 (ATLD): Safety Training and Inspection (OV28, OV29, OV30, OV31, OV32, OV27).

To verify the internal consistency of each factor, Cronbach's Alpha was computed using the group of observed variables associated with each factor. The results are summarized in Table 6. All five factors demonstrated high reliability, with Cronbach's Alpha coefficients ranging from 0.729 to 0.891, exceeding the commonly accepted threshold of 0.6. This confirms that the items within each factor measure coherent latent constructs with acceptable internal consistency.

Table 6. Cronbach's Alpha Coefficients for each factor.

Factor Name	Cronbach's Alpha
Factor 1: Safety Equipment, Tools, and Signage	0.813
Factor 2: Working Conditions and Environment	0.891
Factor 3: Employer's Knowledge, Skills, and Responsibility	0.873
Factor 4: Worker's Knowledge and Compliance	0.729
Factor 5: Safety Training and Inspection	0.888

3.2. AHP Results

The results of AHP produced a clear prioritization of the five safety-related factors, reflecting expert consensus on their relative importance to occupational safety in high-rise construction. The aggregated pairwise comparison matrix yielded a CR of 0.05, indicating high internal coherence and methodological reliability. As listed in Table 7, the matrix incorporates nine levels of comparative intensity, and the direction of preference is visualized through color-coded entries: black text denotes the more critical factor in each comparison, while red text indicates the less preferred counterpart. This allows for immediate interpretation of the dominance relationships between factors. For instance, the comparison between Safety Training and Inspection (ATLD) and Employer's Knowledge, Skills, and Responsibility (NSDLD) yielded a preference ratio of 2.35216, suggesting that experts consider ATLD moderately more influential than NSDLD. Similar patterns are observed in comparisons with other factors, where ATLD consistently receives higher ratings, particularly over Safety Equipment and Signage (TB) (5.378:1) and Working Conditions and Environment (MTLV) (3.898:1).

Table 7. Pairwise comparison matrices of factor groups provided by the experts.

	ATLD	NSDLD	MTLV	TB	KTLND
ATLD		2.352	3.898	5.378	3.776
NSDLD			4.129	3.366	1.059
MTLV				1.644	4.183
TB					4.043
KTLND					

The final normalized weights, presented in Table 8, reaffirm these preferences: ATLD received the highest priority score (0.447), followed by NSDLD (0.216) and Worker's Knowledge and Compliance (KTNLD), at 0.205. The remaining two factors, MTLV and TB, were assigned considerably lower weights of 0.074 and 0.058, respectively. These results highlight a statistically validated hierarchy of safety factors, anchored in expert judgment and supported by consistent comparative reasoning.

Table 8. CI values of factor.

	CI Values
ATLD	0.447
NSDLD	0.216
MTLV	0.074
TB	0.058
KTLND	0.205
Inconsistency = 0.05 with 0 missing judgments	

4. Discussion

Based on a dual application of EFA and AHP methodologies, this study provides an understanding of critical safety drivers in high-rise construction. The five-factor structure derived from EFA encapsulates a holistic view of occupational safety risks. These include (1) Safety Training and Inspection, (2) Employer's Knowledge, Skills, and Responsibility, (3) Worker's Knowledge and Compliance, (4) Working Conditions and Environment, and (5) Safety Equipment, Tools, and Signage. These factors together reflect the procedural, behavioral, organizational, environmental, and technical domains that shape safety outcomes in high-rise construction. Notably, the factor structure was not only statistically valid, explaining over 66% of the total variance, but also conceptually robust, aligning with prevailing theories of safety systems that emphasize a balance between structural controls and human agency.

The AHP results provide an empirically grounded prioritization of these factors, offering new insights into how safety professionals in the field perceive their relative impact. The dominance of ATLD in the AHP results is consistent with the inherent complexity and vertical risk profile of high-rise construction projects. In these environments, the physical scale and multi-tiered workflows expose workers to a wide range of hazards, from falls at height to crane-related incidents and confined-space accidents. Consequently, formal safety training, routine inspection regimes, and structured knowledge reinforcement become essential mechanisms to mitigate the unpredictability and severity of potential incidents. This result reinforces global safety trends that emphasize proactive risk control through human systems, rather than relying solely on post-incident interventions or passive safeguards.

The strong prioritization of NSDLD and KTNLD further highlights the critical role of human capital in safety outcomes. These two factors, together with ATLD, account for nearly 87% of the total priority weight, signaling a strong consensus that organizational behavior and human decision-making are central to effective safety performance. This

prioritization likely stems from the hierarchical nature of construction operations, where managerial oversight determines the consistency of enforcement and where workers' situational awareness directly influences hazard identification and response. In high-rise projects, where construction sequencing is highly interdependent and tolerance for procedural errors is low, the technical competence of managers and the behavioral compliance of laborers become even more consequential.

In contrast, the lower relative weight assigned to MTLV and TB does not suggest these factors are unimportant, but reflects a recognition that their effectiveness is contingent on how they are implemented and monitored. In many cases, safety equipment may be available but improperly used, or warning signage may be present but ignored, without sufficient training and oversight. This underscores a crucial point: technical and environmental controls serve as enablers rather than guarantees of safety, and their impact is ultimately shaped by the procedural systems and human behaviors that surround them. Figure 3 illustrates a set of strategic research directions derived from the prioritized safety factors identified in this study. Four cross-cutting enablers, cultural adaptation, regulatory alignment, digital transformation, and longitudinal evaluation represent critical pathways for integrating these strategies into diverse and evolving construction contexts. Each domain is paired with forward-looking research themes that reflect evolving industry needs and technological advancements. For instance, procedural dimensions emphasize real-time safety monitoring, digital-twin simulation, and adaptive training models [32]. In contrast, organizational and behavioral dimensions point toward leadership development, multicultural communication, and behavior-based safety (BBS) systems. Environmental and equipment-related domains highlight the need for resilience planning, ergonomic design, and innovative safety technologies. Compared to other hybrid decision-support models such as Fuzzy AHP (F-AHP) or Bayesian networks, the EFA-AHP framework adopted in this study offers a practical and accessible approach for early-stage decision-making. F-AHP enhances the ability to handle uncertainty in expert judgments through fuzzy logic, and Bayesian networks are robust in modeling probabilistic dependencies and causal relationships among safety factors. However, these approaches often require extensive prior data, complex calibration, or specialized computational tools, which may be challenging to implement in resource-constrained environments. In contrast, the EFA–AHP framework allows for empirical factor discovery and structured prioritization with greater interpretability and lower implementation barriers. It is well-suited to the Vietnamese construction industry context.

While this study offers meaningful insights and methodological contributions, several limitations should be acknowledged. (1) The AHP results rely on expert judgments, which, despite high internal consistency, may still reflect individual bias influenced by personal experience, organizational roles, or project-specific contexts. (2) The expert panel was limited to professionals operating in high-rise construction projects within Vietnam, which may constrain the generalizability of the findings to other geographic regions or construction typologies. (3) The cross-sectional nature of the data prevents analysis of how safety perceptions and priorities evolve over the life cycle of a project. (4) The factor structure and prioritization outcomes are shaped by Vietnam's regulatory and industry context, which may not reflect safety dynamics elsewhere. Future studies should apply the framework in other regions to evaluate the consistency of safety dimensions across diverse construction environments.

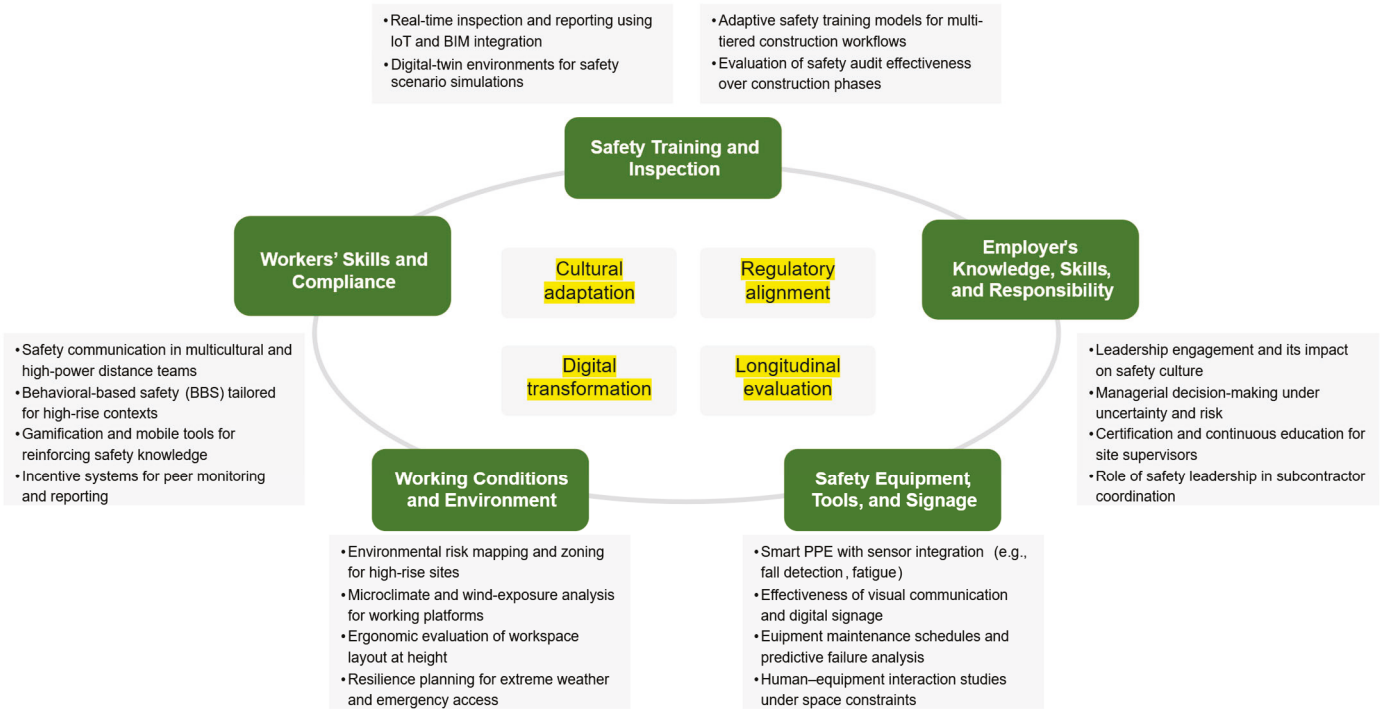

Figure 3. Strategic research directions for enhancing safety in high-rise construction.

5. Conclusions

This study aims to advance construction safety research by identifying and prioritizing the critical factors influencing occupational safety in high-rise building projects. It uses a hybrid methodological framework that integrates EFA and the AHP. By integrating empirical factor identification with expert-informed prioritization, the study bridges the gap between theoretical understanding and actionable insight. The resulting framework provides a structured basis for strategic safety planning, training design, and resource allocation in high-rise construction environments. Since then, the framework has provided valuable lessons learned for developing and underdeveloped countries to improve safety practices toward construction sustainability. Future research should consider expanding the expert sample to include a broader and more diverse range of stakeholders, such as regulatory authorities, subcontractors, and labor representatives. Moreover, future research should incorporate Confirmatory Factor Analysis (CFA), to validate the extracted factor structure. This additional step will enhance the model's statistical robustness and allow for hypothesis testing regarding interrelationships among safety dimensions, especially when applied to larger and more diverse samples. Longitudinal studies could also examine the temporal dynamics of safety interventions and evaluate how the relative importance of safety factors may shift across different construction phases.

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Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Kanan, R.; Elhassan, O.; Bensalem, R. An IoT-Based Autonomous System for Workers' Safety in Construction Sites with Real-Time Alarming, Monitoring, and Positioning Strategies. *Autom. Constr.* **2018**, *88*, 73–86. [CrossRef]
2. Tran, S.V.T.; Yang, J.; Hussain, R.; Khan, N.; Kimito, E.C.; Pedro, A.; Sotani, M.; Lee, U.K.; Park, C. Leveraging Large Language Models for Enhanced Construction Safety Regulation Extraction. *J. Inf. Technol. Constr.* **2024**, *29*, 1026–1038. [CrossRef]
3. Fang, W.; Ding, L.; Love, P.E.D.; Luo, H.; Li, H.; Peña-Mora, F.; Zhong, B.; Zhou, C. Computer Vision Applications in Construction Safety Assurance. *Autom. Constr.* **2020**, *110*, 103013. [CrossRef]
4. Tran, S.V.T.; Pham, H.C.; Le, Q.T.; Lee, U.K. Digital Technologies for Monitoring Hazardous Area Entry in Construction Sites. *Autom. Constr.* **2025**, *177*, 106357. [CrossRef]
5. Kim, K.; Jeong, I.; Cho, Y.K. Signal Processing and Alert Logic Evaluation for IoT–Based Work Zone Proximity Safety System. *J. Constr. Eng. Manag.* **2023**, *149*, 05022018. [CrossRef]
6. U.S. Bureau of Labor Statistics. *National Census of Fatal Occupational Injuries in 2023*; U.S. Bureau of Labor Statistics: Washington, DC, USA, 2024.
7. Tran, S.V.-T.; Lee, D.; Bao, Q.L.; Yoo, T.; Khan, M.; Jo, J.; Park, C. A Human Detection Approach for Intrusion in Hazardous Areas Using 4D-BIM-Based Spatial-Temporal Analysis and Computer Vision. *Buildings* **2023**, *13*, 2313. [CrossRef]
8. Venkatesh, P.; Ergan, S. Classification of Challenges in Achieving BIM-Based Safety-Requirement Checking in Vertical Construction Projects. *J. Constr. Eng. Manag.* **2023**, *149*, 04023131. [CrossRef]
9. Ansari, R.; Dehghani, P.; Mahdikhani, M.; Jeong, J. A Novel Safety Risk Assessment Based on Fuzzy Set Theory and Decision Methods in High-Rise Buildings. *Buildings* **2022**, *12*, 2126. [CrossRef]
10. Junjia, Y.; Alias, A.H.; Haron, N.A.; Bakar, N.A. Development of a Hoisting Safety Risk Framework Based on the STAMP Theory and PLS-SEM Method. *IEEE Access* **2024**, *12*, 122998–123017. [CrossRef]
11. Li, Y.; Ning, Y.; Chen, W.T. Critical Success Factors for Safety Management of High-Rise Building Construction Projects in China. *Adv. Civ. Eng.* **2018**, *2018*, 1516354. [CrossRef]
12. Tripathi, P.; Mittal, Y.K. Risk Assessment and Ranking Methodology for Occupational Hazards in Construction: A Case of Indian High-Rise Projects. *Smart Sustain. Built Environ.* 2024; *ahead of print*. [CrossRef]
13. Kwon, K.; Kang, M.; Kim, D.; Choi, H. Prioritization of Hazardous Zones Using an Advanced Risk Management Model Combining the Analytic Hierarchy Process and Fuzzy Set Theory. *Sustainability* **2023**, *15*, 12018. [CrossRef]
14. Casanovas, M.d.M.; Armengou, J.; Ramos, G. Occupational Risk Index for Assessment of Risk in Construction Work by Activity. *J. Constr. Eng. Manag.* **2013**, *140*, 04013035. [CrossRef]
15. Patel, D.A.; Jha, K.N. Structural Equation Modeling for Relationship-Based Determinants of Safety Performance in Construction Projects. *J. Manag. Eng.* **2016**, *32*, 05016017. [CrossRef]
16. Waqar, A.; Khan, M.B.; Shafiq, N.; Skrzypkowski, K.; Zagórski, K.; Zagórska, A. Assessment of Challenges to the Adoption of IOT for the Safety Management of Small Construction Projects in Malaysia: Structural Equation Modeling Approach. *Appl. Sci.* **2023**, *13*, 3340. [CrossRef]
17. Moosa, M.H.; Oriet, L.P. Factors Affecting Safety Performance in the Construction Industry: An Empirical Study Using Structural Equation Modelling. *Int. J. Occup. Saf. Ergon.* **2022**, *28*, 779–789. [CrossRef]
18. Mosly, I. Factors Influencing Safety Performance in the Construction Industry of Saudi Arabia: An Exploratory Factor Analysis. *Int. J. Occup. Saf. Ergon.* **2022**, *28*, 901–908. [CrossRef]
19. Wang, J.; Chen, Z.; Song, Y.; Liu, Y.; He, J.; Ma, S. Data-Driven Dynamic Bayesian Network Model for Safety Resilience Evaluation of Prefabricated Building Construction. *Buildings* **2024**, *14*, 570. [CrossRef]
20. Goh, K.C.; Goh, H.H.; Omar, M.F.; Toh, T.C.; Mohd Zin, A.A. Accidents Preventive Practice for High-Rise Construction. *MATEC Web Conf.* **2016**, *47*, 04004. [CrossRef]
21. Ayob, A.; Shaari, A.A.; Zaki, M.F.M.; Munaaim, M.A.C. Fatal Occupational Injuries in the Malaysian Construction Sector–Causes and Accidental Agents. *IOP Conf. Ser. Earth Environ. Sci.* **2018**, *140*, 012095. [CrossRef]
22. Manzoor, B.; Othman, I.; Waheed, A. Accidental Safety Factors and Prevention Techniques for High-Rise Building Projects—A Review. *Ain Shams Eng. J.* **2022**, *13*, 101723. [CrossRef]
23. Othman, I.; Kamil, M.; Sunindijo, R.Y.; Alnsour, M.; Kineber, A.F. Critical Success Factors Influencing Construction Safety Program Implementation in Developing Countries. *J. Phys. Conf. Ser.* **2020**, *1529*, 042079. [CrossRef]
24. Zou, P.X.W.; Sunindijo, R.Y. Skills for Managing Safety Risk, Implementing Safety Task, and Developing Positive Safety Climate in Construction Project. *Autom. Constr.* **2013**, *34*, 92–100. [CrossRef]
25. Tran, S.V.T.; Khan, N.; Lee, D.; Park, C. A Hazard Identification Approach of Integrating 4d Bim and Accident Case Analysis of Spatial–Temporal Exposure. *Sustainability* **2021**, *13*, 2211. [CrossRef]
26. Yi, W.; Chan, A.P.C. Critical Review of Labor Productivity Research in Construction Journals. *J. Manag. Eng.* **2013**, *30*, 214–225. [CrossRef]

27. Pedro, A.; Pham-Hang, A.T.; Nguyen, P.T.; Pham, H.C. Data-Driven Construction Safety Information Sharing System Based on Linked Data, Ontologies, and Knowledge Graph Technologies. *Int. J. Environ. Res. Public Health* **2022**, *19*, 794. [CrossRef]
28. Bao, L.; Tran, S.V.T.; Nguyen, T.L.; Pham, H.C.; Lee, D.; Park, C. Cross-Platform Virtual Reality for Real-Time Construction Safety Training Using Immersive Web and Industry Foundation Classes. *Autom. Constr.* **2022**, *143*, 104565. [CrossRef]
29. Pham, H.C.; Dao, N.; Pedro, A.; Le, Q.T.; Hussain, R.; Cho, S.; Park, C.S. Virtual Field Trip for Mobile Construction Safety Education Using 360-Degree Panoramic Virtual Reality. *Int. J. Eng. Educ.* **2018**, *34*, 1174–1191.
30. Hussain, R.; Pedro, A.; Lee, D.Y.; Pham, H.C.; Park, C.S. Impact of Safety Training and Interventions on Training-Transfer: Targeting Migrant Construction Workers. *Int. J. Occup. Saf. Ergon.* **2020**, *26*, 272–284. [CrossRef]
31. Hakro, S.; Jinshan, L. Workplace Employees' Annual Physical Checkup and During Hire on the Job to Increase Health-Care Awareness Perception to Prevent Disease Risk: A Work for Policy-Implementable Option Globally. *Saf. Health Work* **2019**, *10*, 132–140. [CrossRef]
32. Bao, Q.L.; Tran, S.V.T.; Yang, J.; Pedro, A.; Pham, H.C.; Park, C. Token Incentive Framework for Virtual-Reality-Based Construction Safety Training. *Autom. Constr.* **2024**, *158*, 105167. [CrossRef]

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Exploring Factors Impeding the Implementation of Health and Safety Control Measures in the South African Construction Industry

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Abstract

Organisations have provided health and safety (H&S) control measures for construction activities, but the literature suggests that implementing these measures in the construction industry remains a challenge. This study aims to explore the factors impeding the implementation of H&S control measures (barriers). The study followed a qualitative research approach using interview form as a data collection tool designed to collect qualitative data on the factors impeding the implementation of H&S control measures. Purposive sampling method was adopted. The content analysis method was used to analyse the collected data. The findings reveal that the implementation of H&S control measures is affected by different barriers. The study uncovered eight main barriers (lack of management support and commitment, implementation costs, lack of training and education, language and cultural differences, time pressure, prioritisation of production over H&S issues, lack of worker involvement and participation and lack of communication) to the implementation of H&S control measures. Respondents were mainly from H&S background; it would be interesting to explore the perceptions of site managers, engineers, designers, supervisors and field workers through the use of a quantitative approach involving a larger sample. By identifying and understanding these barriers to the implementation of H&S control measures, construction organisations could be in a better position to control construction hazards. This paper adds value to construction organisations and professionals' understanding of barriers to the implementation of H&S control measures on construction sites. The study also recommends measures to remove barriers or facilitate better implementation of H&S control measures on construction sites.

Keywords: implementation; impeding factors; barriers; health and safety; hazard control; construction industry

1. Introduction

Hazards such as working at height, excavation, welding, lifting, driving and manual handling are prevalent at construction sites. Construction industry exposes workers to biological, chemical, physical, mechanical, psychosocial and ergonomic hazards [1]. By contrast, several scholars believe that these hazards can be controlled [2–4]. Likewise, organisations which are unable to deal with these hazards increase the likelihood of workers suffering from injuries, illnesses, diseases and accidents. This can lead to loss of income, life, skills and productivity [5–7]. The construction industry is known for being a source of accidents and ranks high in terms of injury rates. The situation is not different in South Africa and United Kingdom [6,8]. Thus, both developed and developing countries

remain affected by accidents [6,9]. Others have indicated that the accident rate is higher in developing countries than developed countries [10,11]. Ref. [10] in their recent study on health and safety (H&S) practices, recommended that appropriate and preventative actions should be taken to improve H&S in developing countries. Theoretically, lack of control contributes to accidents which may lead to higher accident rates. Several studies have argued that control measures should be implemented to manage hazards. Ref. [12] used a toolbox talk training as one of the measures to reduce the potential for occupational injury, while [13] explored the use of safe work method statement in controlling risks. Similarly, it is stated that implementing H&S management system is key to reducing site risks [13,14]. On the other hand, ref. [15] concluded that the design construction technologies such as building information modelling, virtual reality and augmented reality could be used to predict and control hazards. The above studies show that different H&S measures are used to control hazards on construction sites. H&S specifications, plans, safe working procedures, H&S induction training, method statements, construction design technologies, training, personal protective equipment (PPE), guarding and isolation are some of the examples used to control hazards [2,16–18]. Additionally, hazards can be designed out [19] or eliminated [2,20]. This can reduce costs and time spent dealing with hazards during the construction phase. Several authors have recognised the value of H&S control measures in managing construction activities [2,3,20] or any workplace activities [21,22]. Practically, organisations have provided H&S control measures for construction activities. Ref. [3] explored small business construction industry participants' understanding of H&S risk control. Participants were asked to identify appropriate control measures for skin diseases and fall. Although some barriers and facilitators were identified, a study by [3] focused more on understanding of H&S risk control. Hence, the current study attempts to provide an understanding on the barriers to the implementation of H&S control measures.

On the other hand, ref [2] investigated the quality of control measures for electrical hazards. The reviewed studies suggest that implementing appropriate control measures in the construction industry remains a challenge even though most accidents are attributed to poor hazard identification and control. Previous studies [2,3] on H&S control measures have focused on the application of hierarchy of hazard control and few studies have investigated the implementation of H&S control measures. The current study seeks to provide the factors impeding the implementation of H&S control measures (barriers) in the South African construction industry. The study objective is to identify the factors impeding the implementation of H&S measures. The identification of factors hindering implementation of H&S control measures is critical for adequate and effective hazard control. Given the above, the current study aims to explore the factors impeding the implementation of H&S control measures.

The next section discusses the literature relevant to this study. Topics such as hierarchy of controls, H&S management challenges and challenges relating to implementing H&S control measures are discussed. To achieve study objective, a qualitative study is adopted, and open-ended questions are used to explore the factors impeding the implementation of H&S control measures. The results are presented and discussed. Finally, the study conclusion and recommendations are presented.

2. Literature Review

2.1. Hierarchy of Hazard Controls Theory

The hierarchy of hazard controls theory has been used across different industries as a tool to select appropriate controls. To demonstrate its significance, it has been used for minimising lighting risks [21], integrating urban road safety and sustainable transportation [23], understanding H&S risk controls [3], managing electrical hazards [2] and common

construction activities [16]. However, the hierarchy of hazard control is usually preceded by Hazard Identification and Risk Assessment (HIRA) process. According to [3] HIRA process is followed by identifying and implementing the appropriate controls. Once the hazard is identified and risk assessed, the attention shifts to control measures. Alternatively, if hazard identification is not performed correctly, the determination of control measures becomes irrelevant. This means that unidentified hazards and unassessed risks negate the implementation of control measures. Similarly, ref. [24] states that hazard identification is critical for the assessment of risks and implementation of control measures. Thus, the relationship between HIRA process and selection or implementation of control measures should be understood well when managing H&S on construction sites.

Workers are encouraged to use hazard control hierarchy theory when selecting appropriate control measures [16]. According to this theory, there are five ways in which hazards can be managed: elimination, substitution, engineering, administrative and PPE [3,22,25]. Higher-level controls are also known as technological controls, while lower-level controls are known as behavioural controls [2,3]. The hierarchy of hazard controls further emphasises that top controls are more effective than bottom controls. This is also highlighted by [3,16], who suggest that controls focusing on changing worker behaviour are less effective than those which target hazards at their source, as well as work environment, or those aiming to change hazards. Despite this, a study by [16] found that construction organisations still use training and PPE more than other high-level controls. Similarly, ref. [2] found that behavioural controls were predominant in the construction industry. It is argued that these controls should be used together with the higher controls. This implies that PPE and administrative control should be used in combination with either elimination, substitution or engineering. According to [16] PPE should be used to increase the effectiveness but not used unilaterally, since it cannot ensure complete protection for workers [2]. The effectiveness, reliability and cost benefits of elimination, substitution and engineering controls make them the best options for improving H&S. Similarly, according to [20] the implementation of these controls does not depend on the performance of construction workers, whereas the implementation of behavioural controls requires workers' efforts [2]. As such, substitution and engineering controls should be preferred over administrative and PPE controls. A typical example can be the use of handrail over safety harness, because the latter offers individual protection, while handrail offers collective protection. Consequently, it has become clear that the implementation of control measures is based on their appropriateness and effectiveness. Hence, convenience and availability should not be the key factors when considering control measures.

H&S control measures are many and diverse. Ref. [3] provided examples of H&S control measures such as permanent edge protection, railings and screens guarding openings in roofs, guardrails and toeboards, fixed covers, safety net, avoiding working in windy conditions, regular inspections, warning signs, fall arrest system and working at height training to prevent falls from height. Different control measures are available and can be implemented to control hazards at construction sites. Disconnecting electrical circuits with electricity source, using cordless power tool, using non-conductive ladders, introducing lockout/tagout procedure and providing relevant PPE are identified among the control measures for electrical hazards [2]. Pretask planning, authority to stop work and hazard identification are some of the methods used to control hazards on construction sites [25]. The above studies indicate that different H&S control measures are implemented to control hazards.

2.2. Health and Safety Management Challenges

Several studies have been conducted in the construction industry to investigate the challenges of implementing H&S. Ref. [26] identified the benefits and obstacles of implementing safety management system. Part of the results revealed that lower priority due to cultural differences, workers' high turnover rates, tight project schedules, obstruction by subcontractors and inactive participation by the project team members were identified as obstacles to implementing safety management system. Similarly, ref. [27] conducted a study to identify barriers to the implementation of a safety programme in the construction industry. The study identified barriers such as insufficient safety resources, poor safety commitment, poor accountability, lack of safety training, lack of safety knowledge, lack of safety control, non-existent safety management programme, lack of safety standard, no safety rules and policies, no safety officers, lack of competent workers, tight project schedule and lower priority for safety. Ref. [28] explored factors hindering the implementation of COVID 19 safety regulations. The cost of implementing COVID-19 safety measures, the lack of compliance and ignorance and lack of knowledge were the three top-ranked barriers to the implementation of COVID-19 safety regulations. Ref. [29] determined the obstacles hindering the adoption of H&S programme in the construction industry. The study found unconducive work climate, poor governance, safety awareness and unsupportive industry norms as the four main obstacles to the adoption of H&S programme.

On the other hand, ref. [6] identified limited resources, financial support for training, processes and equipment as main challenges of managing H&S. Some general barriers to the implementation of the H&S programme have been identified. These can include lack of resource, lack of H&S knowledge, training, construction experience, management commitment, poor H&S culture, lack of H&S management system, poor enforcement, lack of legislation, lack of H&S committee, lack of risk control measures [2], time and cost constrains [6,30], poor collaboration among professionals [31] and resistance to change [6]. A study by [32] found implementation costs, poor safety culture, lack of safety commitment from clients, lack of managerial commitment, lack of strict enforcement of H&S regulations and lack of resources to implement safety are the top six barriers to good safety practices among small and medium organisations in Malaysia construction industry. In Australia, a study found that implementation costs, language, education and fear of change were the main barriers to implementing H&S reforms [33]. Barriers to the implementation of H&S have been identified by previous studies.

On the other hand, in South Africa, [34] found that the need to manage hazards, the importance of H&S to organisations, and compliance with H&S legislation were the three top ranking drivers behind the H&S implementation. Study in Nigeria [35] found the significant relationship between the effectiveness of safety intervention programme and communication implementation strategies for reducing accident accidents [36]. Study identified barriers such as resistance to change, gaining managerial commitment, insufficient resources and prioritisation of production over safety for effective implementation of interventions in tackling occupational ill health. Five factors (lack of supervision, lack of worksite inspection, unsafe behaviour and attitudes, poor housekeeping and lack of knowledge) affecting successful implementation of safety control practices on construction projects [37]. Ref. [38] investigated the factors that affect the implementation of occupational health and safety management system on construction sites. The findings revealed that internal factors such as risk control strategies, senior management commitment and support and communication, and external factors such as pressure from clients on project delivery, company reputation, H&S enforcement and government legislation affect the implementation.

Several studies have reported on the importance of controlling risk or hazard and how control measures can be used to control hazards. Legally, organisations are obliged

to control hazards to the best of their ability. The importance of implementing control measures is well documented in the H&S field. Lack of health and safety knowledge can contribute to wrong identification of hazards, misperception of risk and incorrect selection of control measures. According to [6] lack of common understanding of H&S risk control may affect the effective evaluation and correct selection of control measures. Findings by [6] reveal that workers had limited understanding of risk controls and were focused only on administrative and PPE controls. This study further identified the cost of implementing engineering controls, inadequate enforcement, ignorance of risk and failure to consult on material selection as barriers to the implementation of risk control by small business construction organisations. According to [39] other controls such as administrative and PPE can be expensive. Similarly, ref. [40] argued that eliminating or substituting a hazard is unlikely to require additional costs. On the other hand, ref. [39] indicates that the cost of engineering control can be higher when compared with the PPE programme. Ref. [24] investigated the level of safety hazard identification in UK and found that the significant number of hazards remain unidentified. The study further found the barriers to improving hazard identification include lack of information sharing, reliance upon tacit knowledge, subjectivity, lack of standardised approach, undefined structure of tasks and hazards and lack of resources, such as having a full-time safety department. Previous studies on H&S control measures have focused on the application of hierarchy of hazard control, none or few of which have generally investigated barriers to the implementation of H&S control measures. The current study seeks to provide barriers to the implementation of H&S control measures. The identification of the barriers to the implementation of H&S control measures is critical for adequate and effective hazard control.

3. Materials and Methods

3.1. Research Design

This study adopted a qualitative research approach. This approach enabled the researcher to understand the meanings participants attach to the problem. This was important since the study sought to explore factors impeding the implementation of H&S control measures (barriers). Understanding the experiences of construction professionals regarding the barriers to the implementation of H&S control measures is important. Hence, qualitative research focusing on qualitative data is suitable. This kind of study focuses on obtaining deep meaning of the respondents' perceptions instead of mainly relying on numbers [40]. This is also relevant since [19] found that qualitative research method is underrepresented in construction H&S research in developing countries. Recently, ref. [28] adopted a similar research design.

3.2. Population, Sampling and Response Rate

The study focused on construction projects taking place in South Africa. The target respondents included construction professionals involved in hazard identification and risk assessment and control (HIRAC), such as construction managers, supervisors, designers, engineers and H&S professionals. The inclusion of designers and engineers is critical since they suggest H&S control measures in their designs. Moreover, HIRAC requires the involvement of different participants. It should be noted that this process should not be conducted by only one person. The first five questions on the interview form focus on the criteria for selecting respondents. A purposive sampling method was used to select respondents who met the following requirements: willingness to participate, currently working on construction sites in South Africa, involved in implementing H&S control measures, aware of or know about baseline risk assessment and have five years

experiencing working in the construction industry. Purposive sampling was used because the aim was to gain rich, localised and contextualised information.

According to [41], samples between 5 and 25 are adequate for qualitative studies. Reference [28] have used 15 respondents for qualitative study. Hence, for this study, at least five respondents were required to be participate. Furthermore, the qualitative study by [42] used five respondents to explore the construction H&S practices in Lagos, Nigeria. Hence, responses from 11 respondents were considered adequate for data analysis. All the respondents had HIRAC knowledge, direct involvement and over five years' experience in implementing H&S controls on construction sites. A total of 20 self-administered interview forms were distributed. In total, 13 interview forms were returned, and only 11 were deemed usable after data screening.

3.3. Data Collection

Data were collected using interview forms that were sent to construction professionals. Face to face or online interviews would have been ideal; however, respondents did not feel comfortable with their voices being recorded. Hence, the use of interview forms was preferred over face-to-face and online interviews. Interview forms can produce similar results as face to face or online interviews if used properly, because they can allow the exploration of problems or questions without providing predefined answers as in the case of closed-ended questionnaires. The interview form was used to elicit data on participant knowledge and experiences regarding the implementation of control measures. Unlike structured questionnaires, interviews provide respondents with an opportunity to provide explanations or more details on a specific topic. The interview form was used to ensure the researcher poses the same questions to all respondents. Additionally, the use of this data collection method was to improve participation and enable respondents to have greater freedom and privacy. Literature review, researcher's prior experience and feedback from pre-test processes were used to develop interview questions. The interview form was given to five individuals to check for grammatical errors, check whether questions were clear and direct, determine the time for completion, suggest if additional questions should be added and provide any other inputs to facilitate easy completion.

Only three individuals participated in the pre-testing of interview forms and no reason was provided for non-participation. Feedback from these participants suggested that barriers should be added in brackets next to factors impeding the implementation of H&S control measures, as well as a separate question which would allow respondents to elaborate. Two respondents indicated that it took between 20 and 25 min to complete the interview form, while the other respondent said it took between 40- and 45-min. General suggestion was made that the author should check the entire interview form for any grammatical errors. Following the feedback, an interview protocol was revised to include the inputs given. Respondents were given ten days to complete the interview form. Some respondents returned completed interview forms within two to eight days, and regular reminders were sent to other respondents who did not reply in time. The study took place between January and April 2024. The questions were classified into two main groups. The first group focused on the respondent's eligibility to participate in the interview, and this consisted of five questions. The second group focused on the respondent's lived experiences of the factors impeding the implementation of H&S control measures (barriers). A set of open-ended questions were asked, including the following: What are the barriers to the implementation of H&S control measures? How exactly would such barriers hinder or stop the implementation of H&S control measures? Further questions were asked to allow respondents to elaborate and confirm or substitute the information provided in the preceding questions. These questions were motivated by previous studies investigating

challenges or barriers in implementing health and safety in general [27–29], which also provided theoretical basis for this study.

Follow-up questions were included to ensure that the respondents' responses were not limited. To ensure the trustworthiness of the study, the following were considered: confirmability was achieved through methods such as member checking, where the interview draft was sent back to each respondent. Respondents were encouraged to provide comprehensive and detailed explanation to ensure transferability, and dependability was achieved by ensuring a list of interview manuscripts was kept. The respondents had to meet the selection criteria in Section 3.2 to ensure credibility. Furthermore, each participant was given the opportunity to verify and comment on the correctness of data collected. Finally, the researcher included some additional information from the respondents. Respondents were informed that consent is granted upon completing the interview forms, and the ethics clearance certificate was obtained from the institution to conduct the study.

3.4. Data Analysis and Interpretation

The content analysis method was used to analyse collected data. Additionally, an excel spreadsheet was used for better presentation. Past research has shown the importance of content analysis for analysing qualitative data [28]. It is also appropriate in cases where diverse and rich information is available. Since the current study aims to explore factors impeding the implementation of H&S control measures, content analysis was critical in describing the information provided by the respondents. The study followed the six steps as described by [43] for analysing qualitative data: become familiar with the data, generate initial codes, search for themes, review themes, define and rename themes and produce reports. The above method was recently used by [28]. In the current study, the researcher first screened the responses to the open-ended interview questions. Secondly, all the responses were studied and coded manually in an Excel spreadsheet. Thirdly, descriptions were generated from each response. Fourthly, similar themes were grouped together. Responses were identified by calculating frequencies and percentages. Finally, the findings and discussion report were produced. In addition to content analysis, the number of participant responses was counted to determine the level of significancy. Any response mentioned once by the participants was considered less significant, and any response mentioned more than four times was considered significant. This method was used more recently by [44]. Ref. [45] proposed that the frequencies of theme (barriers) should be determined based on the number of individual respondents who mention a particular theme, not on the total number of times a theme appears in the response. Using this method can assist in reaching consensus among the participants. Consensus reaching is consistent with the approach used in qualitative studies [31,45]. For example, if respondent R1 mentioned a theme (barrier) ten times, this does not mean ten is the total number of times the theme appears in the entire study. The total was based on responses given by all respondents. Respondents' names were not required, and symbols R1, R2 and others were used to identify the respondents. Tables were used to present the study results, and the direct responses of participants were used for discussion.

4. Findings

4.1. Respondents' Personal Information

Respondents were asked to indicate if they were currently working on construction sites in South Africa. This question was used to determine if respondents would have relevant experience. Table 1 shows that the majority of the respondents had a minimum of five years' experience working in the construction industry. Respondents had a minimum of diploma qualification. All the respondents knew the baseline risk assessment and

were also involved in the implementation of H&S control measures. Notably, only two respondents indicated that they are currently not working on construction sites, while one respondent had less than five years' experience in the construction industry. The responses from three respondents were not used, since they were either not working on construction sites or had less experience. Only the results from respondents who met the selection requirements are presented in Table 1. It is noted that the respondents have sufficient experience, with no one having less than five years' experience. The average experience of the respondents is nine years.

Table 1. Respondents' details.

Respondent	Knowledge of Baseline Risk Assessment	Involvement in Implementing H&S Controls	Experience in the Construction Industry	Occupation	Qualification
R1	Yes	Yes	5 years	H&S manager	Honours Degree
R2	Yes	Yes	11 years	H&S specialist	Honours Degree
R3	Yes	Yes	8 years	H&S practitioner	Honours Degree
R4	Yes	Yes	15 years	H&S officer	Degree
R5	Yes	Yes	12 years	H&S officer	Honours Degree
R6	Yes	Yes	14 years	H&S agent	Degree
R7	Yes	Yes	6 years	Site manager	Degree
R8	Yes	Yes	8 years	Site supervisor	Diploma
R9	Yes	Yes	10 years	Site manager	Diploma
R10	Yes	Yes	7 years	H&S agent	Advanced Diploma
R11	Yes	Yes	8 years	H&S manager	Advanced Diploma

Author's own creation.

4.2. Factors Impeding the Implementation of Health and Safety Control Measures (Barriers)

Table 2 presents the responses of respondents on the barriers to the implementation of H&S control measures in South African construction industry. Various barriers have been revealed by the respondents. The questions that the respondents were asked were "What are barriers (challenges) you have experienced when implementing health and safety control measures?", "Would you please elaborate more?", You mentioned a few barriers (challenges), how exactly would that hinder or stop the implementation of H&S control measures?, and please continue'. Based on their responses, further questions were asked to gain more information and to allow respondents to share more experiences. The study revealed eight main barriers (lack of management support and commitment, implementation costs, lack of training and education, language and cultural differences, time pressure, prioritisation of production over H&S issues, lack of worker involvement and participation and lack of communication) to the implementation of H&S control measures. The study used the number of times a barrier was mentioned to determine its significancy. For example, if a barrier was mentioned only once by respondents, it was considered less significant. Furthermore, any impeding factor (barrier) mentioned more than four times was considered significant. Notably, the top four significant barriers were lack of management support and commitment, implementation costs, lack of training and education and language and cultural differences. A recent qualitative study by [44] used similar criteria for identifying constraining factors for the use of private sector finance in

delivery of public sector infrastructure in Tanzania. Table 2 shows that a total of 14 impeding factors (barriers) have been identified by the respondents. Barriers were mentioned for a total of 60 times by different respondents. The barriers and frequencies are shown in Table 2.

Table 2. Barriers to the implementation of health and safety control measures.

Barriers	Respondents												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**Frequency**	**Percentage**
Lack of communication	√	√		√						√	√	5	45.0
Resistant to change	√	√	√						√			4	36.0
Lack of management commitment	√	√	√	√	√	√	√	√	√		√	10	90.0
Time pressure	√	√					√			√	√	5	45.0
Language and cultural differences	√		√	√				√	√		√	6	54.0
Implementation costs		√	√		√	√		√	√	√	√	8	72.0
Lack of community cooperation		√										1	9.0
Lack of training and education		√	√			√	√	√		√	√	7	63.0
Compliance issues			√									1	9.0
Lack of consequence management					√							1	9.0
Prioritisation of production over health and safety				√	√		√	√		√		5	45.0
Lack of resources								√				1	9.0
Lack of motivation						√						1	9.0
Lack of worker involvement and participation				√				√	√	√	√	5	45.0

Author's own creation.

5. Discussions of the Findings

Eight themes have been generated based on the study findings. The current study uncovered eight main impeding factors (barriers) that need to be addressed to improve the implementation of H&S control measures. These are lack of management support and commitment, implementation cost, lack of training and education, language and cultural differences, time pressure, prioritisation of production over H&S, lack of worker involvement and participation and lack of communication. The eight main themes are discussed separately in the following subsections. Finally, the limitations of the study are outlined.

5.1. Lack of Management Support and Commitment

The majority of the respondents (90%) indicated the most significant barrier was lack of management support and commitment. The results suggest that management is not providing enough support and commitment to the implementation of H&S control measures. According to [46] organising and implementing H&S policies is dependent on top management commitment. Studies such as [7,9,36,46] identify lack of management support and commitment to be a barrier to H&S performance. Management commitment

can be demonstrated by appointing H&S officers and establishing committees. However, according to [46] management support and commitment should go beyond that. On the other hand, as stated by [47], usually H&S professionals take all the responsibilities for H&S without any support from other project participants or workers. This is because H&S is perceived to be the responsibility of H&S professionals [27]. "The project management team (supervisor and site foreman) were always against safety toolbox talks stating they waste time. Without the support of the management the discussion of risk assessments is impossible" (R2). Thus, effective implementation of H&S control measures is possible with strong management support and commitment.

- "Without strong support and commitment from upper management, it is difficult to effectively implement and enforce safety measures" (R3).
- "Poor safety culture in the organisation, lead to poor performance of health and safety" (R4).
- "When top management does not show interest in safety or lead by example, it can lead to a lack of employee engagement in health and safety control measures" (R5).
- "If management is not assisting, then no one else will follow any proposed control measures" (R6).
- "Management usually does not show commitment to risk assessment and how to implement controls" (R7).
- "Some managers believe implementing control measures do not necessarily prevent accidents" (R9).
- "Some project managers, engineers and designers usually do not have time to implement effective controls" (R10).
- "Some managers believe implementing control measures is the responsibility of H&S officer" (R11).

5.2. Implementation Costs

Implementation costs were mentioned as being the second most significant barrier (72%). The study findings show that cost can be seen as another cause of poor implementation of H&S control measures. According to [33] costs implementation was one of the barriers to effective H&S compliance. Some construction organisations have a limited budget for the funding of H&S interventions [27]. Inadequate funds for safety are one of the barriers to H&S performance. Similarly, ref. [48] found that lack of funds for H&S was found to be one of the main factors affecting effectiveness of H&S laws and regulations. Thus, lack of funding for H&S control measures hinders the implementation of H&S control measures. One of the respondents remarked that "Limited budgets can hinder the purchase of necessary equipment, training programmes, and safety improvements in the workplace" (R3). Lack of direct financial benefits may discourage some organisations from setting costs aside for implementing H&S measures [10,36]. However, ref. [49] observes that H&S budget should be provided to implement accident prevention strategies. The H&S budget is critical as it enables the implementation of any H&S measures. One of the respondents observes that "Some organisations only invest resources in initiatives that directly contribute to their bottom line, disregarding other activities" (R5). According to [50] investing more in safety contributes to better performance. On the other hand, insufficient resources were identified as one of the challenges for SMS implementation [47]. Ref. [51] found that cost was found to be another barrier to effective H&S management. Cost was also an issue in implementing H&S leading indicators [52]. Despite evidence pointing to the benefits of investing in H&S, some organisations argue that financial benefits are still small. Poor investment in H&S may be caused by the lack of understanding of the financial benefits [20]. This is why some organisations still do not set aside enough financial resources for H&S

interventions. Cost is one of the factors affecting the implementation of H&S practices. Finally, the implementation costs can be related to training of workers on H&S control measures, selection, procurement and maintenance of controls.

- "The contractor often underprice the HS items and do not have enough signs for traffic accommodation, with lack of funds the purchasing of traffic accommodation safety measures such signs and flags will not happen" (R2).
- "Most control measures require financial capability, such as installing a steel barrier in rotating equipment to eliminate the risk of amputation or installing a wall to reduce noise exposure" (5). Some employers do not want to spend on implementing safety barriers because it is not budgeted for and will eat into their profits.
- "Cash flow issues affects items to be procured, i.e., promotional items, PPE, barricading nets, etc. That means that there won't be money to implement safety control measures" (R6).
- "Lack of money to implement control measures" (R11).

5.3. Lack of Training and Education

Lack of training and education was mentioned as being the third most significant barrier (63%). Ref. [34] notes that lack of training is one of the several barriers to H&S performance. In addition to lack of training, ref. [9] found that workers' low level of education was one of the main impediments to safety improvement. Ref. [53] found that low levels of literacy were one of the major constraints affecting effective H&S management. Another study by [27] reveals that lack of safety knowledge and risk concept understanding were identified as factors hindering SMS implementation in Hong Kong. One respondent indicated that "some workers do not have enough training in implementing controls"(R10). Lack of training or knowledge to implement H&S programme is one of the factors hindering better project performance. Thus, the inability to consider the level of training required may hamper the implementation of H&S controls. However, effective safety training is critical in reducing accidents [54]. Thus, unsafe acts and conditions can be prevented through effective H&S training. It is suggested that workers who receive H&S education and training are in a better position to identify and control hazards. According to [52] H&S induction training can help workers in identifying hazards and control measures. Similarly, lack of education and H&S training may suggest that workers are unable to properly implement H&S control measures. Another respondent remarked that "without a thorough understanding of potential hazards, it is difficult to implement effective control measures to mitigate risks" (R3). In the same manner, according to [47] training is the most effective tool for reducing risks and managing hazards [55]. "If workers don't get enough awareness training, they might not know about possible dangers or don't have the skills they need to do their jobs safely" (R2). Finally, lack of training and education remains a critical factor for better implementation of H&S control measures.

- "Irrelevant information will mislead employees, and they will implement wrong control measures that will lead to accidents/incidents" (R4).
- "Incompetency of people on the ground affects implementation of safety control measures" (R6).
- "Some workers are unable to read the controls identified and does prevents them from implementing" (R7).

5.4. Language and Cultural Differences

Language and cultural differences were mentioned as being the fourth most significant barrier (54%). Ref. [27] found cultural differences to be a challenge for implementing SMS in Hong Kong. Communication issues and differences in language, religion and culture are

likely to affect workplace safety [55]. Thus, workers from different cultures express themselves in different ways. Language and diverse culture were identified as one of the main barriers to effective H&S implementation [33]. It is noted that examining language and cultural differences is fundamental for the failure or success of H&S controls implementation. Ref. [33] indicates that workers struggle to understand the terms such as risk and hazard used during toolbox talks. For instance, one respondent argues that "Control measures are sometimes difficult to implement because they are communicated and written in only English" (R11). This is common to many construction sites where English is often used to convey critical H&S information. As reported by [56] language barriers affected migrant workers learning and training effectiveness. Another respondent notes that "illiteracy and some workers do not have enough knowledge about risk assessment and controls" (R8).

On the other hand, migrant workers' background and cultural differences were contributors to H&S rules violation [56]. Finally, issues around language and culture should be considered for successful H&S control measures implementation.

- "Language barriers and cultural differences impede effective communication and understanding of safety information" (R1).
- "In multicultural workplaces, language and cultural differences can pose challenges when communicating safety procedures and expectations" (R3).
- "Employees do not understand the language that is used for communication example English" (R4).
- "On our site we use English most of the times, but have more than five different languages spoken by workers and this makes it difficult to understand each other" (R9).

Hazard identification and risk assessment and control involve the workers, supervisor, site manager, safety professionals and other specialists. This study included site supervisors, site managers and safety professionals who usually work together with workers to implement control measures. This interaction allowed them to understand challenges that are faced by workers when implementing control measures. For example, a worker may struggle to read or interpret messages written on noticeboard or notices placed around the construction sites because of the language used. That is how the responses of participants could be interpreted. Hence, site supervisors, managers and safety professionals may have similar challenges when communicating control measures to workers given the many languages used on South African construction sites.

5.5. Time Pressures

Time pressure was mentioned as one of the barriers ranked fifth in significance (45%). This has been the case in other studies such as [47] which identify tight project deadlines as one of the barriers to effective H&S management. A tight project schedule was identified as one of the five main obstacles for SMS implementation [47]. Two respondents note that "Tight project schedules can affect implementation of H&S control measures" (R7 and R11). Poor planning and inclement weather could be one of the causes of time pressures [9]. Tight working schedule was one of the key challenges to effective SMS implementation [47]. Similarly, time pressures have been identified as one of the factors preventing better implementation of H&S practices by contractors [53]. Hence, workers can be forced to work faster and work excessive hours. One of the respondents contends that "clients want us to finish the work quickly because of tight project targets" (R9). Time pressure has been identified as a critical barrier to implementing H&S control measures. As indicated by [27] it can be the contributor to construction accidents. This is because time project schedule adds pressure and stress on management and workers [27]. Ref. [49] states that due to time pressure, workers are encouraged to take shortcuts to finish the job quickly. Another respondent points out that "Pressure to meet tight deadlines may lead to shortcuts being

taken with safety protocols or procedures" (R1). Study findings suggest time pressure is likely to affect the implementation of H&S control measures.

5.6. Prioritisation of Production over Health and Safety

Prioritisation of production over H&S issues was mentioned as one of the barriers ranked fifth in significance (45%). Lack of H&S prioritisation is not only a barrier to the implementation of H&S control measures, but a study by [48] found that lack of priority for H&S was found to be one of the factors affecting effectiveness of H&S laws and regulations. Similarly, a study by [36] found that prioritisation of production over safety was one of the barriers in the implementation of safety interventions for tacking occupational ill health. Managers focus more on productivity, time and saving money than on H&S [47]. One of the respondents remarks that "Some site managers and supervisors do not care about H&S and just push production" (R10). The literature shows that productivity remains a top priority, while H&S issues take back seat. According to [57] the financial benefits of investing in H&S are usually long term, which is less attractive to small organisations. The findings further point that there is a low safety priority within the construction industry. According to [27] poor safety culture is attributed to low safety priority. This happens because H&S issues continue to be disregarded as one of the main project objectives [4]. Thus, poor implementation of H&S control measures may be because of lack of prioritisation of H&S objectives.

- "Workers may prioritise speed over safety, leading to increased risks of accidents and injuries" (R1).
- "Focusing on production and showing negative attitude towards safety" (R7).
- "Disrespecting health and safety" (R8).
- "Many managers believe implementing control measures costs a lot of money, do not want to provide budget for hazard identification and risk assessment" (R8).

5.7. Lack of Worker Involvement and Participation

Lack of worker involvement and participation was mentioned as one of the barriers ranked fifth in significance (45%). Ref. [49] points out that workers should be involved in identifying hazards and controls. Similarly, ref. [27] notes that worker involvement and participation is critical for hazard identification and control. Management commitment and worker participation are critical in H&S management system implementation [48]. To demonstrate the significance of worker involvement and participation, a study by [27] found worker involvement to be one of the safety critical success factors to overall project success. For example, one of the respondents remarks that "They do not seek our inputs, we just seeing control measures written on papers. For example, are given safety gloves which are not suited for the task" (R8). According to [58] worker involvement and empowerment remains a critical factor for improving H&S performance. Thus, it is important for workers to participate in H&S such as hazard control implementation. Without worker participation and involvement, implementing H&S measures becomes difficult [4].

- "Employees don't understand the importance of information that is offered to them, they take it for granted, as they are not involved and don't focus during awareness session" (R4).
- "Sometimes is difficult to have different workers involved in risk assessment and control measures" (R9).
- "Worker inputs is not really welcome and H&S department implement control measures" (R10).
- "Workers are not aware and involved in selecting control measures required" (R11).

5.8. Lack of Communication

Lack of communication was mentioned as one of the barriers ranked fifth in significance (45%). Communication was found to be one of the five critical H&S elements [58]. Ref. [48] notes that poor communication between managers and workers on construction sites can lead to accidents and delays. Similarly, ref. [59] indicates that effectively communicating safety hazards and control measures reduces the probability of accidents. Several other studies have highlighted that communication is a key issue when managing H&S. This implies that effective communication, which considers every worker on site, is required. According to [60] both formal and informal or written and oral communication should be provided to all workers. Communication is not only critical for collaboration [7], but also necessary for hazard control implementation. Communication can help to improve awareness and the implementation of H&S interventions [4]. One of the respondents states that "poor implementation of H&S control measures may be caused by lack of communication. "Miscommunication or lack of communication between different stakeholders can lead to misunderstandings about. This may result in workers not receiving critical safety information or failing to adhere to safety protocols due to confusion or misinformation" (R1). On the other hand, ref. [60] indicates that the differences between low and high rate of accidents was affected by safety communication between managers and workers. Thus, lack of communication exposes workers to safety risks and accidents.

- "If managers and workers don't communicate to each other well about health and safety problems, it can lead to confusion and weaken the safety culture" (R2).
- "If employees don't understand the importance of safety, they won't implement what has been taught during awareness session" (R4).
- "Task risk assessment including control measures are only discussed once and no further communication is made" (R10).
- "Difficulty in communicating control measures to all involved" (R11).

5.9. Limitations of the Study

The interview form was used to uncover factors impeding the implementation of H&S control measures (barriers). Qualitative approach stresses the experiences of participants over that of the researcher, but it can also be limited by the kind of participants that take part. However, according [61] qualitative study relies on quality not quantity. The interview included the questions that could identify only participants who had relevant knowledge and experience in the subject matter to take part. While the findings cannot be generalised, further studies could use other methods to expand or validate the barriers identified based on the completed interview forms. Respondents were mainly from H&S background; it would be interesting to explore the perceptions of site managers, engineers, designers, supervisors and work face workers using a quantitative approach involving a larger sample. Additionally, similar studies can be undertaken in other countries to compare the barriers identified in those countries to the findings of this study. The study is limited to qualitative research, and future studies such as quantitative or mixed method may use the findings of the current study to assess their impact. Literature review was used to provide background to the study and no attempt was made to conduct a systematic literature review. Hence, only limited and general information is provided. The study does not attempt to explore the barriers related to the implementation of hierarchy of hazard controls theory. Other studies may investigate the barriers associated with implementing hierarchy of hazard control theory. However, it could be argued that the impeding factors (barriers) such as implementation costs, lack of management support and commitment, lack of worker involvement and participation, time pressures and prioritisation of production over safety may lead to the adoption of more behavioural controls than technological

controls. Although internal and external factors can impede the implementation of H&S control measures, the findings were more about internal factors. Hence, future studies can exclusively identify external factors that can impede the implementation of H&S control measures.

6. Conclusions and Recommendations

Hazard controls are introduced to eliminate and manage hazardous activities and reduce the likelihood of injuries and accidents. Despite the progress made to control hazards, construction industry still faces several barriers relating to their implementation. With the number of studies on HIRAC, the research interest on specific H&S control measures is still at low levels. The current study uncovered the main barriers affecting the implementation of H&S control measures in the South African Construction Industry. The identified barriers are critical in the quest for zero accidents and imperative for advancing knowledge in hazard control theory and practice. Additionally, construction organisations can use the identified barriers as a starting point for better implementation of H&S controls. This emphasises the importance of control in the HIRAC process. Furthermore, addressing these barriers is important for improving overall H&S performance within the construction industry. Based on the findings, the study highlights key barriers relating to the implementation of H&S control measures. These barriers (impeding factors) hinder the implementation of H&S control measures. By identifying and understanding these barriers, the construction organisations could be in a better position to control construction hazards. Subsequently, this could lead to better management of hazards on construction sites. It can be argued that poor implementation of H&S measures can lead to accidents which have an impact on project progress. The identification of these factors adds to the hazard control theory and provides practical ways in which the implementation of H&S control measures can be improved. Not knowing the barriers affecting the implementation of control hazards has the potential to hamper the H&S interventions and efforts undertaken by the government authorities, professional bodies and organisations. Future studies could use the identified factors to either remove the obstacles or implement the critical factors for better implementation.

Based on the study findings, the following recommendations should be considered to improve the implementation of H&S control measures: These recommendations could be grouped into three levels; project and training and policy.

Project level recommendations that can be considered are as follows:

- H&S issues should be given the same status as production issues.
- The cost of implementing H&S control measures should be considered when planning a new project or activity.
- A sufficient budget should be set aside for H&S, and monitoring of this budget should be undertaken.
- Top management should provide necessary resources and support for the implementation of H&S controls.
- Organisations should involve all workers in HIRAC to ensure better H&S performance and improve any form of communication to facilitate workers' understanding.
- Organisations should develop creative and innovative ways to remove or minimise the identified barriers. Failure to remove them can lead to workers being exposed to hazards and the occurrence of accidents.
- The use of interpreters or translations should be prioritised.

Training level recommendations that can be considered are the following:

- A basic literacy training should be provided to improve workers ability to write and read H&S control measures. This will help workers to meaningfully participate in HIRAC.
- Training on HIRAC should be given to management and workers. Multiple languages or language switching should be used to increase workers' understanding and participation.
- Symbols or pictures could be used to improve workers' knowledge and understanding.

Policy level recommendations that can be considered are the following:

- Government authorities, professional bodies and construction organisations should use the findings of this study in the review of applicable regulations and standards related to H&S hazard controls.
- Universities may use the findings to review their curriculum to address any shortcomings.

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References

1. Charehzehi, A.; Ahankoob, A. Enhancement of safety performance construction site. *Int. J. Adv. Eng. Technol.* **2012**, *5*, 303.
2. Zhao, D.; McCoy, A.; Kleiner, B.; Smith-Jackson, T. Control measures of electrical hazards: An analysis of construction industry. *Saf. Sci.* **2015**, *77*, 143–151. [CrossRef]
3. Lingard, H.; Holmes, N. Understandings of occupational health and safety risk control in small business construction firms: Barriers to implementing technological controls. *Constr. Manag. Econ.* **2001**, *19*, 217–226. [CrossRef]
4. Rantsatsi, N.P. Benefits and challenges relating to the implementation of health and safety leading indicators in the construction industry: A systematic review. *Saf. Sci.* **2023**, *163*, 106131. [CrossRef]
5. Rantsatsi, N.; Musonda, I.; Agumba, J. Identifying factors of collaboration critical for improving health and safety performance in construction projects: A systematic literature review. *Acta Structilia* **2020**, *27*, 120–150. [CrossRef]
6. Okorie, V.N. Beheviour-Based Health and Safety Management in Construction: A Leadership-Focused Approach. Ph.D. Thesis, Nelson Mandela Metropolitan University, Port Elizabeth, South Africa, 2014.
7. Swallow, M.; Zulu, S. Benefits and Barriers to the Adoption of 4D Modeling for Site Health and Safety Management. *Front. Built Environ.* **2019**, *4*, 86. [CrossRef]
8. Amoah, C.; Simpeh, F. Implementation of challenges of COVID-19 safety measures at construction sites in South Africa. *J. Facil. Manag.* **2020**, *19*, 111–128. [CrossRef]
9. Kukoyi, P.O.; Adebowale, O.J. Impediments to construction safety improvement. *J. Eng. Proj. Prod. Manag.* **2021**, *11*, 207–214.
10. Umar, T.; Egbu, C.; Honnurvali, M.S.; Saidani, M.; Al-Bayati, A.J. Briefing: Status of occupational safety and health in GCC construction. *Proc. Inst. Civ. Eng.-Manag. Procure. Law* **2019**, *172*, 137–141. [CrossRef]
11. Manu, P.; Emuze, F.; Saurin, T.A.; Hadikusumo, B. (Eds.) *Construction Health and Safety in Developing Countries*; Routledge: Oxfordshire, UK, 2019.
12. Johnson, K.A.; Ruppe, J. A job safety program for construction workers designed to reduce the potential for occupational injury using tool box training sessions and computer-assisted biofeedback stress management techniques. *Int. J. Occup. Saf. Ergon.* **2002**, *8*, 321–329. [CrossRef]
13. Borys, D. The role of safe work method statements in the Australian construction industry. *Saf. Sci.* **2012**, *50*, 210–220. [CrossRef]

14. Choudhry, R.M.; Fang, D.; Rowlinson, S. Challenging and enforcing safety management in developing countries: A strategy. *Int. J. Constr. Manag.* **2008**, *8*, 87–101. [CrossRef]
15. Afzal, M.; Shafiq, M.T.; Al Jassmi, H. Improving construction safety with virtual-design construction technologies—A review. *J. Inf. Technol. Constr. (ITcon)* **2021**, *26*, 319–340. [CrossRef]
16. Uzun, M.; Bilir, S.; Gurcanli, G.; Cebi, S. Hierarchy of Control Measures for Common Construction Activities: A Field Study. In Proceedings of the 5th international Project and Construction Management Conference (IPCMC2018) Cyprus International University, Kyrenia, Cyprus, 16–18 November 2018; Faculty of Engineering, Civil Engineering Department: North Cyprus, Istanbul, Turkey, 2018.
17. Choudhry, R.M. Behavior-based safety on construction sites: A case study. *Accid. Anal. Prev.* **2014**, *70*, 14–23. [CrossRef]
18. Hallowell, M. Cost-effectiveness of construction safety programme elements. *Constr. Manag. Econ.* **2010**, *28*, 25–34. [CrossRef]
19. Umeokafor, N.; Umar, T.; Evangelinos, K. Bibliometric and scientometric analysis based review of construction safety and health research in developing countries from 1990 to 2021. *Saf. Sci.* **2022**, *156*, 105897. [CrossRef]
20. Tymvios, N.; Gambatese, J. Perceptions about design for construction worker safety: Viewpoints from contractors, designers, and university facility owners. *J. Constr. Eng. Manag.* **2015**, *1*, 2. [CrossRef]
21. Gomes, A.; Gomes, C. Hierarchy of hazard control to minimise lighting risk. In Proceedings of the International Conference on lighting Protection (ICLP), Shanghai, China, 11–18 October 2014; pp. 1218–1227.
22. *ISO 45001*; Occupational Health and Safety Management Systems-Requirements with Guidance for Use. International Labour Organisation: Geneva, Switzerland, 2018.
23. McLeod, S.; Curtis, C. Integrating urban road safety and sustainable transportation policy through the hierarchy of hazard controls. *Int. J. Sustain. Transp.* **2022**, *16*, 166–180. [CrossRef]
24. Ahankoob, A.; Charehzehi, A. Mitigating ergonomic injuries in construction industry. *IOSR J. Mech. Civ. Eng.* **2013**, *6*, 36–42. [CrossRef]
25. Carter, G.; Smith, S.D. Safety hazard identification on construction projects. *J. Constr. Eng. Manag.* **2006**, *132*, 2. [CrossRef]
26. Hallowell, M.R.; Hinze, J.W.; Baud, K.C.; Wehle, A. Proactive construction safety control: Measuring, monitoring, and responding to safety leading indicators. *J. Constr. Eng. Manag.* **2013**, *139*, 04013010. [CrossRef]
27. Yie, N.S.; Chan, D.W.; Shan, M.; Sze, N.N. Implementation of safety management system in managing construction projects: Benefits and obstacles. *Saf. Sci.* **2019**, *117*, 23–32. [CrossRef]
28. Buniya, M.K.; Othman, I.; Sunindijo, R.Y.; Kineber, A.F.; Mussi, E.; Ahmad, H. Barriers to safety program implementation in the construction industry. *Ain Shams Eng. J.* **2021**, *12*, 65–72. [CrossRef]
29. Simpeh, F.; Bamfo-Agyei, E.; Amoah, C. Barriers to the implementation of COVID- 19 safety regulations: Insight from Ghanaian construction sites. *J. Eng. Des. Technol.* **2022**, *20*, 47–65. [CrossRef]
30. Al-Otaibi, A.; Kineber, A.F. Identifying and Assessing Health and Safety Program Implementation Barriers in the Construction Industry: A Case of Saudi Arabia. *Appl. Sci.* **2023**, *13*, 2630. [CrossRef]
31. Rantsatsi, N.; Musonda, I.; Agumba, J. Factors that determine construction health and safety collaboration on construction projects: A Delphi study. *Acta Structilia* **2021**, *28*, 53–77. [CrossRef]
32. Belayutham, S.; Ibrahim, C.K.I.Z. Barriers and Strategies for Better Safety Practices: The Case of Construction SMEs in Malaysia. *Constr. Econ. Build.* **2019**, *19*, 6331. [CrossRef]
33. Loosemore, M.; Andonakis, N. Barriers to implementing OHS reforms- The experiences of small subcontractors in the Australian construction industry. *Int. J. Proj. Manag.* **2007**, *25*, 579–588. [CrossRef]
34. van Heerden, J.H.F.; Musonda, I.; Okoro, C.S. Health and safety implementation motivators in the South African construction industry. *Cogent Eng.* **2018**, *5*, 1446253. [CrossRef]
35. Okoye, P.U.; Okolie, K.C.; Ngwu, C. Multilevel safety intervention implementation strategies for Nigeria construction industry. *J. Constr. Eng.* **2017**, *2017*, 8496258. [CrossRef]
36. Whysall, Z.; Haslam, C.; Haslam, R. Implementing health and safety interventions in the workplace: An exploratory study. *Int. J. Ind. Ergon.* **2006**, *36*, 809–818. [CrossRef]
37. Othman, I.; Mohamad, H.; Napiah, M.; Hashim, Z.; Cai, Z. The framework for effective safety control and implementation at construction project. *Int. J. Eng. Technol. Manag. Res.* **2018**, *5*, 28–42. [CrossRef]
38. Kunodzia, R.; Bikitsha, L.S.; Haldenwang, R. Perceived factors affecting the implementation of occupational health and safety management systems in the South African construction industry. *Safety* **2024**, *10*, 5. [CrossRef]
39. Mutai, I. Prevention of Workplace Injuries and Illnesses. Bachelor's Thesis, Murray State University, Murray, KY, USA, 2019.
40. McComb, C.C. Designing the Characteristics of Design Teams via Cognitively Inspired Computational Modeling. Ph.D. Thesis, Carnegie Mellon University, Pittsburgh, PA, USA, 2016.
41. Thanh, N.C.; Thanh, T.T. The interconnection between interpretivist paradigm and qualitative methods in education. *Am. J. Educ. Sci.* **2015**, *1*, 24–27.

42. Kukoyi, P.O.; Smallwood, J.J. A qualitative study of health and safety construction practices in Lagos. *J. Constr. Bus. Manag.* **2017**, *1*, 1–7. [CrossRef]
43. Braun, V.; Clarke, V. *Thematic Analysis: Handbook of Research Methods in Psychology*, 2nd ed.; APA: London, UK, 2012.
44. Kavishe, N.; Zulu, S.L.; Luvara, V.; Zulu, E.; Musonda, I.; Moobela, C.; Chileshe, N. Exploring constraining factors for use of private sector finance in delivery of public sector infrastructurein Tanzania: A qualitative study. *Front. Built Environ.* **2023**, *9*, 1098490. [CrossRef]
45. Namey, E.; Guest, G.; Thairu, L.; Johnson, L. Data reduction techniques for large qualitative data sets. In *Handbook for Team-Based Qualitative Research*; Guest, G., MacQueen, K., Eds.; AltaMira Press: Lanham, MD, USA, 2008; pp. 137–162.
46. Farooqui, R.U.; Umer, M.; Saqib, M.; Ahmed, S.M. An Empirical Assessment of Contractor Top Management Commitment and Support towards Safety in the US Construction Industry. In Proceedings of the Third International Conference on Construction in Developing Countries (ICCIDC–III) "Advancing Civil, Architectural and Construction Engineering & Management", Bangkok, Thailand, 4–6 July 2012.
47. Yiu, N.S.; Sze, N.N.; Chan, D.W. Implementation of safety management systems in Hong Kong construction industry–A safety practitioner's perspective. *J. Saf. Res.* **2018**, *64*, 1–9. [CrossRef]
48. Eyiah, A.K.; Kheni, N.A.; Quartey, P.D. An Assessment of Occupational Health and Safety Regulations in Ghana: A Study of the Construction Industry. *J. Build. Constr. Plan. Res.* **2019**, *7*, 11–31. [CrossRef]
49. Maliha, M.N.; Abu Aisheh, Y.I.; Tayeh, B.A.; Almalki, A. Safety barriers identification, classification, and ways to improve safety performance in the architectureengineering, and construction (AEC) industry: Review study. *Sustainability* **2021**, *13*, 3316. [CrossRef]
50. Lin, J.; Mills, A. Measuring the occupational health and safety performance of construction companies in Australia. *Facilities* **2001**, *19*, 131–138. [CrossRef]
51. Wong, J.Y.Y.; Gray, J.; Sadiqi, Z. Barriers to good occupational health and safety (OHS) practices by small construction firms. *J. Real Estate Constr. Manag.* **2015**, *30*, 55–66. [CrossRef]
52. Rantsatsi, N.P. Health and safety induction training in the construction industry: A review. *J. Facil. Manag.* **2024**, *12*, 1472–5967. [CrossRef]
53. Kheni, N.A.; Dainty, A.R.J.; Gibb, A. Health and Safety Management in Developing Countries: A Study of Construction Smes in Ghana. *Constr. Manag. Econ.* **2008**, *26*, 1159–1169. [CrossRef]
54. Tezel, A.; Dobrucali, E.; Demirkesen, S.; Kiral, I.A. Critical success factors for safety training in the construction industry. *Buildings* **2021**, *11*, 139. [CrossRef]
55. Mouleeswaran, K. Evaluation of safety performance level of construction firms in and around erode zone. *Int. J. Innov. Res. Sci. Eng. Technol.* **2014**, *3*, 1586–1594.
56. Shepherd, R.; Lorente, L.; Vignoli, M.; Nielsen, K.; Peiró, J.M. Challenges influencing the safety of migrant workers in the construction industry: A qualitative study in Italy, Spain, and the UK. *Saf. Sci.* **2021**, *142*, 105388. [CrossRef]
57. Champoux, D.; Brun, J.P. OSH practices and interventions in small businesses: Global issues in the Québec context. *Policy Pract. Health Saf.* **2015**, *13*, 47–64. [CrossRef]
58. Agumba, J.; Pretorius, J.H.; Haupt, T. health and safety management practices in small and medium enterprises in the South African construction industry. *Acta Structilia J. Phys. Dev. Sci.* **2013**, *20*, 66–88. [CrossRef]
59. Pandit, B.; Albert, A.; Patil, Y.; Al-Bayati, J.A. Fostering safety communication among construction workers: Role of safety climate and crew-level cohesion. *Int. J. Environ. Res. Public Health* **2019**, *16*, 71. [CrossRef]
60. Zulkifle, Z.; Hanafi, W.N.W. Impact of Safety Management Practices Enforcement Toward Employee Safety in Construction Industry. Available online: https://www.europeanproceedings.com/article/10.15405/epsbs.2018.07.02.58 (accessed on 28 May 2025).
61. Creswell, J.W. *Qualitative Inquiry and Research Design: Choosing Among Five Traditions*; Sage: Thousand Oaks, CA, USA, 2013.

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GPT Applications for Construction Safety: A Use Case Analysis

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Abstract

This study explores the use of Large Language Models (LLMs), specifically GPT, for different safety management applications in the construction industry. Many studies have explored the integration of GPT in construction safety for various applications; their primary focus has been on the feasibility of such integration, often using GPT models for specific applications rather than a thorough evaluation of GPT's limitations and capabilities. In contrast, this study aims to provide a comprehensive assessment of GPT's performance based on established key criteria. Using structured use cases, this study explores GPT's strength and weaknesses in four construction safety areas: (1) delivering personalized safety training and educational content tailored to individual learner needs; (2) automatically analyzing post-accident reports to identify root causes and suggest preventive measures; (3) generating customized safety guidelines and checklists to support site compliance; and (4) providing real-time assistance for managing daily safety tasks and decision-making on construction sites. LLMs and NLP have already been employed in each of these four areas for improvement, making them suitable areas for further investigation. GPT demonstrated acceptable performance in delivering evidence-based, regulation-aligned responses, making it valuable for scaling personalized training, automating accident analyses, and developing safety protocols. Additionally, it provided real-time safety support through interactive dialogues. However, the model showed limitations in deeper critical analysis, extrapolating information, and adapting to dynamic environments. The study concludes that while GPT holds significant promise for enhancing construction safety, further refinement is necessary. This includes fine-tuning for more relevant safety-specific outcomes, integrating real-time data for contextual awareness, and developing a nuanced understanding of safety risks. These improvements, coupled with human oversight, could make GPT a robust tool for safety management.

Keywords: construction safety management; large language models; GPT; AI in safety; virtuAI safety assistance; accident analysis; OHS risk prevention

1. Introduction and Literature Review

The construction industry is considered to be one of the most dangerous industries due to the numerous hazards that workers may encounter on jobsites [1]. In 2022, the construction industry accounted for 19.2% of all worker fatalities in the United States, which means that one out of every five worker deaths occurred in this industry [2]. Given the high incidence of workplace fatalities in the construction industry, several efforts have been made to improve safety performance [3]. Considering the low safety managers to worker ratio, automating the safety management process has emerged as a need to elevate safety

in the construction industry [4]. Several methods have been proposed for this purpose, such as using Building Information Modeling (BIM) to identify potential safety issues [5,6], virtual reality (VR) and augmented reality (AR) to provide automated safety training for workers [7–9], using robots and artificial intelligence (AI) to detect and manage safety hazards [10,11], and language models to analyze safety documents for hazard causes [12]. Despite these advancements, the injury rates in construction remain notably high. Therefore, it is clear that further attention is needed to improve safety performance in the construction industry [13].

In recent times, advancements in computational capabilities and the vast amount of available data have contributed to the surge in popularity and effectiveness of Natural Language Processing (NLP) across various sectors. NLP, a subfield of artificial intelligence, trains computers to interpret human language both in written and spoken forms, akin to human comprehension [14]. NLP combines rule-based modeling of human language with statistical, machine learning, and deep learning techniques to enable computers to comprehend the meaning and context of human language, including the speakers' or writers' intentions and emotions [15]. This technology holds particular promise for the construction industry, which is often laden with vast documentation, reports, and correspondence. Given the industry's pressing need to enhance safety and operational efficiency, the application of NLP presents an opportunity for transformational change. In the past few years, the construction industry has increasingly adopted natural language processing (NLP) to increase automation [16,17]. For instance, it has been applied in areas like document management [18], risk management [19], quality assurance [20,21], scheduling [22], and building information modeling (BIM) [23]. Furthermore, the use of NLP and AI on accident datasets has also been recommended by European Statistics on Accidents at Work (ESAW) [24,25]. NLP has especially proven valuable in enhancing safety management in construction projects. Specifically, NLP is used to analyze safety reports [26], extract safety information and knowledge from safety codes and documents [27], and identify the root causes of hazards [28]. Moreover, NLP-based tools have also been developed to generate content from existing information for safety training and education [29], and to determine and analyze the relationship between different safety risk factors [30]. By serving these diverse purposes, NLP has proven to be a promising tool for achieving safer and more efficient construction environments [26].

Recent advancements in NLP have been significantly driven by the emergence of Large Language Models (LLMs), such as OpenAI's Generative Pretrained Transformer (GPT) [31] and Google AI's Bard [32]. These models, trained on extensive text datasets, generate text with human-like fluency, answer questions, and execute a host of language-related tasks with good accuracy [33]. Their inherent strength lies in their extensive pretraining on diverse data, enabling versatility across various applications [34,35]. Given the significant progress made in NLP through Large Language Models, there is a compelling rationale to use them for automating construction safety management. Industries across the spectrum are already tapping into the potential of LLMs [36,37], with applications ranging from coding assistance [38] to education [39] and content generation for advertisement purposes [40]. Notably, the construction industry is also beginning to integrate LLMs, with preliminary efforts on safety training [41] and scheduling [42]. These studies largely emphasize preliminary demonstrations or speculative potential without critically examining how LLMs perform in the nuanced, high-risk context of construction safety. They often present isolated applications rather than synthesizing insights across use cases or rigorously evaluating LLM effectiveness and limitations. As a result, it remains unclear whether LLMs offer tangible benefits beyond automation, particularly in tasks that require domain-specific reasoning, compliance with safety standards, and high levels of

reliability. This gap underscores the need for a systematic assessment of LLMs such as GPT across key safety management tasks to better inform their potential role in real-world construction environments.

In recent times, the wave of popularity of LLMs has led to a significant increase in research proposing their application across a wide range of construction-related tasks. However, much of this momentum appears driven by the trend itself rather than a rigorous evaluation of the LLMs' relevance, effectiveness, or limitations. Consequently, there is growing concern that this rapid adoption of LLMs may eclipse more evidence-based, methodical approaches necessary for addressing the complexities inherent in construction research. This trend is particularly concerning in areas like construction safety, where the misuse of technology can lead to ineffective or even dangerous outcomes. While existing studies have explored general applications of AI and NLP in construction, few have conducted a critical synthesis of how LLMs specifically perform when tasked with safety-critical responsibilities that demand contextual awareness, regulatory alignment, and reliable outputs. There remains a notable absence of systematic evaluations that examine both the capabilities and boundaries of models like GPT when applied across distinct safety functions. Without such evaluations, it is difficult to determine whether current LLMs can truly support the nuanced decision-making required in high-risk environments. Therefore, this study aims to investigate the application of LLMs in construction safety management, with a focus on critically assessing their potential benefits, limitations, and practical viability. By conducting a structured use case evaluation, this research not only explores the practical implications of using LLMs in safety management but also helps to establish a more grounded foundation for future integration of LLMs into safety-critical domains. While several LLMs have emerged recently, GPT stands out as particularly relevant for this study.

GPT is a Large Language Model, based on the transformer architecture. It operates by predicting the next word in a sequence, using patterns learned from large-scale text datasets during its pretraining phase. This autoregressive structure allows GPT to generate fluent and contextually relevant responses across a wide range of topics [43]. Its widespread popularity provides several resources and community support, indicating its potential for more extensive future use in safety-related fields. The model's training on diverse datasets and advanced language processing abilities are especially suited for interpreting and applying complex safety protocols and guidelines in varying contexts, which is crucial for construction safety. Finally, its potential for integration with other technologies positions GPT as a promising choice for developing safety management solutions, anticipating its growing role in safety applications in the future. However, its outputs are shaped entirely by statistical correlations in the data, without any embedded understanding of meaning or intent. Additionally, GPT lacks the ability to verify facts, access real-time information, or incorporate multimodal inputs unless explicitly integrated through external tools or prompt engineering. These architectural features can lead to limitations in high-risk domains like construction safety, including hallucination of inaccurate information, shallow responses in technical scenarios, and limited adaptability to dynamic site conditions. Furthermore, without fine-tuning on domain-relevant safety documents or feedback loops, GPT's outputs may not fully reflect regulatory nuances or site-specific risks. Recognizing these architectural constraints is critical when evaluating GPT's performance in construction safety applications [44–46]. For this study, GPT-4o was selected as the language model due to its accessibility and relevance to general users. As a publicly available version of GPT, it reflects the model capabilities that are most likely to be used in real-world construction environments.

Despite the growing use of LLMs in various domains, there has been no systematic evaluation of their role in construction safety management. Prior work tends to focus on feasibility or isolated applications without assessing the breadth and depth of LLM capabilities across multiple safety functions. This gap limits our understanding of how tools like GPT can be reliably and ethically applied in safety-critical environments. This study addresses this need by evaluating GPT's performance in structured use cases aligned with key construction safety tasks. These use cases are personalized safety training and education, automated post-accident analysis, automated generation of safety guidelines and checklists, and real-time safety management assistance. Construction safety practices are informed by several foundational theories that guide training, analysis, and decision-making processes. Personalized safety training is grounded in constructivist learning [47] theory and adaptive instructional design, which emphasize tailoring educational experiences to individual needs, enabling learners to build knowledge through active engagement and contextual feedback. Root cause analysis theory and systems thinking [48] underpin post-accident evaluations, facilitating a deeper understanding of how organizational and procedural factors contribute to safety incidents. The development of safety guidelines and checklists reflects principles of procedural knowledge and compliance theory [49], focusing on translating regulatory standards into structured, task-specific protocols. Real-time safety management draws from situational awareness theory and decision support frameworks [50], which emphasize timely access to information, hazard recognition, and responsive actions in dynamic site conditions. These theories collectively provide a robust foundation for improving safety outcomes in complex and high-risk construction environments.

The findings of this study are expected to have implications for both the construction industry and the field of safety management research. The study outcomes offer practical insights for effectively integrating GPT into current construction safety management processes, identifying areas where such models can be applied with efficiency and safety. Furthermore, this study identifies the specific strengths and weaknesses of GPT, aiding researchers and decision-makers in making informed choices regarding GPT adoption for safety while also understanding its limitations and leveraging its potential benefits.

Point of Departure

The potential of GPT in improving construction safety is significant, but a comprehensive understanding of their specific value, strengths, and limitations in safety applications is lacking. To fill this gap, this study aims to critically examine and demonstrate the effectiveness of GPT in various construction safety management applications. The study demonstrates the practical application of GPT through various use cases. This helps in comprehending where GPT can be most beneficial and where it might have limitations. It also highlights the opportunities and challenges in its usage for different safety management applications. This analysis also involves identifying the various capabilities that GPT must demonstrate for effective safety management purposes in the future.

While some studies [41,51,52] have explored the integration of GPT in construction safety for various applications, their primary focus has been on the feasibility of such integration, often using GPT models for specific applications rather than a thorough evaluation of GPT's limitations and capabilities. In contrast, this study aims to provide a comprehensive assessment of GPT's performance based on established key criteria, which include interactivity, critical analysis, and comprehension, across different safety management contexts (explained in more detail in Section 2.1). This approach allows for the identification of overarching patterns, potential generalizations, and critical limitations.

Additionally, it facilitates cross-application learning, where insights from one case can inform others.

2. Research Method

This study illustrates the use of GPT in different safety management applications through use cases and evaluates its capabilities and limitations under each application. The use case approach helps predict a technology's behavior under various scenarios as it interfaces with users or other technologies [53,54]. Each use case includes scenarios that illustrate how the technology interacts with the users or other systems to achieve a specific objective. These descriptions typically include the steps that the user or technology will take, expected outcomes, and possible variations in interaction [53]. This approach provides a structured and detailed analysis of technology interactions in real-world scenarios, facilitating a deeper understanding of both its practical applications and potential limitations. Due to its inherent strengths, this approach has been used by researchers in other fields to evaluate LLMs. For example, Saka et al. [54] demonstrated the capabilities and limitations of GPT for the construction industry through use cases in different fields such as sustainability, project management, and safety. In another study, Raj et al. [55] identified the areas of use cases for GPT integration in business operations and analyzed its impacts on the efficiency and effectiveness of the use case areas. Moreover, Ghesmi et al. [56] investigated GPT's ability in construction cost analysis and bid pricing through a case study of a bridge rehabilitation project. In the context of our study, a use case would detail the specific ways in which GPT could be applied to safety management tasks, such as identifying hazards, training workers, or suggesting safety guidelines. It would describe the interactions between the GPT system and its users, thereby providing insights into its limitations and capabilities in each application area. This would allow us to understand its shortcomings and capabilities for each application area.

Using this approach, the study was conducted by following three steps. Figure 1 demonstrates an overview of the steps of the study:

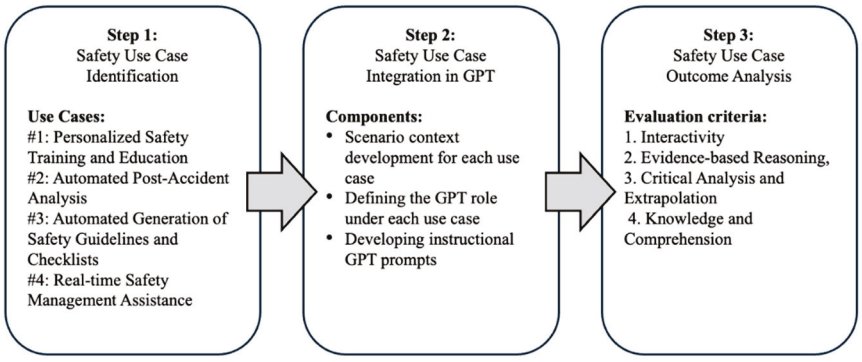

Figure 1. Overview of the methodology.

Step 1: Safety Use Case Identification: The objective was to identify safety use cases for integration of GPT. This included the identification of different application areas where GPT has been used or has the potential to be used in future.

Step 2: Safety Use Case Integration in GPT: This approach entailed assigning specific roles to GPT, corresponding to the responsibilities inherent in each safety management area. The foundational concept used in the integration of GPT was to make GPT emulate the role of human-driven processes in each use case.

Step 3: Safety Use Case Outcome Analysis: Qualitative assessments were carried out by evaluating the responses provided by GPT using four evaluation criteria: (1) Interactivity,

(2) Evidence-based Reasoning, (3) Critical Analysis and Extrapolation, and (4) Knowledge and Comprehension.

The following section discusses these three steps of the study in further detail.

2.1. Step 1: Safety Use Case Identification

A preliminary literature review was undertaken to identify potential safety use cases for GPT. The review included the studies that use LLMs for construction safety management tasks. Given that LLMs are advanced implementations within NLP and text mining, it is reasonable that areas that previously employed these technologies are likely to explore the use of LLMs if they have not already done so. Therefore, these areas were also included. The review uncovered four areas where GPT could play a role in safety management processes, which include the following:

Use Case #1: Personalized Safety Training and Education: using GPT to develop and deliver personalized safety learning content.

Use Case #2: Automated Post-Accident Analysis: using GPT to automatically analyze accident reports to determine the cause of accidents and recommend preventive measures.

Use Case #3: Automated Generation of Safety Guidelines and Checklists: using GPT to automate the creation of safety guidelines and checklists.

Use Case #4: Real-time Safety Management Assistance: using GPT to provide real-time assistance in day-to-day safety management tasks.

The following sections discuss each of these identified use cases in further detail.

2.1.1. Use Case #1

Personalized Safety Training and Education: Personalized training and education involve tailoring instructional approaches to meet the unique needs, preferences, and goals of individual learners [57]. This approach differs from traditional models by emphasizing personalized content, flexible pacing, adaptive technologies, and continuous assessment. Personalized training has been shown to enhance engagement, improve outcomes, increase satisfaction, and address diverse learning needs, ultimately leading to a more effective and inclusive learning experience [58]. Personalization is especially crucial for safety training as it requires equipping individuals with the ability to make context-specific decisions in response to dynamic safety challenges. Personalized safety training, characterized by individualized feedback mechanisms, is essential for the cultivation of critical cognitive skills by providing learners with direct, tailored feedback on their decision-making processes [59].

GPT can deliver accessible and personalized training by dynamically generating tailored scenarios and interactive dialogues based on individual learner profiles and responses. These models can analyze inputs from learners in real-time, offering instant, customized feedback and guidance to enhance decision-making skills [60]. LLMs and their predecessors in NLP have been effective in personalized training and education. For instance, Zhou et al. [45] demonstrated the personalization of safety training through the use of chatbots, which were developed using natural language processing techniques to deliver tailored content via mobile phones. This method significantly enhanced workers' comprehension of safety regulations. More recently, Hussain et al. [39] focused on personalizing safety training by integrating GPT models into VR environments, which provided customized instructions based on individual attributes of migrant workers, helping to overcome language barriers and improve practical safety skills. Similarly, Jamil Uddin et al. [37] investigated the use of GPT in construction safety training, aiming to enhance hazard recognition among construction students. The use of LLMs and NLP in general for personalized education and training extends beyond the construction sector. For example, Sharma et al. [61] introduced an adaptive generative AI system for customized education, which is personalized through

real-time sentiment analysis that adapts the educational content based on the learner's emotional responses, detected via webcam. The growing need for automating personalized safety training in the construction industry, coupled with the increasing utilization of LLMs for personalizing learning content, highlights significant opportunities to integrate LLMs into safety education and training within construction. However, it is crucial to evaluate the limitations and capabilities of GPT for this specific application to ensure its effective and appropriate use in enhancing safety training outcomes.

2.1.2. Use Case #2

Automated Post-Accident Analysis: Post-accident analysis in construction safety management involves retrieving and examining relevant accident case reports to understand the tacit knowledge about when, why, and how accidents occurred, thereby establishing measures to prevent future accidents [19,62]. This analysis is critical for improving safety as it provides actionable insights that can significantly mitigate risks and reduce the frequency of future incidents. Traditionally, this task has been performed by human experts because it requires a nuanced understanding of complex safety standards, legal implications, and situational specifics. Human analysts are adept at interpreting subtle cues and contexts that might be overlooked by automated systems, making their role indispensable in the thorough and accurate assessment of accidents.

With the latest developments in NLP, there is potential to augment this traditional approach. AI can assist by rapidly processing large volumes of accident reports and extracting key patterns and data points that might not be immediately obvious to human analysts. This capability speeds up the analysis process and enhances the depth of insights gained by identifying trends and correlations across multiple incidents [62]. For instance, Kim and Chi [26] automated the extraction of critical safety-related information from unstructured accident reports through NLP, specifically identifying the causal factors of each incident by categorizing hazard objects, positions, and associated work processes, thereby enhancing the effectiveness and precision of post-accident analysis. Similarly, Pan et al. [63] developed a graph-based deep learning framework to automate the identification of accident types, injury types, and body part factors from unstructured construction accident reports. Moreover, Xu et al. [64] developed a text mining and deep learning approach to automate the identification of hot work accident causes from unstructured accident reports, thereby providing detailed insights into causation that aid safety managers in formulating targeted interventions for improved on-site safety management. In another study, Zhang [65] developed a hybrid structured deep neural network with Word2Vec for the automatic classification of construction accident causes, which offers detailed insights into causation through post-accident analysis, facilitating the implementation of precise preventive measures to enhance safety.

Building on these advancements, LLMs offer further opportunities to enhance post-accident analysis in construction safety management. LLMs excel in understanding and generating human-like text, which allows for a more nuanced extraction of data from accident reports, including implicit information and subtleties that may not be explicitly stated. By applying advanced sentiment analysis, context recognition, and predictive analytics, LLMs can provide deeper and more accurate insights into the causes of accidents and potential preventative strategies [66].

2.1.3. Use Case #3

Automated Generation of Safety Guidelines and Checklists: The generation of safety guidelines and checklists is a structured process that involves identifying potential hazards associated with specific job tasks, determining appropriate control measures to mitigate

these risks, and documenting these findings in detailed, step-by-step instructions to ensure workplace safety and compliance [67]. This process is critical for safety as it provides clear, actionable instructions to workers, helping to prevent accidents and ensuring that safety protocols are consistently followed. Traditionally, this task has been performed by human experts because it requires a deep understanding of the specific work environment, job tasks, and relevant safety regulations. Human analysts excel at interpreting complex safety data and tailoring guidelines to the unique conditions of each worksite, ensuring that all potential hazards are addressed comprehensively.

Advancements in AI (especially NLP) have provided opportunities to automate this process by quickly analyzing large volumes of safety data and generating initial drafts of safety guidelines and checklists. These systems can identify common hazards and control measures from past reports, project documents, and standards, accelerating the generation process and ensuring critical information is included [68]. For example, Wang and El-Gohary [69] utilized NLP and deep learning to automate the extraction of fall protection requirements from construction safety regulations. The extracted data was organized into a knowledge graph, developing automated tools for compliance checking by providing a framework to assess whether construction site operations adhere to the stipulated safety regulations. Extracting guidelines from regulations or project documents using NLP has also been explored. For example, Borjigin et al. [70] developed a framework that utilizes NLP to extract information from compliance-checking construction regulatory documents, combined with template matching and multidomain semantic modeling.

With recent developments in LLMs, there are new opportunities for refining and enhancing the creation of safety guidelines and checklists. LLMs can generate safety guidelines and checklists automatically by processing vast amounts of textual data, such as past accident reports, safety regulations, and industry best practices. They can extract relevant information, identify patterns and common hazards, and then compile this data into coherent and comprehensive safety documents.

2.1.4. Use Case #4

Real-time Safety Management Assistance: Real-time assistance refers to providing immediate support and information as needed. In the context of safety, real-time safety assistance involves delivering instant guidance and information to managers or workers during operations. For example, if an unfamiliar piece of equipment is introduced, safety managers might want to know the safety requirements of its operation. Similarly, if a hazardous situation arises, such as exposure to hazardous materials, a construction manager might want to immediately know the protocols for addressing the issue and ensuring worker safety. Traditionally, real-time safety assistance has been a human-driven process, where safety managers or experts are responsible for finding the necessary information. This often involves searching through relevant standards and guidelines or seeking advice from other experts, which can be time-consuming and may not always provide immediate solutions.

In the context of Industry 4.0, it is viewed as a virtual assistant or query-answering system designed to provide information support through natural language-based human–machine dialogue [71]. A safety assistant, in this context, is defined as a real-time virtual assistant that provides safety information to support safety managers or workers. The concept is not new in construction and NLP has been used to develop real-time virtual assistants before. For instance, Wang et al. [72] used NLP to assist in information extraction from building information models, facilitating the development of a query-answering system that supports construction project team members by analyzing natural human language queries, identifying relevant building information, and generating comprehensible

responses. Similarly, Lin et al. [73] proposed an innovative NLP-based methodology for efficient data retrieval and visualization from cloud BIM. More recently, LLMs have also been utilized to develop real-time safety assistants; for example, Wang and Issa [52] employed LLMs and transfer learning to develop a construction safety chatbot that enhances access to OSHA fall protection regulations. By using models like T5 and GPT-3, their system generates questions from regulatory texts, improving safety guideline comprehension and potentially reducing workplace accidents. In another study, Tian et al. [74] suggested a deep learning, NLP-based technique that can provide automated responses to safety hazard inquiries.

These research efforts collectively illustrate the potential of GPT to be utilized as a safety management assistant capable of responding to safety inquiries from workers. Further evidence of this lies in the extensive research on chatbots [75] that have been successfully employed for various purposes in fields beyond construction, indicating a promising avenue for the deployment of LLMs in similar capacities.

2.2. Step 2: Safety Use Case Integration in GPT

Four detailed scenarios were created to better illustrate how GPT could be used in each use case. Drawing upon existing safety protocols and typical tasks in the construction industry, these scenarios were designed to authentically replicate situations where GPT could be effectively deployed for each of the four application areas. Using inputs from safety standards [76], training resources [77,78], and historical incident data from OSHA and NIOSH [79,80], the scenarios were tailored to present realistic yet demanding challenges, providing an opportunity for a thorough evaluation of GPT capabilities in the next step of the study. Table 1 demonstrates different safety contexts that GPT will be tested in and also its roles.

Table 1. Safety context and GPT's role under each use case.

Use Cases	Scenario Context
Use Case #1: Personalized Safety Training and Education	Safety Context: a session that includes safety training with hazard recognition, hazard management, and safety compliance as learning objectives. GPT Role: creating and delivering the above safety training content.
Use Case #2: Automated Post-Accident Analysis	Safety Context: a detailed real accident report obtained from NIOSH to be analyzed. GPT Role: analyzing the accident report and extracting relevant safety information to identify the causal factors and suggest preventive measures.
Use Case #3: Automated Generation of Safety Guidelines and Checklists	Safety Context: safety guidelines and checklists for welding while working at height. GPT Role: creating safety guidelines and checklists, ensuring alignment with the OSHA safety standards and site-specific requirements.
Use Case #4: Real-time Safety Management Assistance	Safety Context: queries from three key areas of safety management: (1) hazard recognition, (2) hazard evaluation, and (3) hazard control. GPT Role: providing practical answers to the questions by assuming the role of a safety assistant that provides support to the safety manager.

After outlining each scenario, the details of each use case context were provided to GPT using the instructional prompts shown in Table 2. The instructional prompts were

employed to clarify GPT's responsibility in interacting with the data, specifying the type of processing it should undertake and outlining the expected outcomes for each use case. (See Appendix A for detailed descriptions of these instructional GPT prompts to create the four use cases).

Table 2. Instructional GPT prompts for each use case.

Use Cases	Instructional GPT Prompts
Use Case #1: Personalized Safety Training and Education	Contextualizing Safety: The instructional prompt provided the topic of "*working on height*" with hazard recognition, hazard management, and safety compliance defined as the learning objectives of the training. GPT was instructed to incorporate specific training material from OSHA and NIOSH material to create the learning content. The training progression was also provided to GPT as follows: instruction on first learning objective → pause for user's questions → assessment scenario for the learning objective → feedback on user performance → subsequent scenarios based on user performance → feedback → repeat for the next learning objective. Clarifying GPT's Responsibility: GPT was tasked to introduce itself, create interactive and accurate safety training content, deliver training, answer user-asked questions, create safety scenarios and questions to evaluate user's understanding, and create follow-up scenarios based on user's performance until a satisfactory result is conceived.
Use Case #2: Automated Post-Accident Analysis	Contextualizing Safety: GPT was tasked to analyze an accident report to achieve three specific objectives that include extracting key information from accident reports, identifying the root cause and causal factors of accident, and proposing preventive measures. Clarifying GPT's Responsibility: GPT's responsibility was using its knowledge base, reasoning capacity, and relevant standards and guidelines to answer 9 key questions framed around the objectives listed above.
Use Case #3: Automated Generation of Safety Guidelines and Checklists	Contextualizing Safety: GPT was provided with a construction scenario that included specific task (arc welding), specific component of the building (roof framing of a steel structure building), and specific location (third floor roof). Clarifying GPT's Responsibility: GPT was instructed to generate safety guidelines and checklists for the construction scenario using OSHA regulations and standards. Moreover, GPT was tasked to provide relevant OSHA standards to be considered for the work
Use Case #4: Real-time Safety Management Assistance	Contextualizing Safety: GPT was tasked to provide answers to diverse safety-related questions that are typically expected from safety assistants from three areas: (1) hazard recognition, (2) hazard evaluation, and (3) hazard control. Clarifying GPT's Responsibility: GPT was tasked to provide detailed answers with references from OSHA standards and reliable safety resources and come up with follow-up questions to enhance user's understanding of the topic.

As detailed in Appendix A and Table 2, prompts were designed to reflect realistic construction safety scenarios and the types of responsibilities GPT would be expected to assume in practice. Each use case assigned GPT a distinct role, such as safety trainer, safety manager, or assistant, to align with the specific task. Prompts were structured with neutral, context-relevant language and avoided suggestive phrasing to minimize response bias. Importantly, the tasks were designed to mirror the actual responsibilities, expected interactions, and intended outcomes associated with each professional role in a real-world construction safety setting. For Use Case #1 (Personalized Safety Training and Education),

GPT was instructed to act as a certified safety trainer and conduct an interactive height safety training session, including small talk, OSHA-cited content delivery, question-and-answer interaction, and scenario-based knowledge assessment with adaptive difficulty. In Use Case #2 (Automated Post-Accident Analysis), GPT was prompted to analyze a detailed accident report and respond to structured questions regarding hazard identification, OSHA standards, injury details, and causal analysis. For Use Case #3 (Automated Generation of Guidelines and Checklists), GPT was asked to generate safety documentation based on a specific construction scenario while citing relevant OSHA regulations. In Use Case #4 (Real-time Safety Management Assistance), GPT played the role of a virtual safety assistant, beginning with conversational onboarding and user profiling, then offering support by answering user questions based on OSHA, NIOSH, and other credible safety sources, while proposing relevant follow-up queries to deepen understanding.

To ensure consistency and minimize bias, only the first GPT-generated response was used for evaluation. However, additional output generations were reviewed to confirm response stability and verify that outputs did not deviate significantly from the initial generation. This approach enabled a reliable and reproducible evaluation of GPT's performance across all use cases while preserving the contextual integrity of the tasks.

2.3. Step 3: Safety Use Case Analysis

After defining the use cases for GPT using instructional prompts, each created use case was assessed using a series of User–GPT interactions. Table 3 provides examples of how such interactions were conducted between users and GPT under each use case. Appendix B also provides all these interactions with complete details.

Table 3. User–GPT interaction under each use case.

Use Cases	User–GPT Interactions
Use Case #1: Personalized Safety Training and Education	GPT Role: GPT was tasked to assume the role of an "expert construction safety trainer" and train a construction worker. User Role: user assumed the role of a new construction worker who has limited understanding of the safety topic that is being taught.
Use Case #2: Automated Post-Accident Analysis	GPT Role: GPT had the role of a construction accident investigator who analyzes the past accidents and develops guidelines and preventive measures for the future. User Role: not applicable.
Use Case #3: Automated Generation of Safety Guidelines and Checklists	GPT Role: GPT assumed the role of a safety expert and provided safety guidelines and checklists for the given construction scenario. User Role: user provides a specific construction settings to GPT and requests guidelines and checklists for the task.
Use Case #4: Real-time Safety Management Assistance	GPT Role: GPT assumed the role of a safety management assistant. User Role: user assumed the role of a construction manager and asked safety-related questions within three key areas of safety management.

The User–GPT interaction for each use case was analyzed to evaluate GPT's performance, capabilities, and limitations. The following criteria were selected for the qualitative assessment of the User–GPT interaction based on the established literature on language model evaluation [81–83] and their relevance to the demands of safety-critical domains. The criteria include interactivity, evidence-based reasoning, critical analysis and extrapolation, and knowledge and comprehension. These reflect core competencies required to effectively carry out the tasks represented in each use case, such as delivering training, analyzing incidents, generating safety documentation, and providing real-time assistance. Together, they provide a structured framework for assessing GPT's ability to support construction

safety management in a manner that aligns with both domain expectations and model performance benchmarks.

2.3.1. Interactivity

One of the critical features of GPT is its inherent interactive capability to ensure a user-centric interaction. This includes effective dialogue, contextual understanding, and user-friendly responses. GPT's proficiency in extrapolating from the content of the user's input, or from instructions given as a system prompts, makes it an invaluable tool in safety management where prompt and accurate information exchange is crucial.

- *GPT Assessment Procedure*: to evaluate the interactive ability of GPT qualitatively, two researchers observed and assessed the responses of GPT based on following criteria.
    - *Comprehensive Language Processing*: GPT's ability to understand and interpret the nuances and variations in human language was evaluated, particularly its handling of complex queries and generation of coherent follow-up responses.
    - *Contextual Understanding*: GPT's capacity to maintain conversational continuity by remembering and integrating previous information and context into its subsequent responses was assessed.
    - *Human-like Responses*: the degree to which GPT's responses replicate human conversational patterns was examined, focusing on its ability to demonstrate empathy, personalization, and a natural flow in interactions.
- *Assessed Use Cases*: This assessment was conducted for use cases #1 (Personalized Safety Training and Education) and #4 (Real-time Safety Management Assistance), where user interaction is critical. Use case #2 (Automated Post-Accident Analysis) and #3 (Automated Generation of Safety Guidelines and Checklists) were excluded as no conversation takes place between the user and GPT in those use cases.

2.3.2. Evidence-Based Reasoning

Evidence-based reasoning refers to the ability of GPT to process information and generate conclusions that are logically sound and rooted in factual data. This capability is crucial for GPT, as it ensures that the decisions or recommendations made by it are reliable and grounded in evidence. These criteria are essential because they underpin the trustworthiness of the outputs GPT generates, which is particularly critical when it is applied in domains requiring high accuracy and reliability.

- *GPT Assessment Procedure*: Evidence-based reasoning was assessed by comparing the generated information to (1) established regulations and standards, (2) relevant safety documents, and (3) a similar analysis conducted by a human expert, whenever applicable. The following criteria were used for assessment:
    - *Using Factual Information*: GPT's ability to generate answers based on reliable, factual information was evaluated, with a focus on minimizing hallucination.
    - *Detecting Incorrect Inputs*: GPT's capability to identify and flag user mistakes or incorrect input information was assessed.
    - *Extracting Correct Information from User's Given Documents*: GPT's effectiveness in extracting accurate and relevant information from documents and instructions provided by the user was examined.
- *Assessed Use Cases*: this assessment was conducted for all use cases as evidence-based reasoning is equally important for all application areas.

2.3.3. Critical Analysis and Extrapolation

Critical analysis of available information and data involves the capacity to analyze textual data, discern pertinent information, and make connections between different data points. This analytical capability is essential for LLMs like GPT to contextualize, prioritize, and infer based on the data in order to provide nuanced and informed responses or make decisions. The extrapolation aspect involves going a step further and using this analyzed data to make educated inferences or hypothesize about underlying reasons and potential future outcomes.

- *GPT Assessment Procedure*: GPT's performance was qualitatively evaluated by two researchers and also benchmarked against the analysis conducted by human experts (from NIOSH and OSHA) for the same task, providing a comparative perspective on their ability to critically understand and apply safety-related information. Existing safety regulations and documents were also used for comparison. The following criteria were used for assessment:
    - *Depth of Analysis*: GPT's ability to thoroughly analyze textual data, identifying key information and relevant details that are crucial for understanding safety contexts, was assessed. This analysis was compared to the depth achieved by human experts from NIOSH and OSHA wherever applicable.
    - *Connection and Contextualization*: GPT's ability to link disparate pieces of information to form a cohesive understanding of safety scenarios was evaluated. The assessment includes determining whether GPT can contextualize safety information in a manner comparable to insights from existing safety regulations and documents.
    - *Inferencing and Extrapolation*: GPT's ability to infer and extrapolate from analyzed data to predict potential safety risks or recommend preventive measures was examined.
- *Assessed Use Cases*: This assessment was conducted for use cases #2 (Automated Post-Accident Analysis), #3 (Automated Generation of Safety Guidelines and Checklists), and #4 (Real-time Safety Management Assistance) where critical analysis and extrapolation from given information is important for GPT to deliver appropriate results.

2.3.4. Knowledge and Comprehension

The expansive knowledge base of GPT is one of its most notable attributes as it determines its effectiveness in interpreting and responding to complex queries. Knowledge refers to the breadth of information GPT can access, while comprehension involves the depth of understanding of this information and of user inputs. These elements are crucial for GPT to provide accurate, relevant, and contextually appropriate responses.

- *GPT Assessment Procedure*: GPT's performance was qualitatively evaluated by comparing the generated information to (1) regulations and standards, (2) relevant safety documents, and (3) human responses whenever applicable. The following criteria were used for this assessment.
    - *Breadth of Knowledge*: GPT's ability to cover a wide range of topics was assessed by assessing its responses to diverse queries from different domains of safety management to evaluate its capacity to retrieve and accurately present information across a broad spectrum of subjects.

- *Depth of Comprehension*: GPT's depth of understanding was evaluated, focusing on its ability to grasp complex concepts and contextual nuances in its responses.

- *Assessed Use Cases*: this assessment was conducted for all use cases.

3. Results of the Safety Use Case Analysis

This section discussed the analysis results for each use case based on the four criteria of (1) Interactivity, (2) Evidence-based Reasoning, (3) Critical Analysis and Extrapolation, and (4) Knowledge and Comprehension.

3.1. Analysis Results for Use Case #1 (Personalized Safety Training and Education)

In this use case, GPT provided safety training experience about fall-related hazards and working on heights. The training was provided through the following phases. Figure 2 depicts these interaction phases:

- Introduction: GPT introduced itself as a virtual trainer, establishing a welcoming and engaging tone similar to that of a human trainer. This initial interaction was designed to build rapport and ease the trainee into the learning environment, setting the stage for effective communication and learning.
- Training Content Delivery: GPT delivered educational content focused on fall-related hazards and safe practices for working at height. After presenting the material, GPT invited questions from the user to ensure clarity and understanding. This interaction allowed the trainee to engage actively with the content, moving the training forward based on the user's responses or expressed understanding.
- Safety Scenario: GPT presented customized safety scenarios along with questions to evaluate the user's understanding. These scenarios were crafted to simulate real-life situations, thereby testing the practical application of the learned safety measures and GPT's ability to assess critical understanding.
- Provide Feedback: Based on the user's answers to scenario questions, GPT provided personalized feedback, identifying areas of strength and those needing improvement. This step was crucial for evaluating GPT's instructional effectiveness and enhancing the trainee's learning experience. The process progressed with the user either asking further questions or confirming their understanding of the feedback.
- Adjust Scenario Complexity and Introduce New Scenarios: Depending on the user's level of understanding, GPT adjusted the complexity of the safety scenarios. This iterative process of scenario presentation and feedback continued until the user consistently demonstrated satisfactory responses, ensuring a deep and practical understanding of the safety topics covered.
- Closure: The training session concluded with GPT summarizing the key points and confirming that the user had achieved a comprehensive understanding of the material, akin to the closure provided by a human trainer. This final interaction was designed to reinforce the training outcomes and provide the trainee with confidence in their new knowledge.

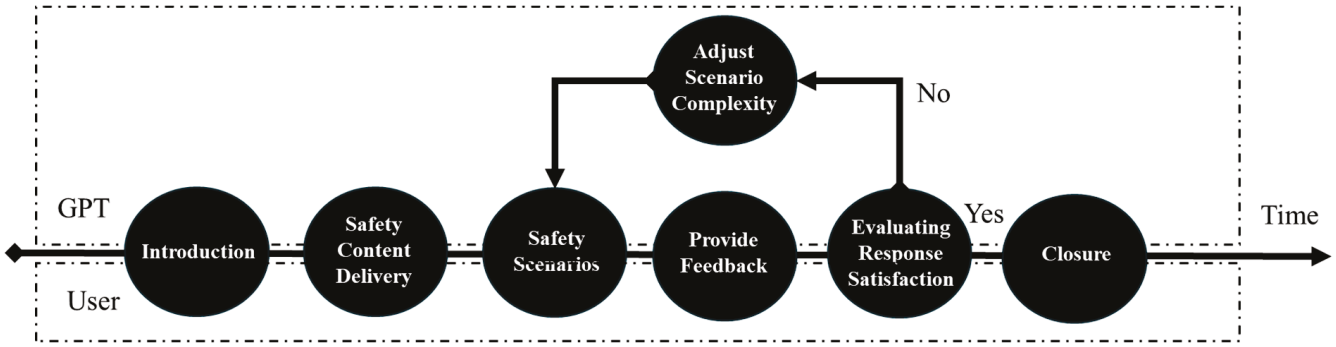

Figure 2. User–GPT interaction phases for use case #1 (Personalized Safety Training and Education).

The analysis results for use case #1 (Personalized Safety Training and Education) are as follows:

Interactivity: During the training experiment, GPT demonstrated responsiveness and engagement in conversations with a trainee. Overall, GPT's interactive ability was found to be acceptable for this use case based on the following observations.

- Comprehensive Language Processing: GPT exhibited the capability to process and understand the user's questions correctly. It effectively comprehended the nuances and variations in the user's language, successfully interpreting complex queries. For instance, when presented with a slightly jumbled question, "What's my next step if I notice the safety harness seems wrecked just before I'm supposed to start working up high?", GPT accurately deciphered the underlying safety concern despite the informal phrasing and potential ambiguity around "seems wrecked". It responded appropriately: "Cease use immediately and report the issue to ensure a replacement harness is provided." Additionally, GPT handled a follow-up question accurately: "And if there's no replacement available immediately?", to which it replied, "Utilize alternative safety measures such as a scaffold with guardrails or delay the task until the proper equipment is available." These responses were relevant, but more importantly for this evaluation criteria, contextually appropriate, demonstrating a high level of linguistic accuracy and detail.
- Contextual Understanding: GPT's ability to maintain continuity and context throughout the conversation was notably demonstrated during a session. At the beginning of the training, the user asked, "What steps should I take if I notice loose scaffolding at a worksite?" GPT advised to immediately cordon off the area and report the issue to the site supervisor for urgent repairs. Much later in the session, during the safety scenario phase of the training, the user inquired, "During my inspection, should I re-check previously reported issues like the scaffolding?" Remembering the earlier conversation, GPT responded, "Yes, verify that the previously loose scaffolding has been securely fixed as reported. Do not proceed with work in that area until all necessary repairs are confirmed." This response shows how GPT successfully linked the initial identification of a hazard to subsequent safety verification procedures.
- Human-like Responses: The session began with GPT introducing itself and engaging in some initial small talk to set a friendly tone, saying, "Nice to meet you, Ali! How are you doing today? Are you ready to dive into some safety training for working at heights?" This helped to ease the trainee into the learning environment. During the training, GPT exhibited mixed performance in its human-like interactions. For instance, when a trainee expressed concern about feeling unsafe while working at heights, saying, "I always get nervous on a ladder, even with all the gear" GPT responded empathetically, "It's completely normal to feel nervous, and it's good

that you're cautious. Remember to double-check your gear before ascending and keep your focus on the task. I'm here to help you through this." GPT also offered positive reinforcement, such as "Good job" or "Well done, that's exactly right," which effectively supported the trainee's learning progress.

However, there were instances where GPT's responses lacked the necessary human subtlety. For example, when delivering training material, other than the initial interaction which was "Absolutely, Ali! Let's dive deeper into each area of safety training for working at heights," the rest of the content was mere technical information delivery, same as any that can be read in a book or a research paper which lacks human subtlety. The overall performance of GPT in providing human-like responses was mixed. While it successfully demonstrated empathy and engagement in certain interactions, it occasionally failed to appropriately address trainee emotions or simplify complex information when needed. These moments highlighted areas where further refinement in GPT's model could enhance its ability to more consistently mirror the nuanced and supportive communication style of an effective human trainer.

Evidence-based Reasoning: The evidence-based reasoning was evaluated using the feedback that GPT provided to the trainee and the training content generated by GPT. For this use case, GPT demonstrated acceptable evidence-based reasoning based on the following observations:

- Using Factual Information: The material and information that were provided to the trainee as part of the training aligned with OSHA guidelines and standards and established training practices. For each different part of training, GPT referenced the correct OSHA standard number; for example, for hazard management, it correctly used "OSHA Standard: 29 CFR 1926.502—Fall protection systems criteria and practices," which is aligned with the context of the training.
- Detecting Incorrect Inputs: GPT demonstrated the ability to detect incorrect answers and provide targeted feedback based on user responses. Additionally, it could recognize partially correct answers, identify areas of misunderstanding, and guide the trainee toward the correct information. For instance, in the first scenario, when asked, "You are working on a construction site, and you notice that a coworker is about to use a ladder that appears to be damaged. The ladder has a split side rail and a couple of bent rungs. What steps would you take to address this situation?", the user responded partially correctly by stating, "I will choose a new ladder to use." While this response was on the right track, it missed key steps such as stopping the coworker, reporting the damage, and tagging the ladder. GPT emphasized these missing elements to improve the user's understanding. To reinforce the learning, GPT introduced a follow-up scenario addressing the gaps identified in the previous response. It asked, "You are assigned to work on a rooftop that is 20 feet above the ground. The rooftop has no guardrails installed. What fall protection measures should you implement to ensure your safety while working on the rooftop?" This allowed the user to apply the knowledge gained from the earlier feedback and demonstrate improved understanding.
- Extracting Correct Information from User's Given Documents: in this scenario, the user did not provide any document to GPT, so this criterion was not assessed.

Knowledge and Comprehension: During the training session, it was observed that GPT produced training content based on accurate OSHA standards and covered the necessary aspects for the given subject. However, certain issues were observed, as discussed in detail below.

- Breadth of Knowledge: The training session addressed all the predefined objectives provided to GPT. Specifically, GPT covered various safety management areas, such as hazard control, by identifying and discussing hazards like falls from ladders, unprotected edges and openings, and scaffold stability. Additionally, GPT addressed hazard management by outlining preventive measures, including the use of guardrails, personal fall arrest systems (PFASs), and proper ladder usage. This coverage of a wide range of safety management topics demonstrates the breadth of knowledge imparted during the training.
- Depth of Comprehension: In some instances, the training lacked depth, focusing primarily on more obvious content. This limitation was evident in most of the training material provided by GPT. While the training covered all the predefined objectives, the deeper insights that a human trainer could offer were notably absent. Even when a user requested a more in-depth explanation by asking, "Can you dive a bit deeper into each subject?", although GPT's subsequent response was more detailed, it still lacked the necessary depth and specificity. For example, when addressing scaffolding guardrails and planking, GPT provided the instruction, "Ensure scaffolds have proper guardrails and fully planked walkways," which omitted crucial details related to hazard recognition in this context.

This gap could potentially be resolved by fine-tuning the model with more specific training data or by specifying the desired depth of coverage during the initial setup. Moreover, this issue suggests that GPT's training delivery was largely user-driven. If the user requested more detailed information, GPT provided it; however, this approach may be problematic for users with limited prior knowledge of the subject. In such cases, critical information could be omitted without the user realizing it, which may result in gaps in understanding and safety practices.

In conclusion, use case #1 (Personalized Safety Training and Education) highlights both the strengths and limitations of GPT in the context of interactive safety training. While GPT demonstrated strong capabilities in processing complex and informal queries, maintaining contextual continuity, and providing evidence-based reasoning aligned with OSHA standards, its performance in interactivity was mixed. GPT effectively responded to user inputs with relevant and detailed safety guidelines, reflecting a broad knowledge base. However, two key limitations were observed. First, GPT's ability to deliver consistently human-like responses was less reliable, especially when addressing user emotions or providing empathetic feedback. Second, its depth of comprehension was inconsistent, often requiring explicit prompts to offer more nuanced insights. These observations suggest that while GPT can serve as a valuable tool in safety training, further refinement is necessary to enhance its interactive capabilities and ensure it meets the needs of users with varying levels of expertise. Furthermore, integrating GPT into formal safety training programs presents practical challenges, including alignment with certified curriculum standards, ensuring content accuracy, and preventing over-reliance on AI-driven instruction. Ethical considerations such as maintaining instructor accountability and protecting learners from misinformation must be addressed before widespread adoption.

3.2. Analysis Results for Use Case #2 (Automated Post-Accident Analysis)

In this use case, GPT analyzed a past accident report of a real construction accident from NIOSH. The following steps are the interaction between the user and GPT. Figure 3 depicts these interaction phases:

- Input: in this step, user provided GPT with the accident report from NIOSH.

- Extracting Key Information from Accident Reports: This task evaluated GPT's ability to understand and pull relevant details from complex documents. The accuracy and relevance of extracted information from NIOSH reports are crucial for understanding the context and specifics of each accident.
- Utilizing Relevant Standards and Guidelines: This task gauged GPT's ability to effectively use its extensive knowledge base. By retrieving and applying relevant OSHA standards and guidelines, GPT showcases its capability to provide informed, contextually appropriate recommendations and references.
- Analyzing Causes and Proposing Preventive Measures: this task assessed GPT's reasoning skills. By analyzing the causes of accidents and suggesting preventive strategies, GPT demonstrates its capacity to interpret data, understand underlying issues, and apply problem-solving techniques.

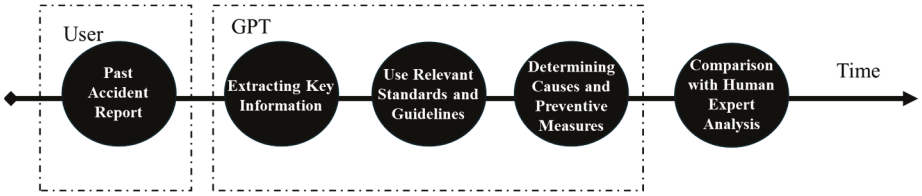

Figure 3. User–GPT interaction phases for use case #2 (Automated Post-Accident Analysis).

The analysis results for use case #2 (Automated Post-Accident Analysis) are as follows:

- **Evidence-based Reasoning**: GPT showcased acceptable evidence-based reasoning ability. This ability was measured by comparing the GPT responses to relevant OSHA regulations and analysis completed by the safety experts at NIOSH for the same accident report. Below are the details of assessment results.
    - Using Factual Information: GPT demonstrated strong evidence-based reasoning ability by identifying specific hazards and linking them correctly to the corresponding OSHA standards. This could be seen for all of the hazards that GPT detected. Moreover, when GPT was tasked to provide the name of the injured person, it replied with "The victim's name is not provided in the report", which indicates that the responses created by GPT are not hallucinations and it is drawing its answers from given factual information. The responses indicated that GPT could be utilized as a valuable tool for automating the process of extracting necessary information from accident report databases and analyzing it to draw meaningful inferences. This saves time and resources, allowing professionals to focus on other critical tasks.
    - Detecting Incorrect Inputs: this criterion did not apply to this use case as there was no user interaction.
    - Extracting Correct Information from User's Given Documents: Based on the responses provided by GPT, it is evident that the model is proficient in extracting relevant information from the given accident report. The responses to questions focused on information extraction (see questions 4 to 9 in Appendix A) demonstrated complete alignment with the details described in the accident report. For example, when GPT was asked to name the location of the accident, it replied, "the accident took place at a residential house where roof replacement work was being carried out", or when the type and severity of injury were asked of GPT, it replied "the victim suffered severe head injuries, resulting in her remaining unconscious and ultimately leading to her death", which completely aligned with the facts included in the provided accident

report. These highlight the model's capability to effectively understand and interpret the information contained within such reports.

- **Critical Analysis and Extrapolation**: This use case indicated that although there are areas where GPT had acceptable performance in critically analyzing the information, certain limitations need to be addressed to effectively use it as a tool for accident analysis. Below are detailed observations for this criterion.
    - Depth of Analysis: The analysis of responses revealed differences between GPT's observations and the human analysis conducted by NIOSH. While the human analysis did not identify any misuse of the forklift, GPT highlighted the potential hazard of using a homemade box to transport construction materials and equipment. This observation by GPT, which was overlooked by human experts, appears to be relevant to this accident. Another important observation was that GPT did not recognize the worker's young age and potential lack of experience as a contributory factor to the accident. While NIOSH analysis cited this as a possible contributing element, it was inferred through extrapolation of facts rather than being directly evidenced in the report. This strict reliance on concrete evidence underscored GPT's capability to reduce the impact of biases and subjective interpretations that might influence human analysis. Such a characteristic is invaluable, especially in situations where objective analysis is crucial. However, to fully account for the range of potential risks in construction safety, future improvements should consider incorporating controlled extrapolation into GPT, enabling it to identify indirect or nuanced factors while retaining its unbiased approach.
    - Connection and Contextualization: This can be seen when GPT was tasked to provide reasons and analysis when determining hazards in the provided scenario. For example, when GPT recognizes inadequate training and supervision, the analysis implies the following: "The owners verbally reminded the male laborer and the victim to be careful while working, but there is no mention of formal training or supervision. OSHA standard number: 1926.21—Safety Training and Education. This standard mandates employer to provide proper training and supervision to employees to ensure their safety". The analysis indicates that there was not adequate training based on the fact that the owner was not present when the accident happened and the fact that there was no indication of adequate training. Further, this hazard was connected to proper safety regulations and documents. This indicates that GPT is capable of establishing an understanding of the presented scenario and contextualizing safety information based on the existing regulations.
    - Inferencing and Extrapolation: GPT provided a detailed analysis of each hazard, such as fall risks, inadequate training, unsafe equipment use, and ladder safety concerns. However, the depth of GPT's analysis, while detailed, does not always capture the broader, systemic considerations of safety management. For example, the human response included broader, more generalized recommendations for preventive measures, such as developing a comprehensive safety and occupational health program. This reflects an understanding that preventing accidents often requires systemic changes and a holistic approach, rather than just addressing specific hazards. GPT, in contrast, provided more direct and specific solutions tied closely to the information presented in the report, which could have been seen by GPT's recommendation to use fall hazard protection equipment or appropriate equipment.

- **Knowledge and Comprehension**: Evaluating the information referenced in GPT's responses revealed that they were consistent with OSHA regulations and established standards of practice. This suggests that GPT was drawing information from accurate and factual sources, as indicated by the observations discussed below.
    - Breadth of Knowledge: GPT demonstrated the ability to analyze the accident report and identify multiple issues contributing to the accident, as well as suggest relevant prevention strategies. Its knowledge was demonstrated through its ability to accurately reference and apply various sections of OSHA regulations, including fall protection, safety training and education, rigging equipment for material handling, and ladder safety, in the correct context of the details mentioned in the accident report. These references were consistent with OSHA standards. For example, GPT correctly identified the requirement for employers to provide fall protection systems and training for work at heights above 6 feet, aligning with OSHA requirements.
    - Depth of Comprehension: GPT demonstrated a good depth of understanding in its responses, indicating that it comprehended the accident report thoroughly. For instance, it detected fall hazard as the primary cause of accident and noted, "The victim fell approximately 26 feet from the roof to the stone patio". In its analysis, GPT stated, "The victim was not wearing any fall protection equipment while working on the roof, which exposed her to the risk of falling," demonstrating its ability to consider the contextual nuances of the accident report. For preventive measures, GPT recommended, "Employers should provide and enforce the use of proper fall protection equipment, such as harnesses and guardrails, when working at heights. Adequate training on fall protection measures should also be provided," which also suggests a deeper understanding of how an accident such as the one mentioned in the report could be prevented.

In use case #2 (Automated Post-Accident Analysis), the exploration of GPT's capabilities and limitations within construction safety revealed mixed results. GPT demonstrated a robust ability to perform evidence-based reasoning, effectively extracting and analyzing information from accident reports. This capability suggests that GPT could serve as a valuable tool for automating data extraction and initial analysis, potentially saving considerable time and resources. However, the model exhibited limitations in critical analysis and extrapolation. While GPT identified hazards not noticed by human experts, it occasionally missed broader, systemic safety issues, such as the need for comprehensive safety programs that require more nuanced understanding. Moreover, GPT's strict reliance on explicit information sometimes prevented it from recognizing less obvious, contributory factors such as experience or indirect risks. Addressing these limitations by enhancing GPT's ability to perform controlled extrapolation could make it a more effective tool for comprehensive safety analysis. From a practical perspective, integrating GPT into existing incident analysis systems would require oversight protocols to verify the accuracy of extracted insights and to ensure compliance with legal and regulatory reporting standards. Additionally, ethical concerns such as attributing causation based on AI reasoning and the risk of overlooking contextual factors underscore the importance of human validation.

3.3. Analysis Results for Use Case #3 (Automated Generation of Safety Guidelines and Checklists)

In this use case, GPT generated safety guidelines and checklists for an arc-welding scenario that takes place at height. The following interaction between the user and GPT was used in this use case. Figure 4 demonstrates these interaction phases:

- Input: in this step, the user provided GPT with the construction activity scenario.

- Creating Guidelines: This task involved GPT generating guidelines that are specific to the construction scenario. This task assessed the knowledge, comprehension, and critical analysis abilities of GPT as it needed to understand the scenario, determine the accidents that can take place, and generate guidelines to prevent them.
- Creating Checklists: In this task, GPT had to generate a checklist based on the construction scenario and the guidelines it generated. This task targeted GPT's ability to reason as it had to utilize the guidelines to generate appropriate questions for the checklist.
- Identifying relevant Standards: In this step, GPT was tasked to provide relevant standards from OSHA for the items in the guidelines and checklist that it generated. The objective was to assess knowledge and comprehension.

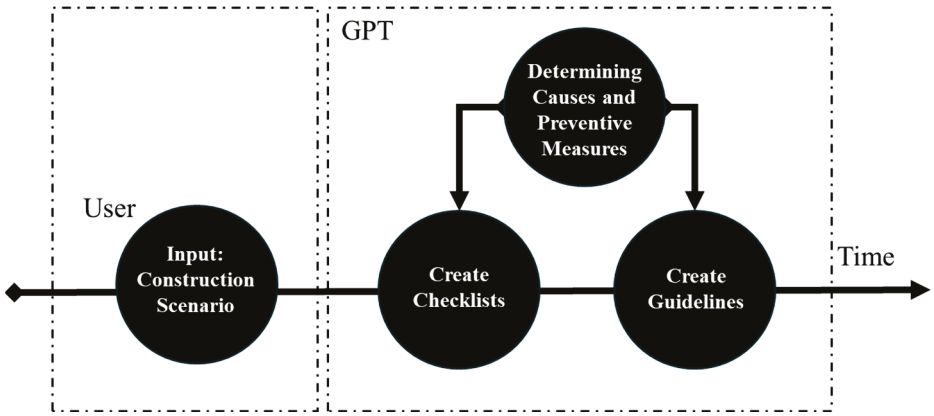

Figure 4. User–GPT interaction phases for use case #3 (Automated Generation of Safety Guidelines and Checklists).

The qualitative analysis results for use case #3 (Automated Generation of Safety Guidelines and Checklists) are as follows:

- **Evidence-based Reasoning**: GPT's response in generating safety guidelines and checklists for arc welding demonstrated robust evidence-based reasoning capabilities, particularly in its understanding and application of safety protocols and regulations.
    - Using Factual Information: GPT aligned its recommendations with correct OSHA standards such as OSHA 1910.252 for welding, cutting, and brazing and 1926.501 for fall protection. It also used the information from the user input about work being at height and considered this fact in creating guidelines and checklists. For example, for fall protection, GPT mentions that "Implement appropriate fall protection measures, such as guardrails, safety harnesses, or safety nets."
    - Detecting Incorrect Inputs: this criterion did not apply to this use case as there was no interaction between the user and GPT.
    - Extracting Correct Information from User's Given Documents: in this scenario, the user did not provide any document to GPT, so this criterion was not assessed.
- **Critical Analysis and Extrapolation**: GPT's critical analysis in this case was acceptable. However, certain issues need attention before GPT can be further used for this use case.
    - Depth of Analysis: GPT listed safety measures that are needed for the specific task. For example, it mentioned proper PPE, fall protection, fire prevention, ventilation, and electrical safety. However, certain regulations, like the prohi-

bition against immersing the electrode in water, were omitted. This omission is understandable as the generated output focused on general guidelines and checklists, which typically do not include such detailed instructions. These specifics are more appropriately conveyed in safety training sessions designed to address potential hazards in greater depth. Also, the guidelines appeared to only consider the static scenario, without accounting for potential changes in the work environment. A more critically analyzed response would consider dynamic factors, such as changing conditions or the presence of other workers in the vicinity, which could affect safety measures. Lastly, GPT's response would benefit from a more comprehensive risk assessment, accounting for the interplay of multiple hazards specific to the task, such as electrical risks, working at heights, and exposure to welding fumes, requiring a deeper understanding of these combined threats.

- Connection and Contextualization: When comparing GPT-generated guidelines and checklists for arc welding with OSHA regulations, it became clear that GPT covered most of the relevant safety protocols. For example, in the safety checklist for arc welding, GPT correctly included specific PPE requirements, such as "Have all workers been provided with appropriate PPE, including welding helmets, gloves, and safety glasses?" Additionally, GPT captured the environmental context by including fall protection measures, considering the task's execution at significant heights, even though no explicit fall hazards were mentioned in the user input. However, it did not necessarily prioritize guidelines based on the specific risks or likelihood, which is important to provide a more targeted set of guidelines. This issue could be resolved by tailoring the instructions given to GPT for the particular task.
- Inferencing and Extrapolation: The analysis of guidelines and checklists indicates that these were tailored to the specific hazards present in the scenario. For example, GPT highlighted relevant concerns such as, "Is the work area adequately ventilated to control welding fumes?" and "Have all workers been provided with appropriate PPE, including welding helmets, gloves, and safety glasses?" as well as "Have fall protection measures been implemented for workers working at heights?" These examples illustrate GPT's ability to identify and address key hazards in the scenario, such as fall risks and fire-related dangers. Additionally, GPT developed checklists aimed at mitigating these workplace hazards, demonstrating its potential to enhance safety protocols through targeted hazard identification and prevention strategies.

- **Knowledge and Comprehension**: The response included accurate safety protocols for welding from OSHA, indicating a solid base of knowledge in construction safety. While GPT displayed a general comprehension of safety protocols, its depth of knowledge might be limited, particularly in dealing with the specific complexities of arc welding at height.
  - Breadth of Knowledge: GPT was able to reference various sections of OSHA relevant to the given task, such as welding, cutting, and brazing, gas welding and cutting, and fall protection. This demonstrates its capacity to align generated guidelines with established safety standards. However, while GPT did acknowledge the importance of safety education and training within the guidelines and checklists it produced, it notably did not reference the specific OSHA standard number related to safety training and education among the citations it utilized. Neither did it refer to OSHA or any standard training for welding work or working at height, which a human safety manager would have. This

indicates that retraining or fine-tuning GPT on specific safety documents may be necessary for future research.

- Depth of Comprehension: Unlike other use cases, GPT demonstrated a good depth of understanding in this use case. The detailed references to OSHA regulations in GPT's output are strong indicators of its depth of comprehension, particularly in understanding the contextual nuances of the given scenario. For example, when addressing Hot Work Permits, GPT advised, "Obtain a hot work permit before commencing welding activities, as required by OSHA regulations," and further emphasized, "Follow the permit's specific requirements and ensure it is displayed at the work location." This level of detail showcases GPT's attention to critical safety procedures and its thorough understanding of the regulations, reinforcing its capability to generate precise and contextually appropriate guidelines.

To summarize, in use case #3 (Automated Generation of Safety Guidelines and Checklists), GPT exhibited significant capabilities but also revealed some limitations. The model effectively compiled safety protocols and checklists that align with established standards, demonstrating its utility in streamlining the preparation of essential safety documentation. This capability ensures that users can quickly generate reliable and standardized safety materials, enhancing overall safety compliance and awareness. However, the limitations can be seen in the model's inability to incorporate highly specific or uncommon safety rules without direct input and its challenges in prioritizing safety measures based on specific risks or operational contexts. This underscores the need for human oversight in verifying the output. To optimize its application, future improvements should focus on enhancing the model's understanding of contextual and risk-based prioritization in safety guideline formulation by fine-tuning it with more safety documents and validated guidelines and checklists created by human experts. To be implemented in practice, GPT would need to be integrated with project-specific data sources and reviewed by safety professionals to avoid applying generic checklists to complex site conditions. Operational risks include the potential misapplication of AI-generated guidelines without sufficient context, which could undermine safety protocols or introduce liability concerns.

3.4. Analysis Results for Use Case #4 (Real-Time Safety Management Assistance)

In this use case, GPT played the role of a safety management assistant who answered the user's questions. The following steps show the interaction between the user and GPT in this use case. Figure 5 demonstrates these interaction phases:

- Input: in this step, a safety-related question was asked from GPT by the user.
- Response: in this step, GPT provided a response to the user's query based on the given instructions.
- Suggesting Follow-up Questions to the User: After answering the user's question, GPT suggested follow-up questions to help the user better understand the concept. The user could agree or disagree with these questions if they wanted to engage further on this topic.
- Response to the Follow-up Question: in this step, GPT provided the user with an answer to the follow-up question.
- The process repeated for the next question.

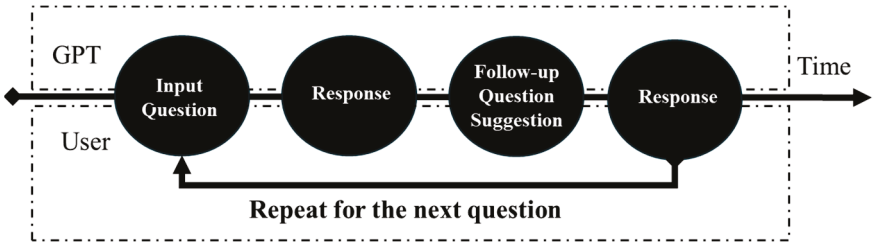

Figure 5. Use case #4 (Real-time Safety Management Assistance) User–GPT interaction phases.

The analysis results for use case #4 (Real-time Safety Management Assistance) are as follows:

- **Interactivity**: GPT demonstrated acceptable interactivity as it was able to comprehend the user's questions and keep the discussion warm and friendly with the user.
    - Comprehensive Language Processing: Like other use cases, GPT exhibited a robust capacity to process and comprehend user queries, effectively navigating the nuances and variations in language. It demonstrated an ability to interpret complex questions, even when presented in an informal or ambiguous manner. For instance, when confronted with the somewhat disorganized query, "Give me a checklist for equipment inspection before they start?", GPT accurately discerned the underlying safety concern despite the non-standard phrasing. It provided a detailed and relevant response, highlighting critical components such as harness and lifeline inspection, ladder safety, and tool and material storage while offering thorough explanations for each element. This answer is acceptable, given that the previous question targeted a scenario involving workers working at height. This illustrates GPT's proficiency in interpreting varied linguistic inputs and delivering responses that align with essential safety considerations.
    - Contextual Understanding: This ability was seen when GPT provided follow-up questions, and the user agreed to engage more on the topic. For example, in one of the questions, "Our multistoried construction site is surrounded by pedestrian traffic. Can you please analyze the fall hazard risks here?", GPT provided the necessary answer but followed up with asking the user, "Would you like some tips on effective barricading or signage strategies for such environments?" This indicates that GPT is able to decipher the context behind the given question and suggest relevant follow-up questions to enhance the user's understanding.
    - Human-like Responses: GPT initiated the interaction with an introduction and informal conversation, creating a more personable and approachable atmosphere. For example, it began by saying, "Hello! I'm here to assist with all your construction safety needs. How has your day been at the site so far?" Additionally, GPT inquired about the user's expertise in tailoring its responses accordingly. After the user mentioned they were a student conducting research on safety, GPT replied, "That's a fascinating area of study! Your research must be providing valuable insights into improving safety protocols on construction sites." This illustrates GPT's effort to establish a more conversational and human-like interaction. However, when the conversation shifted to technical topics (for example, when the user asked safety-related questions), GPT's responses were largely focused on delivering accurate information, lacking emotional engagement, and offering strictly technical answers. While this limits the conversational aspect, it can be addressed by refining the instructional

prompts or fine-tuning the model with real conversation transcripts between safety managers and users to improve its ability to balance technical accuracy with human-like interaction.

- **Evidence-based Reasoning**: The responses generated by GPT in this use case were predominantly evidence-based, consistently referencing existing safety standards and guidelines. However, its knowledge base, while extensive, still lacks coverage of certain critical safety literature. Expanding GPT's database to include more comprehensive safety resources would be beneficial for future research, enhancing its ability to provide more complete and accurate guidance in safety-related contexts. The following are more detailed observations.
    - Using Factual Information: Throughout this scenario, GPT demonstrated acceptable performance using factual information. For instance, when addressing fall hazards associated with skylights, GPT identified the risk regarding the described situation. Similarly, in discussing the impact of rainy weather on fall hazards, the responses adhered to standard OSHA guidelines, reflecting a commitment to providing information that is accurate and practically applicable. Yet, there were instances where the conversation could benefit from more diverse sources, such as recent case studies or emerging research in construction safety. This would enhance the usefulness of the information provided and ensure that the most current and comprehensive safety practices are being conveyed.
    - Detecting Incorrect Inputs: this was not evaluated for this use case as there was no instance where the user provided any information to GPT other than the questions they asked.
    - Extracting Correct Information from User's Given Documents: in this scenario, the user did not provide any document to GPT, so this criterion was not assessed.
- **Critical Analysis and Extrapolation**: GPT showcased good critical analysis ability and proved to be effective in answering safety-related questions.
    - Depth of Analysis: GPT demonstrated an ability to go beyond surface-level responses by addressing the complexities involved in construction safety, indicating a strong depth of analysis. For example, when asked, "Our multistoried construction site is surrounded by pedestrian traffic. Can you please analyze the fall hazard risks here?", GPT's recommendations went beyond fall hazards and included using high-visibility barriers and clear signage, showing an understanding of practical safety management in complex environments. This suggests that GPT effectively recognizes and incorporates critical details from the query to provide a relevant and actionable solution to the safety concern.
    - Connection and Contextualization: In this use case, GPT's ability to connect and contextualize safety information is user-dependent, as it requires detailed or follow-up questions from the user for GPT to provide more in-depth responses. However, even with brief, single-line queries, GPT's performance remains adequate. For example, when asked, "I have a team of six crews who I would like to send to install the skylight. What other equipment do I need to provide for safety?", GPT offered a comprehensive list, including hard hats, safety glasses, non-slip safety boots, gloves, visibility vests, and communication devices. It also explained the relevance of each item to the specific task. Interestingly, it went beyond regulatory requirements, tried to contextualize the scenario, and added scenario-specific advice. For instance,

it suggested communication devices "For clear communication among the crew, especially in noisy environments or over distances," which aligns well with the nature of the task, where workers may be spread out across different areas. This demonstrates GPT's ability to contextualize safety information in a manner that aligns with regulatory standards and is practical for the scenario at hand. For this use case, GPT showed competence in recognizing key situational factors, making its recommendations relevant and applicable to real-world construction environments.

- Inferencing and Extrapolation: Multiple questions on hazard identification were presented to evaluate GPT's ability to infer and extrapolate safety hazards. For example, when asked, "I would like to install a skylight on top of the building. What safety hazards should I be concerned about?", GPT accurately identified key risks such as fall hazards, roof load capacity, and concerns about skylight strength. These responses indicate that GPT can infer potential risks based on the contextual information provided. Additionally, GPT's follow-up question, "Do you need details on specific fall protection measures for this task?" demonstrates its ability to anticipate further necessary details, highlighting an understanding of the need for preventive measures. It went on to recommend specific solutions, such as guardrails, personal fall arrest systems (PFASs), and skylight covers, explaining their relevance to the task. However, GPT's extrapolation remains limited, as its responses focus primarily on the immediate hazards presented without fully considering more complex or indirect risks that could arise in a dynamic work environment. While GPT performs adequately in predicting and addressing obvious risks, expanding its capability to anticipate less apparent hazards or longer-term safety concerns would improve its overall performance. This suggests that while GPT can infer risks and propose preventive measures, its extrapolation could benefit from further refinement to capture a broader range of potential safety issues.

- **Knowledge and Comprehension**: GPT was able to draw from correct safety documents for the solutions it provided, indicating that it uses the training knowledge effectively. The following are some observations.
  - Breadth of Knowledge: GPT was tested with multiple questions across various aspects of construction safety management, including hazard identification, evaluation, and control. These questions covered a diverse range of scenarios, such as working at heights, safety requirements during bad weather, equipment safety, and managing pedestrian traffic. In each case, GPT demonstrated its breadth of knowledge by providing accurate responses based on existing safety regulations and documents as mentioned before. This indicates GPT's ability to draw from a wide range of safety management criteria and apply relevant guidelines across different situations, reflecting its comprehensive understanding of construction safety protocols.
  - Depth of Comprehension: GPT demonstrated a certain level of depth in its responses, as seen in several instances. For example, when asked, "My crews need to transit between different heights frequently, what additional fall risks should be evaluated in this scenario?", GPT identified the risks and also provided explanations. For instance, it mentioned, "Transition Points: Increased risk at points where workers move from ladders to roofs or scaffolds. Ensure secure handholds and stable platforms at these transition areas." This response reflects a sound understanding of the specific risks associated with transitioning between different heights and is consistent with existing safety regulations

and documents. However, the depth of comprehension remains somewhat limited, as GPT's responses are constrained to surface-level issues and do not fully explore more complex or indirect hazards. For instance, while GPT recognized transition points, it did not address other nuanced factors, such as how weather conditions or worker fatigue might compound the risk at these points. Expanding its analysis to consider such variables would demonstrate a more advanced level of comprehension.

In conclusion, use case #4 (Real-time Safety Management Assistance) demonstrates GPT's potential in providing safety assistance, with several notable strengths and some key limitations. GPT effectively processed and interpreted user queries, even when they were informal or ambiguous, and provided detailed, relevant safety advice. It was able to maintain a warm and friendly tone, making interactions approachable. However, the model's interactivity was mixed; while it handled technical information well, it sometimes fell short in offering human-like responses, particularly in maintaining emotional engagement with the user when discussing technical topics. The model's responses, grounded in existing safety standards, underscored its capacity for evidence-based reasoning. However, expanding its database to include more diverse and current sources could further enhance its effectiveness. While it demonstrated a degree of depth in analyzing safety concerns, its responses often lacked the ability to fully extrapolate or account for more complex or indirect hazards, such as dynamic environmental factors. Overall, while GPT can effectively utilize established knowledge, continuous updates and broader information access are essential for advancing its utility in construction safety. For real-world use, deploying GPT as an on-site assistant would require reliable data connectivity, integration with sensor or wearable systems, and clear protocols for human override. Ethical risks include the possibility of delayed or inappropriate responses in time-sensitive situations, reinforcing the need for human supervision in all safety-critical decision-making.

4. Conclusions

This study investigated the potential of LLMs, specifically GPT, in construction safety management. Given the critical need to improve safety on construction sites due to high injury rates, the study aimed to explore how GPT could contribute to reducing workplace accidents and enhancing safety performance. Structured use cases were employed to demonstrate GPT's application in various safety management tasks and to identify its strengths and limitations. These use cases were selected based on areas where LLMs or their predecessors have been applied in safety or where future applications are promising. GPT's performance was evaluated in four use cases: #1 Personalized Safety Training and Education, #2 Automated Post-Accident Analysis, #3 Automated Generation of Safety Guidelines and Checklists, and #4 Real-time Safety Management Assistance. For each use case, GPT was assessed using four fundamental evaluation criteria critical for its applications in safety management: interactivity, evidence-based reasoning, critical analysis and extrapolation, and knowledge and comprehension.

For use case #1 (Personalized Safety Training and Education), GPT demonstrated effective interactive communication and delivered safety training content aligned with OSHA guidelines. This suggests promising potential for using LLMs to scale personalized safety training, addressing a significant challenge in current training practices. However, the study found that the depth of the training content was somewhat limited. Therefore, it concludes that with more refined model training and fine-tuning to incorporate greater detail and nuanced topic coverage, LLMs could become highly effective tools for delivering comprehensive and personalized safety training.

For use case #2 (Automated Post-Accident Analysis), GPT showcased a strong ability to perform evidence-based reasoning, efficiently extracting and analyzing information from accident reports. It demonstrated an aptitude for identifying specific causal factors of accidents and recommending appropriate prevention strategies. Interestingly, it identified factors that were missed by human experts and strictly relied on the facts, and did not extrapolate. However, the model's limitations became apparent in critical analysis and extrapolation. While GPT identified certain direct hazards and causal factors, it sometimes failed to recognize broader systemic issues, such as the need for comprehensive safety programs, and often missed subtler contributory factors like worker experience or indirect risks. Therefore, this study concludes that to fully leverage GPT's capabilities for post-accident analysis, it is important to enhance its ability to conduct controlled extrapolation. However, GPT (as is) still holds significant potential for automating data extraction and initial analysis, which could lead to substantial time and resource savings. This analysis should, however, be supplemented with human oversight to ensure a thorough and nuanced understanding of accident causation.

For use case #3 (Automated Generation of Safety Guidelines and Checklists), GPT successfully produced guidelines that aligned with basic safety protocols. However, its capability to adapt these guidelines to construction sites' dynamic and often unpredictable nature might be limited. This points to the importance of updating LLMs with real-time, site-specific data, thereby ensuring the relevance and applicability of the safety protocols in various construction scenarios. Therefore, the study concludes that while GPT can be used to generate basic and general-purpose guidelines and checklists, it needs to be integrated with systems that can provide real-time site information to leverage its capabilities to generate site-specific checklists and guidelines. In addition, GPT or LLMs, in general, should be fine-tuned with relevant safety literature to help prioritize hazards and their prevention while creating safety guidelines.

Use case #4 (Real-time Safety Management Assistance) demonstrated GPT's proficiency in maintaining responsive and interactive dialogues. The responses were correct, in accordance with established guidelines and protocols, and relevant to the questions. Yet, the scope of safety solutions and advice offered by GPT was somewhat limited, indicating a need for broader and more current safety data integration into its training. This would enhance the depth and diversity of the safety management assistance provided by GPT. These results collectively suggest that while GPT has a significant potential role in construction safety management, its optimal utilization presently requires synergistic operation with human expertise. The current study's findings advocate for future developments to focus on increasing the depth of GPT's knowledge, its context-awareness, integration with real-time data, and adaptability to the dynamic construction environment.

Across the four use cases, GPT demonstrated promising utility in supporting construction safety tasks. It was effective in delivering personalized training aligned with OSHA standards, though the depth of content was limited. In accident analysis, GPT showed strong evidence-based reasoning and the ability to identify factual hazards, but it struggled with systemic insight and extrapolation. For guideline generation, it produced compliant safety checklists but lacked adaptability to dynamic, site-specific conditions. In real-time assistance, GPT maintained accurate and interactive communication but offered a limited range of solutions. These findings suggest that while GPT can support structured, rule-based safety tasks, its optimal performance requires integration with real-time data, contextual fine-tuning, and ongoing human oversight.

In translating these findings into practice, several integration challenges must be considered. These include ensuring compatibility between GPT and existing safety management systems, maintaining the reliability and relevance of underlying data, and align-

ing AI-generated outputs with current regulatory frameworks. Additionally, effective implementation would require user training to ensure that safety personnel interpret GPT responses appropriately and do not over-rely on automated outputs in safety-critical decisions. Addressing these challenges is essential for realizing the practical value of GPT in real-world construction safety management.

This study contributes to the growing body of research on the use of LLMs by systematically evaluating their performance across key safety tasks. By demonstrating GPT's effectiveness in automating key safety tasks and identifying areas for improvement, the study provides a foundation for developing more efficient, scalable, and personalized safety solutions. Its findings could lead to safer construction environments, reduced accidents, and significant time and resource savings, ultimately driving innovation in safety protocols and management.

Study Limitations

While the study provided some valuable insights, there are certain limitations that need to be discussed. A primary constraint is the exclusive focus on GPT for evaluation. While GPT is amongst the most prominent and extensively used LLM models, a comprehensive assessment of other models is crucial for a more rounded understanding of the field. The results obtained from GPT might not wholly translate to other models, as each may have unique limitations and capabilities. Secondly, the approach of using structured use cases to assess the effectiveness of GPT presents a methodological limitation in itself. While this approach has allowed for a concentrated exploration of GPT's capabilities in defined contexts, it inherently narrows the scope of the study. Relying solely on particular use cases may not capture the full spectrum of GPT's potential applications in construction safety management. Future research should consider a wider range of use cases, offering a more comprehensive assessment of GPT's utility across diverse scenarios. Moreover, while the study focused on qualitative analysis, it did not incorporate quantitative validation. This was intentional, as the qualitative findings were needed to first uncover how GPT performs in context-specific safety tasks. These findings now serve as a foundation for designing future quantitative evaluations with more appropriate performance metrics tailored to construction safety applications. The third limitation of this study is the development and reliance on a single scenario for each use case. This approach restricts the diversity of data and insights that could be garnered from varied scenarios. Different parameters, questions, and prompts in multiple scenarios could reveal a richer array of findings and highlight different facets of GPT's capabilities and limitations. Another limitation is the absence of direct input from safety professionals across all use cases. While regulatory standards (e.g., OSHA) and expert analyses (e.g., NIOSH reports) were used for comparison, future studies should incorporate safety professionals' feedback to validate and refine GPT's outputs in each application area. Furthermore, while GPT shows promise in supporting safety-related tasks, its application in safety consultancy or evaluation raises important ethical considerations. These include the potential for misinformation, over-reliance on AI-generated content, and lack of accountability in decision-making. Given the high-risk nature of construction environments, GPT should be used strictly as an assistive tool under the supervision of qualified safety professionals. Final decisions must remain the responsibility of certified experts to ensure regulatory compliance, ethical responsibility, and worker safety. Future studies should aim to create and analyze multiple scenarios for each application area, thereby enhancing the depth and breadth of the research. However, it is important to recognize that the results obtained from the current approach still offer valuable, targeted insights into GPT's application in construction safety management. Furthermore, to move beyond proof-of-concept, future research should include longitudinal

studies and real-world implementation trials to evaluate the sustained utility, reliability, and impact of GPT-assisted systems in active construction environments.

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Appendix A

Appendix A.1 Use Case #1

You are a safety trainer. You need to provide the safety training for working on heights to a construction worker, the role of which I will be filling (you will be training me).

First, introduce yourself ask the user their name, and have small talks with them after receiving response from the user you can start the training.

The training should cover hazard recognition, hazard management, and safety compliance. (During teaching, provide OSHA standard numbers for each part that you cover)

After providing the user with safety training, allow them to ask questions about the delivered content and answer their question if they do not have any questions (they will say I do not have any questions), proceed to the next step (you need to wait for my response).

Then provide interesting construction scenarios and ask questions about that specific scenario to evaluate their understanding of the training content. After you receive a response, provide feedback based on their answer.

Based on their performance, generate a new scenario which will have a different difficulty level (lower if the answer is incorrect, higher if the answer is correct). Follow the same procedure for this step as mentioned above.

Keep generating scenarios until the user answers at least 80 percent of the questions correctly.

You need to generate at least three scenarios before assessing the 80 percent threshold.

If they reach the 80 percent threshold, you can finish the training.

Appendix A.2 Use Case #2

You are required to act as a safety manager and assess the accident report which is going to be given to you in the following prompts. The objectives are as follows:

First, conduct a thorough hazard analysis of the accident report that will be provided in the next prompt and then answer the following questions:

1. Identify the hazards and cite the OSHA standard number for each hazard (include the reasons for the identified hazard).
2. Include a detailed analysis of the flaws that lead to the accidents and discuss them.
3. What are the methods that could be used to prevent the determined hazards?
4. What is the date of the accident?
5. Where did the accident take place?
6. Include the name of the witnesses.
7. What is the name of the victim?
8. What was the type of injury and its severity?

9. Include the name of the company.

Appendix A.3 Use Case #3

You are required to act as a safety manager and generate safety guidelines and checklists for the specific construction scenario that is going to be provided in the next prompt. Please include all the OSHA regulations that you used to generate the output.

Appendix A.4 Use Case #4

You need to fill the role of a safety management assistant. Your role is to play a day-to-day safety companion of a construction safety manager or a construction worker.

Your answer should be based on OSHA, the US department of Labor, NIOSH guidelines, and insights from leading industry experts.

The assistant needs to follow this structure:

Start Initializing Construction Safety Assistant.

You introduce yourself and have a small talk with the safety manager.

Ask the role and experience of the user.

After that, allow them to ask the questions that they need assistance with.

Suggest follow-up questions for deeper understanding of the query.

Appendix B

Appendix B.1 Use Case #1

GPT response: Hello! My name is [ChatGPT], and I'll be your safety trainer for today's session. We will be focusing on safety procedures for working at heights. Before we get started, could you please tell me your name?

User: My name is Ali.

GPT response: Nice to meet you, Ali! How are you doing today? Are you ready to dive into some safety training for working at heights?

User: Yes.

GPT response:

Great to hear, Ali! Let us get started with the training.

Hazard Recognition

When working at heights, it is essential to recognize potential hazards. Here are some key points:

1. Unprotected Edges and Openings: ensure all edges and openings are properly guarded.
2. Falls from Ladders: ensure ladders are in good condition and used correctly.
3. Scaffolding Hazards: ensure scaffolds are properly constructed and maintained.

OSHA Standard: 29 CFR 1926.501—Duty to have fall protection.

Hazard Management

Now, let us talk about managing these hazards:

Guardrails and Safety Nets: use guardrails or safety nets around unprotected edges.

1. Personal Fall Arrest Systems (PFASs): always wear a harness connected to a secure anchor point.
2. Proper Ladder Use: inspect ladders before use and ensure they are on stable ground.

OSHA Standard: 29 CFR 1926.502—Fall protection systems criteria and practices.

Safety Compliance

To ensure compliance with safety regulations:

1. Training: ensure all workers are trained on fall hazards and the proper use of equipment.
2. Inspections: regularly inspect all fall protection equipment and systems.
3. Recordkeeping: maintain records of training, equipment inspections, and incidents.

OSHA Standard: 29 CFR 1926.503—Training requirements.

That covers the basics of hazard recognition, management, and safety compliance for working at heights. Do you have any questions about what we have discussed so far?

User: Can you dive a bit deeper in each subject?

GPT response:

Absolutely, Ali! Let us dive deeper into each area of safety training for working at heights.

Hazard Recognition

1. Unprotected Edges and Openings:
   - Roof Edges: be cautious around roof edges, particularly during roofing work or when performing maintenance.
   - Floor Openings: openings in floors should be covered or guarded to prevent falls.
   - Wall Openings: openings in walls should also be guarded to prevent accidental falls.
2. Falls from Ladders:
   - Incorrect Placement: Ladders should be placed on a stable, level surface. Avoid placing them on slippery or unstable ground.
   - Damaged Ladders: Regularly inspect ladders for damage. Broken or missing rungs, split side rails, or any other damage can lead to falls.
   - Incorrect Use: Ensure ladders are used properly. Always maintain three points of contact (two hands and one foot or two feet and one hand).
3. Scaffolding Hazards:
   - Construction: scaffolds must be properly constructed and capable of supporting the intended load.
   - Stability: Scaffolds should be stable and level. Use base plates, mud sills, or other means to ensure stability.
   - Guardrails and Planking: ensure scaffolds have proper guardrails and fully planked walkways.

OSHA Standard: 29 CFR 1926.501—Duty to have fall protection.

Hazard Management

1. Guardrails and Safety Nets:
   - Guardrails: Install guardrails around unprotected edges. They should be at least 42 inches high, with a mid-rail at 21 inches.
   - Safety Nets: Use safety nets when guardrails are not feasible. They should be installed as close as possible under the working surface.
2. Personal Fall Arrest Systems (PFAS):
   - Harnesses: workers should wear full-body harnesses that distribute the force of a fall over the thighs, pelvis, waist, chest, and shoulders.
   - Anchorage: secure the harness to an anchor point that can support at least 5000 pounds per worker attached.
   - Lanyards and Lifelines: use lanyards and lifelines that limit the fall distance and reduce impact forces.
3. Proper Ladder Use:
   - Selection: Choose the right ladder for the job. Ensure it is long enough to extend 3 feet above the landing point.
   - Inspection: inspect ladders before each use for defects like cracks, bends, or missing parts.

- Angle: position ladders at the correct angle (1 foot out for every 4 feet up) to ensure stability.

OSHA Standard: 29 CFR 1926.502—Fall protection systems criteria and practices.
Safety Compliance

1. Training:
   - Fall Hazard Training: train workers to recognize fall hazards and the proper use of fall protection systems.
   - Equipment Use: provide hands-on training on how to properly don, adjust, and use personal fall arrest systems.
2. Inspections:
   - Regular Inspections: regularly inspect fall protection equipment and systems for wear, damage, or other issues that could compromise safety.
   - Document Inspections: keep detailed records of inspections and any corrective actions taken.
3. Recordkeeping:
   - Training Records: maintain records of all training sessions, including dates, topics covered, and attendance.
   - Incident Records: document any fall-related incidents, including investigations, corrective actions, and outcomes.

OSHA Standard: 29 CFR 1926.503—Training requirements.

That provides a more in-depth look at hazard recognition, management, and safety compliance for working at heights. Do you have any questions about these detailed points?

User: What is my next step if I notice the safety harness seems wrecked just before I am supposed to start working up high?

GPT response: Cease use immediately and report the issue to ensure a replacement harness is provided. Can I help you with anything else?

User: And if there is no replacement available immediately?

GPT response: Utilize alternative safety measures such as a scaffold with guardrails or delay the task until the proper equipment is available. Can I help you with anything else?

User: What steps should I take if I notice loose scaffolding at a worksite?

GPT response: Immediately cordon off the area and report the issue to the site supervisor for urgent repairs. Do you have other questions?

User: No

GPT response: Great to hear, Ali! Let us move on to some scenarios to test your understanding of the training content. I will present a scenario, and you can tell me how you would handle the situation based on what we have discussed.

Scenario 1:

You are working on a construction site, and you notice that a coworker is about to use a ladder that appears to be damaged. The ladder has a split side rail and a couple of bent rungs. What steps would you take to address this situation?

User: I will choose a new ladder to use.

I always get nervous on a ladder, even with all the gear.

GPT response: It is completely normal to feel nervous, and it is good that you are cautious. Remember to double-check your gear before ascending and keep your focus on the task. I am here to help you through this. It is important to ensure that you are using safe equipment. However, there are a few more steps you should take to fully address the situation:

Stop the Coworker: prevent your coworker from using the damaged ladder to ensure their safety.

Report the Damage: report the damaged ladder to your supervisor or the site safety officer so it can be removed from service.

Tag the Ladder: if possible, tag the damaged ladder as "Do Not Use" to prevent others from using it.

Great job! Let us move on to the next scenario.

Scenario 2:

You are assigned to work on a rooftop that is 20 feet above the ground. The rooftop has no guardrails installed. What fall protection measures should you implement to ensure your safety while working on the rooftop?

User: Install guardrails around unprotected edges. They should be at least 42 inches high, with a mid-rail at 21 inches.

I will use PFAS.

GPT response: Excellent, Ali! Your response demonstrates a good understanding of the necessary fall protection measures. Installing guardrails and using a Personal Fall Arrest System (PFAS) are both effective ways to ensure safety when working on a rooftop.

Let us move on to the next scenario.

Scenario 3:

You are working on scaffolding that is 30 feet high. You notice that the planking on one section of the scaffold is loose and could potentially give way if someone steps on it. What steps would you take to address this situation?

User: The plank should be changed and fixed.

I will also notify the workers who are working on the scaffolding.

During my inspection, should I re-check previously reported issues like the scaffolding?

GPT response: Great response, Ali! Changing and securing the loose plank is essential for maintaining the stability of the scaffolding. Additionally, notifying other workers about the hazard ensures that everyone remains safe until the issue is resolved.

Yes, verify that the previously loose scaffolding has been securely fixed as reported. Do not proceed with work in that area until all necessary repairs are confirmed.

You have done well so far. Let us continue with one more scenario to evaluate your understanding.

Scenario 4:

While working on a multi-story building, you notice that a coworker is not wearing a harness while working near the edge of a floor 25 feet above the ground. What actions should you take to ensure their safety and compliance with safety regulations?

User: I will prevent him from working.

I will ask him to use proper PFAS.

GPT response: Excellent, Ali! Preventing your coworker from working without proper fall protection and ensuring they use a Personal Fall Arrest System (PFAS) are crucial steps to maintain safety and compliance with OSHA regulations.

Let us assess your performance:

Scenario 1: correctly identified the need to stop using damaged equipment and take further safety steps.

Scenario 2: correctly identified the use of guardrails and PFAS.

Scenario 3: correctly identified the need to fix the loose plank and inform coworkers.

Scenario 4: correctly identified the need to stop unsafe work and ensure proper use of fall protection.

You have demonstrated a solid understanding of the training content and answered 100% of the questions correctly.

Congratulations, Ali! You have successfully completed the safety training for working at heights. Do you have any final questions or comments?

User: No thank you.

GPT response: You are welcome, Ali! Great job on completing the training. Stay safe out there, and if you ever have any questions or need further assistance, do not hesitate to reach out. Have a safe and productive day!

Appendix B.2 Use Case #2

User: On 2 July 2007, at approximately 7:00 a.m., Owner 2, the victim, and the male laborer arrived in the same vehicle at a residential house where they were replacing the roof. Owner 1 was already at the site. This was everyone's second day working at this site. According to the OSHA compliance officer, as they began work, the owners verbally reminded the male laborer and the victim to be careful while working.

They started the roof work on the rear of the house. In order to access the roof, an extension ladder was set and placed on the third-floor fire escape. A construction box was used to haul down used roofing shingles and to bring construction tools and supplies up to the roof. The construction box was attached to the forks of a forklift. The wooden box was homemade and was approximately 14 feet wide with three sides and a diamond plate steel bottom. The victim would use a ladder to climb up onto the roof, and then she would throw trash and used roofing shingles into the construction box. When new roofing shingles were needed on the roof, the construction box would be lowered to the ground and the victim would load the bales of roofing shingles into the box. The owners or the male laborer would move the forklift with the construction box attached and relocate it near the area where the roof work was being completed.

At approximately 2:15 p.m., roofing shingles were needed on the roof. The construction box was raised and positioned approximately 4 feet below the lowest of the two wooden planks. Directly below the construction box was a small protruding "eyebrow" roof, approximately nine feet below the main roof and seventeen feet above the stone patio. The victim accessed the roof from an extension ladder at the fire escape and walked down to the lowest wooden plank; she then sat down on the plank and lowered herself into the raised construction box. While standing in the construction box, the victim picked up new bales of roofing shingles and placed them above her on a wooden plank. After placing the bales on the plank, the victim climbed up and out of the construction box and sat on the plank. The wooden plank was approximately ten inches wide and approximately 12 feet in length. While sitting on the wooden plank, the victim handed roofing bales to Owner 2 and the male laborer working on the roof.

While Owner 2 and the male laborer worked on the roof, they observed the victim sitting on the plank. Approximately two minutes later, Owner 2 and the male laborer were using nail guns when they both heard a "thud" sound. According to the OSHA compliance officer, it appeared that as the victim sat on the wooden plank, she slid forward to get back down into the construction box, when one leg of her shorts got caught on the tip of a roof bracket that was holding the wooden plank, and it caused her to get upended and fall approximately 26 feet to the stone patio. Owner 1 and the male laborer looked over across the roof towards the plank and they did not see the victim, so they crawled over to the edge of the roof. When they looked down to the ground, they saw the victim lying face down on the stone patio (Photo 5). Owner 2 and the male laborer ran to the access ladder and climbed down. Owner 2 yelled down to Owner 1 in the yard area and told him to go check on the victim. When Owner 2 got to ground level, he called 911 for help, while Owner 1 checked the victim. The victim was lying unconscious with her head bleeding profusely.

At approximately 2:35 p.m., Emergency Medical Services (EMS) and the state police were dispatched to the incident scene. At approximately 2:40 p.m., EMS and the state police arrived at the incident scene. At approximately 2:45 p.m., EMS transported the victim via ambulance to an area hospital. At the hospital, the victim was stabilized, then airlifted to another hospital, where she remained unconscious in critical condition. She died of her injuries nine days later on 11 July 2007.

GPT's response:

1. *Identified hazards and corresponding OSHA standards*:
    a. Fall hazard: The victim fell approximately 26 feet from the roof to the stone patio. OSHA standard number: 1926.501—Fall Protection. This standard requires employers to provide fall protection systems and training when working at heights above 6 feet.
    b. Inadequate training and supervision: The owners verbally reminded the male laborer and the victim to be careful while working, but there is no mention of formal training or supervision. OSHA standard number: 1926.21—Safety Training and Education. This standard mandates the employer to provide proper training and supervision to employees to ensure their safety.
    c. Unsafe use of homemade construction box: The construction box used to transport materials was homemade and not designed to industry standards. OSHA standard number: 1926.251—Rigging Equipment for Material Handling. This standard requires employers to use proper and tested rigging equipment for material handling to prevent accidents.
    d. Improper use of a ladder: The victim used a ladder to access the roof, but there is no mention of securing the ladder or following ladder safety guidelines. OSHA standard number: 1926.1053—Ladders. This standard provides guidelines for safe ladder use, including securing the ladder and ensuring proper ladder setup.
2. *Analysis of factors leading to the accident*:
    a. Lack of fall protection measures: the victim was not wearing any fall protection equipment while working on the roof, which exposed her to the risk of falling.
    b. Inadequate hazard communication: while the owners verbally reminded the workers to be careful, there is no indication that a comprehensive hazard assessment was conducted or that specific hazards were communicated to the workers.
    c. Unsafe work practices: the victim sat on a wooden plank while handing roofing bales to others, which compromised her stability and exposed her to the risk of falling.
    d. Use of an unsafe construction box: the homemade construction box was not designed to industry standards, potentially compromising its structural integrity and safety.
3. *Methods to prevent the hazards*:
    a. Fall hazard prevention: Employers should provide and enforce the use of proper fall protection equipment, such as harnesses and guardrails, when working at heights. Adequate training on fall protection measures should also be provided.
    b. Comprehensive training and supervision: Employers should ensure that workers receive proper training and supervision on safe work practices, hazard recognition, and the use of equipment. Regular safety meetings and toolbox talks can reinforce safety protocols.

c. Use of appropriate equipment: Employers should provide and use industry-standard equipment and tools, including rigging equipment, ladders, and other necessary safety devices. Homemade or improvised equipment should be avoided.
d. Job hazard analysis: conducting a thorough job hazard analysis before starting work can help identify potential hazards and implement appropriate preventive measures.

4. *Date of the accident*: the accident happened on 2 July 2007.
5. *Location of the accident*: the accident took place at a residential house where roof replacement work was being carried out.
6. *Witnesses*: the report does not mention the presence of any witnesses.
7. *Injured person's name*: the victim's name is not provided in the report.
8. *Type and severity of injury*: the victim suffered severe head injuries, resulting in her remaining unconscious and ultimately leading to her death.
9. *Company name*: the report does not mention the name of the company involved in the accident.

Appendix B.3 Use Case #3

User: A welding activity is going to take place on the third floor of a building. The type of welding is arc-welding in this scenario. The activity is carried out during the installation phase of the steel frame of the building.

GPT's response:

Safety Guidelines:

(1) Personal Protective Equipment (PPE):
   (a) Ensure all workers wear appropriate PPE, including welding helmets with proper shade lenses, protective clothing (flame-resistant), gloves, safety glasses, and steel-toed boots.
   (b) Provide respiratory protection if required based on the presence of fumes or gases.

(2) Ventilation:
   (a) Ensure the work area is adequately ventilated to prevent the accumulation of welding fumes.
   (b) Use local exhaust ventilation systems, such as fume extraction hoods or fans, to remove welding fumes at the source.

(3) Fire Prevention:
   (a) Clear the work area of flammable materials and establish a fire-safe perimeter.
   (b) Have a fire extinguisher readily available and ensure workers are trained in its use.

(4) Hot Work Permit:
   (a) Obtain a hot work permit before commencing welding activities, as required by OSHA regulations.
   (b) Follow the permit's specific requirements and ensure it is displayed at the work location.

(5) Electrical Safety:
   (a) Inspect welding equipment and cables for any signs of damage or fraying.
   (b) Use ground-fault circuit interrupters (GFCIs) to prevent electrical shocks.

(6) Welding Equipment Safety:

(a) Ensure welding equipment is properly maintained and in good working condition.
(b) Follow manufacturer's instructions for the setup, operation, and maintenance of welding machines.

(7) Fall Protection:
(a) Implement appropriate fall protection measures, such as guardrails, safety harnesses, or safety nets, if working at heights where fall hazards exist.

(8) Hazard Communication:
(a) Train workers on the potential hazards associated with arc welding, including the dangers of UV radiation, fumes, and gases.
(b) Provide Material Safety Data Sheets (MSDSs) for welding materials used on-site.

(9) Training and Supervision:
(a) Ensure all workers involved in arc welding activities receive proper training on safe welding practices, equipment operation, and emergency procedures.
(b) Assign a competent person to supervise the welding activities and enforce safety protocols.

OSHA Regulations:

(1) OSHA Standard 1910.252: Welding, Cutting, and Brazing.
(2) OSHA Standard 1926.350: Gas Welding and Cutting.
(3) OSHA Standard 1926.353: Ventilation and Protection in Welding, Cutting, and Heating.
(4) OSHA Standard 1926.451: General Requirements for Scaffolding.
(5) OSHA Standard 1926.501: Fall Protection.
(6) OSHA Standard 1910.146: Permit-Required Confined Spaces.
(7) OSHA Standard 1910.120: Hazardous Waste Operations and Emergency Response.

Safety Checklist:

(1) Are all workers trained and familiar with safe welding practices and procedures?
(2) Is the work area adequately ventilated to control welding fumes?
(3) Have all workers been provided with appropriate PPE, including welding helmets, gloves, and safety glasses?
(4) Are welding machines and equipment properly maintained and in good working condition?
(5) Is a hot work permit obtained before starting welding activities?
(6) Are flammable materials removed from the work area, and is a fire extinguisher readily available?
(7) Have fall protection measures been implemented for workers working at heights?
(8) Have workers been informed about the hazards associated with arc welding and the proper handling of welding materials?
(9) Is there a competent person assigned to supervise the welding activities and enforce safety protocols?
(10) Are proper communication channels established for reporting any safety concerns or incidents?

Appendix B.4 Use Case #4

GPT response: Hello! I am here to assist with all your construction safety needs. How has your day been at the site so far?

Before we get into specifics, could you tell me more about your role and how long you have been involved in construction safety management? This will help me tailor my support to your experience level and responsibilities.

Please feel free to ask any safety-related questions you have, whether they are about compliance issues, best practices, risk assessments, or anything else.

If you need guidance on a particular issue, could you provide some details about the context? This will help me give you the most accurate and relevant advice.

User: I am currently a construction management PhD student and I have been doing research in construction safety for 3 years.

GPT response: That is a fascinating area of study! Your research must be providing valuable insights into improving safety protocols on construction sites.

What specific aspect of construction safety are you currently focusing on in your research? And how can I assist you today with your questions or challenges related to your studies or field observations? If there is a particular safety standard or regulation you are examining, let me know, and I can provide detailed information or resources on that topic.

Hazard Identification

1. **Hey, I would like to install a Skylight on top of the building. What safety hazards do I need to be worried about?**

GPT response: When installing a skylight, consider these key safety hazards: fall risks through the opening, ensuring skylight strength, and roof safety for workers. It is crucial to have proper fall protection like guardrails and to check the skylight's load capacity. Do you need details on specific fall protection measures for this task?

User: Yes, sure, that would be helpful to know

GPT response: For skylight installation, key fall protection measures include the following: 1) Guardrails: install temporary guardrails around the skylight opening to prevent falls, 2) Personal Fall Arrest Systems (PFASs): workers should use harnesses attached to secure anchor points, 3) Covers: use strong, secure covers for skylight openings when not actively working on them. Would you like guidance on selecting appropriate harnesses and anchor points, or information on skylight cover specifications?

2. **I have a team of six crewmembers. I would like to send them to install the Skylight. What other equipment do I need to have with them including PFAS for safety?**

GPT response: For a team of six installing a skylight, along with Personal Fall Arrest Systems (PFASs), consider these additional safety equipment: (1) Hard Hats: to protect from any falling debris, (2) Safety Glasses: for eye protection during installation, (3) Non-slip Safety Boots: to ensure secure footing on the roof, (4) Gloves: to protect hands and improve grip, (5) Visibility Vests: for easy identification of team members, (6) Communication Devices: for clear communication among the crew, especially in noisy environments or over distances. Would you like information on the correct usage and standards for these equipment items, or any other support for your crew's safety training?

3. **Hey, it seems to be raining here soon and my crews have already started installing the skylight. What things do I need to be cautious about for their safety in these weather conditions?**

GPT response: In rainy conditions, while installing a skylight, consider these safety precautions: (1) Slippery Surfaces: Roofs become very slippery when wet. Ensure your crew uses non-slip boots and tread cautiously. (2) Electrical Safety: Be cautious with any electrical tools or equipment. Use covers and ground-fault circuit interrupters (GFCIs) to prevent electrical hazards. (3) Visibility: Reduced visibility can increase risks. Use appropriate lighting and ensure all crew members are visible to each other. (4) Secure Tools and Materials: Wet conditions can make tools and materials more difficult to handle. Secure them to prevent slipping or dropping. (5) Monitoring Weather: Continuously monitor the weather. If conditions worsen, consider postponing the installation for safety. Would it be

helpful to discuss a contingency plan for weather-related delays or additional protective gear for working in the rain?

Hazard Evaluation

4. **My crews need to transit between different heights frequently. What additional fall risks should be evaluated in this scenario?**

GPT response: When your crew is frequently transiting between different heights, consider these additional fall risk factors: (1) Transition Points: Increased risk at points where workers move from ladders to roofs or scaffolds. Ensure secure handholds and stable platforms at these transition areas. (2) Adjusting Fall Protection: Each height change may require adjustments to fall protection gear. Ensure harnesses and lifelines are correctly adapted and anchored at each level. (3) Fatigue and Distraction: Constant movement can lead to fatigue, reducing alertness. Ensure regular breaks and encourage focus on safety at all times. Would you like more information on best practices for managing transition points or tips on effective use of fall protection equipment during height transitions?

5. **Our multistoried construction site is surrounded by pedestrian traffic. Can you please analyze the fall hazard risks here?**

GPT response: Absolutely, in a multi-story site near pedestrian areas, you have added fall risks to consider. Firstly, there is the danger of tools or materials falling off edges and injuring pedestrians below. You will also need to be extra cautious about securing and marking any overhead loads. It is crucial to set up sturdy barricades and clear signage to keep pedestrians safely away from potential fall zones. Would you like some tips on effective barricading or signage strategies for such environments?

User: Yes.

GPT response: Absolutely, here are a couple of tips: For barricading, use high-visibility barriers that clearly mark off the construction zone. Make sure they are sturdy enough to withstand accidental bumps. For signage, use large, easily readable signs warning of potential hazards and directing pedestrians away from risky areas. Want to dive into more specifics on the types of barriers or signs that work best in busy urban settings?

Hazard Control

6. **Our construction crew is about to engage in roofing work on the project. Please design a quick safety briefing for me.**

GPT response: Sure thing! For your roofing crew, emphasize these key points: First, double-check that everyone is wearing their Personal Fall Arrest Systems properly. Remind them about maintaining three-point contact when climbing ladders. Stress the importance of staying aware of the roof's edge at all times. Finally, ensure that all tools and materials are securely stored to prevent slips or falls.

7. **Give me a checklist for equipment inspection before they start.**

GPT response: Great, here is a quick checklist: (1) Harness and Lifeline Inspection: Check for any wear or damage. Ensure harnesses fit well and lifelines are securely anchored. (2) Ladder Safety: verify ladders are stable and extend at least 3 feet above the landing point. (3) Tool and Material Storage: ensure tools are organized and materials are secured, reducing trip hazards. Would you like guidance on conducting a team safety huddle before work begins, to reinforce these points?

8. **Hey, what new technologies could be integrated into fall hazard management to enhance safety on our site?**

GPT response: Modern sites can benefit from wearable tech for monitoring and alerts, drones for aerial inspections, VR for training, AR for hazard visualization, advanced

fall detection systems, mobile apps for safety information, smart guardrails, AI for risk analysis, robotic assistants for high-risk tasks, and biometric scanning for monitoring worker alertness and balance. These technologies can make fall hazard management more efficient and safer. Are you interested to know more about any of them in particular?

References

1. Choudhry, R.M.; Fang, D. Why operatives engage in unsafe work behavior: Investigating factors on construction sites. *Saf. Sci.* **2008**, *46*, 566–584. [CrossRef]
2. Bureau of Labor Statistics. National Census of Fatal Occupational Injuries in 2022. Available online: https://www.bls.gov/news.release/pdf/cfoi.pdf (accessed on 11 March 2024).
3. Zhou, Z.; Goh, Y.M.; Li, Q. Overview and analysis of safety management studies in the construction industry. *Saf. Sci.* **2015**, *72*, 337–350. [CrossRef]
4. Jeon, J.; Cai, H. Classification of construction hazard-related perceptions using: Wearable electroencephalogram and virtual reality. *Autom. Constr.* **2021**, *132*, 103975. [CrossRef]
5. Haji, M.D.; Behnam, B.; Sebt, M.H.; Ardeshir, A.; Katooziani, A. BIM-based safety leading indicators measurement tool for construction sites. *Int. J. Civ. Eng.* **2023**, *21*, 265–282. [CrossRef]
6. Zhang, S.; Sulankivi, K.; Kiviniemi, M.; Romo, I.; Eastman, C.M.; Teizer, J. BIM-based fall hazard identification and prevention in construction safety planning. *Saf. Sci.* **2015**, *72*, 31–45. [CrossRef]
7. Jeelani, I.; Han, K.; Albert, A. Development of virtual reality and stereo-panoramic environments for construction safety training. *Eng. Constr. Arch. Manag.* **2020**, *27*, 1853–1876. [CrossRef]
8. Le, Q.T.; Pedro, A.; Lim, C.R.; Park, H.T.; Park, C.S.; Kim, H.K. A framework for using mobile based virtual reality and augmented reality for experiential construction safety education. *Int. J. Eng. Educ.* **2015**, *31*, 713–725.
9. Zhu, Z.; Jeelani, I.; Gheisari, M. Physical risk assessment of drone integration in construction using 4D simulation. *Autom. Constr.* **2023**, *156*, 105099. [CrossRef]
10. Jeelani, I.; Asadi, K.; Ramshankar, H.; Han, K.; Albert, A. Real-time vision-based worker localization & hazard detection for construction. *Autom. Constr.* **2021**, *121*, 103448. [CrossRef]
11. Baker, H.; Hallowell, M.R.; Tixier, A.J.-P. AI-based prediction of independent construction safety outcomes from universal attributes. *Autom. Constr.* **2020**, *118*, 103146. [CrossRef]
12. Tixier, A.J.-P.; Hallowell, M.R.; Rajagopalan, B.; Bowman, D. Automated content analysis for construction safety: A natural language processing system to extract precursors and outcomes from unstructured injury reports. *Autom. Constr.* **2016**, *62*, 45–56. [CrossRef]
13. Charehzehi, A.; Ahankoob, A. Enhancement of safety performance at construction site. *Int. J. Adv. Eng. Technol.* **2012**, *5*, 303.
14. Kang, Y.; Cai, Z.; Tan, C.-W.; Huang, Q.; Liu, H. Natural language processing (NLP) in management research: A literature review. *J. Manag. Anal.* **2020**, *7*, 139–172. [CrossRef]
15. Zhou, M.; Duan, N.; Liu, S.; Shum, H.-Y. Progress in Neural NLP: Modeling, Learning, and Reasoning. *Engineering* **2020**, *6*, 275–290. [CrossRef]
16. Wu, C.; Li, X.; Guo, Y.; Wang, J.; Ren, Z.; Wang, M.; Yang, Z. Natural language processing for smart construction: Current status and future directions. *Autom. Constr.* **2022**, *134*, 104059. [CrossRef]
17. Moon, S.; Lee, G.; Chi, S. Automated system for construction specification review using natural language processing. *Adv. Eng. Inform.* **2022**, *51*, 101495. [CrossRef]
18. Hassan, F.U.; Le, T. Automated requirements identification from construction contract documents using natural language processing. *J. Leg. Aff. Disput. Resolut. Eng. Constr.* **2020**, *12*, 04520009. [CrossRef]
19. Zou, Y.; Kiviniemi, A.; Jones, S.W. Retrieving similar cases for construction project risk management using Natural Language Processing techniques. *Autom. Constr.* **2017**, *80*, 66–76.
20. Guo, E.; Onstein, E.; La Rosa, A.D. A semantic approach for automated rule compliance checking in construction industry. *IEEE Access* **2021**, *9*, 129648–129660.
21. Jallan, Y.; Brogan, E.; Ashuri, B.; Clevenger, C.M. Application of natural language processing and text mining to identify patterns in construction-defect litigation cases. *J. Leg. Aff. Disput. Resolut. Eng. Constr.* **2019**, *11*, 04519024. [CrossRef]
22. Zhao, X.; Yeoh, K.-W.; Chua, D.K.H. Extracting construction knowledge from project schedules using natural language processing. In Proceedings of the 10th International Conference on Engineering, Project, and Production Management, Berlin, Germany, 2–4 September 2019; Springer: Berlin/Heidelberg, Germany, 2020; pp. 197–211.
23. Shen, Q.; Wu, S.; Deng, Y.; Deng, H.; Cheng, J.C.P. BIM-Based Dynamic Construction Safety Rule Checking Using Ontology and Natural Language Processing. *Buildings* **2022**, *12*, 564. [CrossRef]

24. Lombardi, M.; Mauro, F.; Fargnoli, M.; Napoleoni, Q.; Berardi, D.; Berardi, S. Occupational Risk Assessment in Landfills: Research Outcomes from Italy. *Safety* **2023**, *9*, 3. [CrossRef]
25. European Regulation no 349/2011. Available online: https://www.legislation.gov.uk/eur/2011/349/introduction/2011-04-11 (accessed on 25 June 2025).
26. Kim, T.; Chi, S. Accident Case Retrieval and Analyses: Using Natural Language Processing in the Construction Industry. *J. Constr. Eng. Manag.* **2019**, *145*, 04019004. [CrossRef]
27. Xu, N.; Ma, L.; Wang, L.; Deng, Y.; Ni, G. Extracting domain knowledge elements of construction safety management: Rule-based approach using Chinese natural language processing. *J. Manag. Eng.* **2021**, *37*, 04021001. [CrossRef]
28. Baker, H.; Hallowell, M.R.; Tixier, A.J.-P. Automatically learning construction injury precursors from text. *Autom. Constr.* **2020**, *118*, 103145. [CrossRef]
29. Yeung, C.L.; Cheung, C.F.; Wang, W.M.; Tsui, E.; Lee, W.B. Managing knowledge in the construction industry through computational generation of semi-fiction narratives. *J. Knowl. Manag.* **2016**, *20*, 386–414. [CrossRef]
30. Na, X.; Jianping, W.; Jie, L.; Guodong, N. Analysis on Relationships of Safety Risk Factors in Metro Construction. *J. Eng. Sci. Technol. Rev.* **2016**, *9*, 150–157. [CrossRef]
31. OpenAI. June 16 Version. Available online: https://chat.openai.com/chat (accessed on 20 December 2023).
32. Google AI. Bard. Available online: https://ai.google/ (accessed on 20 December 2023).
33. Kasneci, E.; Sessler, K.; Küchemann, S.; Bannert, M.; Dementieva, D.; Fischer, F.; Gasser, U.; Groh, G.; Günnemann, S.; Hüllermeier, E.; et al. ChatGPT for good? On opportunities and challenges of large language models for education. *Learn. Individ. Differ.* **2023**, *103*, 102274. [CrossRef]
34. Min, B.; Ross, H.; Sulem, E.; Veyseh, A.P.B.; Nguyen, T.H.; Sainz, O.; Agirre, E.; Heintz, I.; Roth, D. Recent Advances in Natural Language Processing via Large Pre-trained Language Models: A Survey. *ACM Comput. Surv.* **2023**, *56*, 30. [CrossRef]
35. Arteaga, C.; Park, J. A large language model framework to uncover underreporting in traffic crashes. *J. Saf. Res.* **2025**, *92*, 1–13. [CrossRef]
36. Tsai, M.-L.; Ong, C.W.; Chen, C.-L. Exploring the use of large language models (LLMs) in chemical engineering education: Building core course problem models with Chat-GPT. *Educ. Chem. Eng.* **2023**, *44*, 71–95. [CrossRef]
37. Goldberg, D.M. Characterizing accident narratives with word embeddings: Improving accuracy, richness, and generalizability. *J. Saf. Res.* **2022**, *80*, 441–455. [CrossRef]
38. Surameery, N.M.S.; Shakor, M.Y. Use chat gpt to solve programming bugs. *Int. J. Inf. Technol. Comput. Eng. IJITC* **2023**, *3*, 17–22.
39. Bewersdorff, A.; Seßler, K.; Baur, A.; Kasneci, E.; Nerdel, C. Assessing student errors in experimentation using artificial intelligence and large language models: A comparative study with human raters. *Comput. Educ. Artif. Intell.* **2023**, *5*, 100177. [CrossRef]
40. Rivas, P.; Zhao, L. Marketing with ChatGPT: Navigating the ethical terrain of GPT-based chatbot technology. *AI* **2023**, *4*, 375–384. [CrossRef]
41. Uddin, S.M.J.; Albert, A.; Ovid, A.; Alsharef, A. Leveraging ChatGPT to Aid Construction Hazard Recognition and Support Safety Education and Training. *Sustainability* **2023**, *15*, 7121. [CrossRef]
42. Prieto, S.A.; Mengiste, E.T.; de Soto, B.G. Investigating the Use of ChatGPT for the Scheduling of Construction Projects. *Buildings* **2023**, *13*, 857. [CrossRef]
43. Achiam, J.; Adler, S.; Agarwal, S.; Ahmad, L.; Akkaya, I.; Aleman, F.L.; Almeida, D.; Altenschmidt, J.; Altman, S.; Anadkat, S.; et al. GPT-4 technical report. *arXiv* **2023**, arXiv:2303.08774.
44. Kikalishvili, S. Unlocking the potential of GPT-3 in education: Opportunities, limitations, and recommendations for effective integration. *Interact. Learn. Environ.* **2024**, *32*, 5587–5599.
45. Lecler, A.; Duron, L.; Soyer, P. Revolutionizing radiology with GPT-based models: Current applications, future possibilities and limitations of ChatGPT. *Diagn. Interv. Imaging* **2023**, *104*, 269–274.
46. Jagdishbhai, N.; Thakkar, K.Y. Exploring the capabilities and limitations of GPT and Chat GPT in natural language processing. *J. Manag. Res. Anal.* **2023**, *10*, 18–20. [CrossRef]
47. Wen, Q.; Liang, J.; Sierra, C.; Luckin, R.; Tong, R.; Liu, Z.; Cui, P.; Tang, J. AI for education (AI4EDU): Advancing personalized education with LLM and adaptive learning. In Proceedings of the KDD '24: The 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Barcelona, Spain, 25–29 August 2024; pp. 6743–6744.
48. Andersen, B.; Fagerhaug, T. *Root Cause Analysis*; Quality Press: Milwaukee, WI, USA, 2006.
49. Georgeff, M.P.; Lansky, A.L. Procedural knowledge. *Proc. IEEE* **1986**, *74*, 1383–1398.
50. Stanton, N.A.; Chambers, P.R.; Piggott, J. Situational awareness and safety. *Saf. Sci.* **2001**, *39*, 189–204.
51. Hussain, R.; Sabir, A.; Lee, D.-Y.; Alam Zaidi, S.F.; Pedro, A.; Abbas, M.S.; Park, C. Conversational AI-based VR system to improve construction safety training of migrant workers. *Autom. Constr.* **2024**, *160*, 105315. [CrossRef]
52. Wang, N.; Issa, R.R. Transfer Learning-Based Question Generation for Building a Construction Safety Chatbot. In *Computing in Civil Engineering*; ASCE: Reston, VA, USA, 2023; pp. 688–694.
53. Tellis, W. Application of a case study methodology. *Qual. Rep.* **1997**, *3*, 1–19.

54. Saka, A.; Taiwo, R.; Saka, N.; Salami, B.A.; Ajayi, S.; Akande, K.; Kazemi, H. GPT models in construction industry: Opportunities, limitations, and a use case validation. *Dev. Built Environ.* **2024**, *17*, 100300. [CrossRef]
55. Raj, R.; Singh, A.; Kumar, V.; Verma, P. Analyzing the potential benefits and use cases of ChatGPT as a tool for improving the efficiency and effectiveness of business operations. *BenchCouncil Trans. Benchmarks Stand. Eval.* **2023**, *3*, 100140. [CrossRef]
56. Ghasemi, A.; Dai, F. Can ChatGPT assist in cost analysis and bid pricing in construction estimating? A pilot study using a bridge rehabilitation project. *Smart Constr.* **2024**, *1*, 1–26. [CrossRef]
57. Dorobăt, I.; Năstase, F. Personalized training in Romanian SME's ERP implementation projects. *Management* **2010**, *37*, 32.
58. Taylor, D.; Yeung, M.; Bashet, A.Z. Personalized and Adaptive Learning. In *Innovative Learning Environments in STEM Higher Education: Opportunities, Challenges, and Looking Forward*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 17–34.
59. Jeelani, I. Personalized Hazard Recognition Training for Construction Workers. Master's Thesis, North Carolina State University, Raleigh, NC, USA, 2016; p. 30727254. Available online: https://ufl-flvc.primo.exlibrisgroup.com/openurl/01FALSC_UFL/01FALSC_UFL:UFL?url_ver=Z39.88-2004&rft_val_fmt=info:ofi/fmt:kev:mtx:dissertation&genre=dissertations&sid=ProQ:ProQuest+Dissertations+&+Theses+Global&atitle=&title=Personalized+Hazard+Recognition+Training+for+Construction+Workers&issn=&date=2016-01-01&volume=&issue=&spage=&au=Jeelani,+Idris&isbn=9798381021769&jtitle=&btitle=&rft_id=info:eric/&rft_id=info:doi/ (accessed on 18 December 2023).
60. Gan, W.; Qi, Z.; Wu, J.; Lin, J.C.-W. Large Language Models in Education: Vision and Opportunities. In Proceedings of the 2023 IEEE International Conference on Big Data (BigData), Sorrento, Italy, 15–18 December 2023; pp. 4776–4785.
61. Sharma, S.; Raj, M.; Ali, M.M.; Sharma, K.; Singh, A.; Singh, S. Design of Structure using an Adaptive Generative AI System for Customised Eduction for Individuals. In Proceedings of the 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), Greater Noida, India, 9–10 February 2024; Volume 5, pp. 276–280.
62. Goh, Y.M.; Chua, D.K.H. Case-based reasoning for construction hazard identification: Case representation and retrieval. *J. Constr. Eng. Manag.* **2009**, *135*, 1181–1189. [CrossRef]
63. Pan, X.; Zhong, B.; Wang, Y.; Shen, L. Identification of accident-injury type and bodypart factors from construction accident reports: A graph-based deep learning framework. *Adv. Eng. Inform.* **2022**, *54*, 101752. [CrossRef]
64. Xu, H.; Liu, Y.; Shu, C.-M.; Bai, M.; Motalifu, M.; He, Z.; Wu, S.; Zhou, P.; Li, B. Cause analysis of hot work accidents based on text mining and deep learning. *J. Loss Prev. Process. Ind.* **2022**, *76*, 104747. [CrossRef]
65. Zhang, F. A hybrid structured deep neural network with Word2Vec for construction accident causes classification. *Int. J. Constr. Manag.* **2022**, *22*, 1120–1140. [CrossRef]
66. Liu, H.; Ning, R.; Teng, Z.; Liu, J.; Zhou, Q.; Zhang, Y. Evaluating the logical reasoning ability of chatgpt and gpt-4. *arXiv* **2023**, arXiv:2304.03439.
67. Occupational Safety and Health Administration. Job Hazard Analysis Guide. Available online: https://www.osha.gov/publications/publication-products?publication_title=3071 (accessed on 12 May 2024).
68. Jeon, J.; Xu, X.; Zhang, Y.; Yang, L.; Cai, H. Extraction of construction quality requirements from textual specifications via natural language processing. *Transp. Res. Rec. J. Transp. Res. Board* **2021**, *2675*, 222–237. [CrossRef]
69. Wang, X.; El-Gohary, N. Deep learning-based relation extraction and knowledge graph-based representation of construction safety requirements. *Autom. Constr.* **2023**, *147*, 104696. [CrossRef]
70. Borjigin, S.G.; Austin, M.A.; Zontek-Carney, E.J. Semiautomated Development of Textual Requirements: Combined NLP and Multidomain Semantic Modeling Approach. *J. Manag. Eng.* **2022**, *38*, 04022053. [CrossRef]
71. Park, Y.; Kang, S. Natural language generation using dependency tree decoding for spoken dialog systems. *IEEE Access* **2018**, *7*, 7250–7258. [CrossRef]
72. Wang, N.; Issa, R.R.A.; Anumba, C.J. NNLP-based query-answering system for information extraction from building information models. *J. Comput. Civ. Eng.* **2022**, *36*, 04022004. [CrossRef]
73. Lin, J.-R.; Hu, Z.-Z.; Zhang, J.-P.; Yu, F.-Q. A Natural-Language-Based Approach to Intelligent Data Retrieval and Representation for Cloud BIM. *Comput. Civ. Infrastruct. Eng.* **2016**, *31*, 18–33. [CrossRef]
74. Tian, D.; Li, M.; Ren, Q.; Zhang, X.; Han, S.; Shen, Y. Intelligent question answering method for construction safety hazard knowledge based on deep semantic mining. *Autom. Constr.* **2023**, *145*, 104670. [CrossRef]
75. Ma, H.; Wang, J.; Lin, H.; Zhang, Y. Hierarchical matching network for multi-turn response selection in retrieval-based chatbots. *Soft Comput.* **2021**, *25*, 9609–9624. [CrossRef]
76. OSHA. Law and Regulations. Available online: https://www.osha.gov/laws-regs (accessed on 5 July 2023).
77. OSHA. Outreach Training Program for Construction. Available online: https://www.osha.gov/training/outreach/construction (accessed on 20 August 2023).
78. NIOSH. Training and Workforce Development. Available online: https://www.cdc.gov/niosh/training/default.html (accessed on 20 August 2023).
79. NIOSH. Seventeen Year Old Female Laborer Falls From Residential Roof and Dies Nine Days Later—Connecticut. Available online: https://www.cdc.gov/niosh/face/In-house/full200710.html (accessed on 2 July 2023).

80. NIOSH. Fatality Assessment and Control Evaluation (FACE) Program. Available online: https://wwwn.cdc.gov/NIOSH-FACE/Default.cshtml?state=ALL&Incident_Year=ALL&Category2=0021&Submit=Submit (accessed on 22 June 2023).
81. Chen, C.; Shu, K. Combating misinformation in the age of LLMs: Opportunities and challenges. *arXiv* **2023**, arXiv:2311.05656.
82. Creswell, A.; Shanahan, M.; Higgins, I. Selection-inference: Exploiting large language models for interpretable logical reasoning. *arXiv* **2022**, arXiv:2205.09712.
83. Haleem, A.; Javaid, M.; Singh, R.P. An era of ChatGPT as a significant futuristic support tool: A study on features, abilities, and challenges. *BenchCouncil Trans. Benchmarks Stand. Eval.* **2022**, *2*, 100089. [CrossRef]

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