

Article

Modelling Work Safety in the Machining Process: A Multi-Criteria Decision Analysis Using FAHP

Justyna Patalas-Maliszewska ^{1,*} , Hanna Łosyk ¹ and Małgorzata Szmolda ²

¹ Institute of Mechanical Engineering, University of Zielona Góra, ul. Licealna 9, 65-417 Zielona Góra, Poland; h.losyk@iim.uz.zgora.pl

² The Doctoral School of Exact and Technical Sciences, Institute of Mechanical Engineering, University of Zielona Góra, Licealna 9, 65-417 Zielona Góra, Poland; 947d@g.elearn.uz.zgora.pl

* Correspondence: j.patalas-maliszewska@iim.uz.zgora.pl

Abstract

In manufacturing enterprises, work safety assessments mostly focus on technical requirements and regulatory compliance, whereas the influence of workplace environmental quality is still not adequately addressed. To bridge this gap, this paper develops a novel approach to work safety analysis that incorporates both quantitative and qualitative parameters characterizing the working environment of employees involved in machining processes. This framework consists of: (1) a description of the workstation, (2) a set of quantitative and qualitative indicators characterizing the working environment of employees involved in machining processes, and (3) the Fuzzy Analytic Hierarchy Process (FAHP) method. Overall, the developed analytical framework consists of eight quantitative parameters representing workplace environmental values specified in legal regulations, and eight qualitative parameters reflecting selected aspects of environmental quality and work comfort. The results of the FAHP analysis revealed that the sense of security in the use of machinery and equipment and the level of concentration/distraction were identified as the most significant qualitative factors influencing work safety among employees engaged in machining processes. Next, the findings of our study enabled the development of a new method, namely occupational safety index (OSI). Finally our paper introduces the main challenges and directions: (1) monitor a continuous change as new technologies are introduced and implemented in machining process, (2) assess and analyse the necessary competencies to ensure the safe operation of modern technological systems, (3) and incorporate the ongoing monitoring and regular updating of work safety assessment results into the organization's strategic management framework.

Keywords: work safety; machining process; FAHP; decision analysis



Academic Editors: Lucian-Ionel Cioca
and Mario Fagnoli

Received: 31 May 2026

Revised: 7 July 2026

Accepted: 13 July 2026

Published: 6 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

The dynamic development of industrial technologies and occupational safety systems reveals a research gap regarding the impact of environmental conditions and human factors on the level of work safety. In industrial practice, work safety assessment is most often focused on technical requirements and regulatory compliance, while the influence of workplace environmental quality and the psychophysical condition of operators remains insufficiently addressed. At the same time, contemporary production environments are characterized by high variability in operational parameters, such as noise, temperature, air quality, and operator workload. These factors may directly affect workers' concentration,

fatigue levels, and decision-making abilities, thereby influencing the level of operational safety. The motivation for undertaking this research is the need to develop an integrated approach enabling the simultaneous analysis of both quantitative and qualitative parameters characterizing the working environment of employees involved in machining processes. The application of a selected multi-criteria decision-making (MCDA) method makes it possible to account for uncertainty and the subjective nature of expert judgments, thereby enabling a more realistic assessment of work safety under dynamic industrial conditions. Applying these methods allow for the simultaneous consideration of diverse technical, environmental, and human-related factors, as well as the integration of quantitative and qualitative data within a single safety assessment framework.

A review of the literature highlights the critical importance of safety of employees involved in machining processes and compliance with safety standards. A key element is the definition and implementation of safety protocols (e.g., those outlined in AS/NZS 4024.1:2019) [1], which help reduce the risk of machinery-related accidents [2]. Equally important is the adoption of structured safety management frameworks and ensuring compliance with established standards (e.g., ISO 12100, ISO 26262) [3,4]. From a regulatory perspective, one of the fundamental obligations of employers is to provide occupational health and safety (OHS) training and to carry out risk assessments necessary for identifying potential hazards [5]. Within this context, workplace factors are typically classified into three main categories: hazardous, harmful, and burdensome (or nuisance) factors. Values are considered hazardous or harmful to health when they exceed the limits defined by applicable regulations or the maximum permissible exposure levels. In the work environment, parameters such as temperature, humidity, and dust levels are inherently variable, and their fluctuations can directly affect employee well-being as well as increase the risk of health issues with prolonged exposure [6]. Therefore, a recommended direction is to extend traditional safety approaches by incorporating dynamic management of environmental conditions.

Real-time monitoring of working conditions, combined with consideration of the worker's psychophysical state, followed by an analysis of the environmental impact on human performance ensure compliance with formal requirements and contribute to a tangible improvement in the protection of employees' health and safety, as well as the stability of production processes [7,8]. However, such an approach requires the development of a comprehensive set of indicators that go beyond those mandated by legal regulations. To identify the key indicators, it is necessary to apply methods, e.g., selected Multiple Criteria Decision Analysis (MCDA), which support the decision-making process in establishing a standardized framework for work safety analysis integrating both quantitative and qualitative parameters characterizing the working environment of employees involved in machining processes. Therefore, when considering the role played by work safety analysis and MCDA, two key research questions were formulated:

RQ1: How can work safety be analysed and assessed based on the characteristics of the working environment of employees involved in machining processes?

RQ2: How can decision-making aimed at improving work safety be supported through the analysis of the working environment of employees involved in machining processes?

So, this research is based on a systematic identification and assessment of quantitative and qualitative safety-related criteria, where accidents may result in severe injuries, fatalities, and operational disruptions [9]. Firstly, the literature review indicates the need to develop a new approach to work safety analysis due to the necessity of increasing employees' awareness of safety when working in environments incorporating new technologies and of work comfort. Subsequently, a framework was developed consisting of: (1) a description of the workstation, (2) a set of quantitative and qualitative indicators characterizing

the working environment of employees involved in machining processes, and (3) the Fuzzy Analytic Hierarchy Process (FAHP) method. Finally, a study based on expert opinions was conducted to determine the relative importance of the identified parameters in the assessment of work safety.

The study contributes to the development of a comprehensive decision-support framework for improving work safety of employees involved in machining processes and supports the implementation of advanced safety management strategies aligned with the principles of sustainable and human-centric manufacturing [10].

2. Literature Review

2.1. Work Safety of Employees Involved in Machining Processes

In the European context, work safety assessment is primarily based on the requirements of the Framework Directive 89/391/EEC, which establishes general principles for the prevention of occupational hazards, the protection of workers' health and safety, and the obligation to conduct occupational risk assessments. This directive serves as the foundation for a range of specific directives addressing machinery safety, workplace organization, the use of personal protective equipment, and the control of exposure to physical, chemical, and biological hazards. In the field of occupational safety management, the ISO 45001:2018 standard [11] is also widely applied, providing requirements for a systematic approach to hazard identification, risk assessment, and the continuous improvement of working conditions. Despite the broad scope of these regulations, work safety assessment remains focused primarily on technical and organizational aspects, whereas the impact of dynamic environmental conditions and human factors on operational safety continues to receive comparatively limited attention. Moreover, the necessity of developing a novel approach for harmonizing the assessment of occupational and process safety risks, in our case work safety in machine processes, is emphasized by Stefan and Paltrinieri [12]. Also, Wang et al. [13] underscored the importance of conducting safety assessments at the organizational level, highlighting their role in improving overall safety performance. So, based on the assumption that the level of safety is determined by the interactions among technical, organizational, environmental, and human factors [14], work safety in machine processes is analysed in four fundamental dimensions: technical, organisational, environmental, and human (Figure 1).

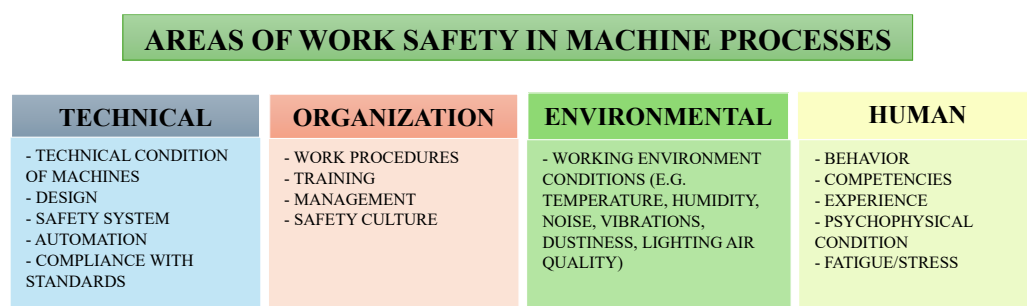


Figure 1. Dimensions of work safety in machine processes.

Work safety in machine processes is based on ISO 12100:2010, which provides principles for machinery risk assessment and risk reduction, and ISO 45001:2018, which specifies requirements for occupational health and safety management systems aimed at preventing workplace injuries and ensuring continuous improvement of safety performance.

The technical aspect should be understood as, among other things, compliance with standards and regulations (e.g., the Machinery Directive 2006/42/EC), the implementation of safety systems, the level of automation, as well as the design and inherent safety of ma-

chinery [15]. It also includes the application of engineering controls, fail-safe mechanisms, and risk reduction measures integrated into machine construction and operation [16]. In turn, the organisational aspect encompasses all activities related to the management of work processes within an organisation, including safety management systems, safety culture, operational procedures, and employee training in the operation of machines and equipment [17]. It also covers supervision practices, maintenance planning, and the continuous improvement of safety-related workflows. In practice, both the technical and organisational dimensions are often developed at a relatively high level, largely due to strong regulatory frameworks and industry standards that require the implementation of specific safety solutions. This regulatory pressure, combined with increasing awareness of occupational risks and the adoption of modern safety management approaches, contributes to the systematic improvement of both engineering and managerial safety practices in industrial environments. The environmental aspect refers directly to workplace conditions, including temperature, humidity levels, noise exposure, and dust concentration [18]. These parameters have a direct impact on employees' well-being as well as their cognitive and physical performance. Inadequate environmental conditions increase the risk of fatigue, reduced concentration, and the development of health-related issues, which in turn significantly raises the likelihood of human error and occupational accidents [19].

In contrast, the human aspect is primarily related to the competencies, behaviour, and psychophysical state of workers. It includes factors such as professional experience, level of training, fatigue, stress, and overall psychological and physiological readiness to perform tasks in machine-based environments [20]. This dimension is increasingly recognised as critical, as human performance variability remains one of the key determinants of safety outcomes in complex industrial systems. According to data from EU-OSHA [21], one-third of workers in the European Union are already exposed to hazards related to extreme temperatures, adverse weather events, or air pollution, and 31% of employees express concerns about the impact of environmental hazards on their safety and health at work. This indicates that environmental factors and human factors constitute significant risk areas that should be adequately addressed within occupational safety and health management systems through appropriate risk assessment procedures and the implementation of technical and organizational control measures.

2.2. MCDA Applications in Work Safety and Ergonomics

Multiple Criteria Decision Analysis (MCDA) methods are widely applied to support decision-makers in solving complex problems involving the selection of the best alternative from a set of competing options characterised by multiple, often conflicting qualitative and quantitative criteria. Due to the inherent complexity of such problems, particularly in industrial and safety-related systems where data originate from technical, organisational, environmental, and human domains, MCDA provides a structured and systematic framework for modelling, evaluation, and prioritisation of decision alternatives. MCDA methods are applied to support decision-making in multi-criteria contexts, where it is necessary to consider multiple, often conflicting, criteria simultaneously [22]. MCDA methods are widely applied to support decision-makers in solving complex problems involving the selection of the best alternative from a set of competing options characterised by multiple, often conflicting qualitative and quantitative criteria. Due to the inherent complexity of such problems, particularly in industrial and safety-related systems where data originate from technical, organisational, environmental, and human domains, MCDA provides a structured and systematic framework for modelling, evaluation, and prioritisation of decision alternatives. MCDA methods can generally be divided into two main categories [23].

- Classical methods are based on the assumption that input data are deterministic and precisely defined during the evaluation process [24]. This group includes, among others: the Analytic Hierarchy Process (AHP), the Analytic Network Process (ANP), the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VIKOR, ELECTRE, PROMETHEE, and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method [25].
- Fuzzy methods incorporate uncertainty, subjectivity, and imprecision of input data into the decision-making process [26]. This class of approaches includes, among others: Fuzzy Analytic Hierarchy Process (FAHP), Fuzzy TOPSIS (FTOPSIS), Fuzzy VIKOR (FVIKOR), Fuzzy Analytic Network Process (FANP), Fuzzy DEMATEL (FDEMATEL), as well as the Pythagorean Fuzzy Analytic Hierarchy Process (PFAHP) [27].

To address RQ1, a literature review was conducted on the application of MCDA methods in the areas of safety, ergonomics, and occupational risk within the industrial sector (Table 1).

Table 1. Literature review on the application of MCDA in work safety and ergonomics in the industrial sector.

No.	MCDA Methods	Approach	Application Area	References
1	F-TOPSIS PF-AHP	Methodology for quantifying occupational risk ratings; parameters subjectively assessed by occupational health and safety experts, with importance levels assigned accordingly.	A comparative outline for quantifying risk ratings in occupational health and safety risk assessment.	[28]
2	F-AHP F-TOPSIS	Methodology for enhancing Health, Safety and Environment (HSE) strategies; prioritization and classification of leading and lagging indicators.	Prioritizing leading and lagging safety and health indicators using Fuzzy-AHP and TOPSIS methods	[29]
3	AHP TOPSIS	Occupational risk assessment in the manufacturing industry; ranking of identified hazards by severity and likelihood	Application of AHP and TOPSIS in occupational risk assessment: a case study in manufacturing industry	[30]
4	F-AHP	Ergonomic assessment of workstations in industrial environments	Ergonomic risk assessment using Fuzzy Analytic Hierarchy Process (F-AHP) in industrial environments	[31]
5	DEMATEL ANP	Analysis of interdependencies between occupational risk and safety factors using cause-and-effect mapping	Analyzing occupational safety factors using Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP) methods	[32]
6	VIKOR AHP	Selection of optimal workplace safety improvement strategies through multi-criteria ranking	Selection of safety improvement strategies using AHP and VIKOR methods	[33]
7	F-TOPSIS	Assessment and ranking of hazards in heavy and process industries under uncertainty	Risk assessment in process industries using Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (F-TOPSIS)	[34]
8	ELECTRE III	Decision support for industrial risk management using outranking-based methodology	Application of ELECTRE (Elimination and Choice Expressing Reality) methods in industrial risk management	[35]
9	AHP PROMETHEE	Multi-criteria ergonomic assessment of operator comfort and working conditions	Multi-criteria ergonomic assessment using AHP and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)	[36]
10	F-VIKOR	Decision optimization in occupational health and safety management systems under fuzzy conditions	Fuzzy VIKOR approach for occupational health and safety management	[37]

Based on the literature review results (Table 1), the main application areas of MCDA methods in the context of work safety and ergonomics can be identified as follows:

- Work environment optimisation, where MCDA methods enable the integration of both measured data and expert judgments, as well as support the selection of optimal environmental parameters to improve working conditions [38].
- Safety and risk assessment, where MCDA approaches assist in hazard identification, risk evaluation, and the selection of appropriate preventive and corrective actions [39].
- Ergonomic design, where MCDA methods facilitate the analysis of workload and support the assessment of comfort, usability, and the fit between workers and workstation design [40].
- Safety management systems, where MCDA techniques are applied to prioritise key safety performance indicators and support decision-making in Work safety management [41].

Table 1 presents examples of the application of MCDA methods for work safety assessment, taking into account multiple criteria simultaneously, such as environmental parameters, workplace ergonomics, human factors, and occupational risk. The reviewed studies demonstrate that MCDA methods enable the simultaneous evaluation of both measurable workplace environmental parameters and qualitative factors related to operator performance and behaviour. Therefore, based on the results of the literature review on work safety (Section 2.1) and the potential application of MCDA methods (Table 1), a new approach is proposed, indicating that a comprehensive assessment of work safety in machining processes requires a multicriteria approach that integrates both quantitative and qualitative factors within a decision-making model.

3. Materials and Methods

3.1. A Description of the Workstation in Machining Processes

The study was conducted on an experimental workstation designed for the execution and monitoring of machining processes located in the Institute of Mechanical Engineering at the University of Zielona Gora, Poland. The workstation is equipped with a computer numerical control (a DMG Mori CLX 350 CNC) machine tool and a measurement infrastructure that enables the acquisition and recording of technological and operational parameters throughout the machining process. An integral component of the workstation is an Internet of Things (IoT)-based sensor system, which facilitates continuous collection of data related to machine operation, process performance, and selected environmental conditions. The acquired data are used to analyze process characteristics, assess process stability, and identify factors influencing the quality of manufactured components. The workstation enables the analysis of cutting parameters, and the determination of indicators describing the efficiency and quality of technological operations. The collected information provides a basis for evaluating process performance and supports activities aimed at process optimization and continuous improvement. The operator is responsible for the following tasks:

- preparing the workstation for the machining process, including the setup and positioning of the workpiece, selection and inspection of cutting tools, as well as initiating and supervising the machining operations,
- monitoring the proper functioning of the machine tool, responded to any deviations from the pre-scribed process parameters, and performed quality control of the manufactured components.

This description of the workstation serves as the industrial context for the application of the proposed framework. Its purpose is to provide the necessary background and operational conditions required to demonstrate the practical implementation and evaluation of the methodology in a real industrial environment.

3.2. Defining Qualitative and Quantitative Parameters Describing the Environment of Workers Performing a Machining Process

Answering the first RQ, we found the key workplace environmental parameters defined in relevant work safety and health regulations and international guidelines (Table 2). The listed indicators describe the physical and chemical conditions of the working environment that directly influence human performance, comfort, and safety in machining processes. The eight quantitative indicators (Table 2) were not selected arbitrarily: each one is anchored to a specific regulatory or normative source already cited in the manuscript—e.g., national labour regulations for temperature [39] for relative humidity, WHO indoor air quality guidelines for CO₂, PM_{2.5} and PM₁₀. Two additional parameters considered in earlier stages of indicator screening (PM₁ and PM₄, see the note under Table 2) were excluded specifically because no recommended/limit values exist for them in the applicable standards, which made them unsuitable for the quantitative, regulation-anchored part of the framework. Next, Table 3 presents qualitative indicators describing subjective human-related factors associated with occupational safety, including mental comfort, fatigue, concentration, emotional well-being, and perceived safety during machine operation. These factors (Table 3) are selected firstly based on the analysis of literature and occupational safety standards (ISO 45001:2018, ISO 6385:2016, PN-N-18002:2011, EU-OSHA) [42–45]. Secondly, indicators were selected according to inclusion criteria: (1) direct influence on operator safety, cognitive performance, or decision-making during machine operation; (2) relevance to machining processes; (3) the assumption that an increase in the indicator level increases the likelihood of human error occurrence or occupational accidents. Due to the subjective and difficult-to-measure nature of these variables, a five-point assessment scale was adopted, ranging from Level I (very favorable conditions) to Level V (very unfavorable conditions). The application of a five-level scale was considered appropriate because it enables a sufficiently detailed differentiation of expert and employee assessments while maintaining clarity and interpretability of results. Furthermore, the adopted approach is consistent with occupational risk assessment methodologies commonly applied in Poland and corresponds to the principles of risk estimation described in the Polish Standard PN-N-18002:2011 “Occupational safety management systems—General guidelines for occupational risk assessment”. The interpretation of the rating levels was standardized across all indicators, with each successive level reflecting an increasing degree of mental workload, reduced work capacity, and higher occupational risk. Next, the adopted five-point scale enables the transformation of qualitative expert judgments into linguistic variables that can subsequently be represented using fuzzy numbers within the FAHP framework.

As a result, subjective perceptions related to psychological load, stress, fatigue, and workplace comfort can be systematically incorporated into the multi-criteria decision-making model alongside measurable environmental and operational parameters.

The factors presented in Table 3 relate to the psychophysical functioning of the operator, as the literature indicates that work safety in machine-based processes depends not only on technical parameters but also on cognitive abilities, mental workload, and the employee’s emotional state. The selected indicators cover areas that directly affect human reliability during the performance of operational tasks. Indicators associated with concentration, fatigue, and task preparedness were included in the model because these factors directly influence the operator’s reaction time, decision-making ability, and the likelihood of human errors during machine operation. In addition, indicators related to psychological comfort, emotional well-being, and perceived safety were considered, as prolonged mental strain and stress may reduce cognitive performance and increase operational risk. Furthermore, work and workspace comfort, as well as the availability

of organizational support, were incorporated into the analysis because ergonomic and organizational factors affect employee workload, task performance quality, and the stability of work processes. The selected indicators therefore enable a comprehensive assessment of work safety from the perspective of human factors, which are increasingly recognized as one of the key elements in reducing occupational risk in modern industrial environments.

Table 2. Workplace environmental parameter values defined in legal regulations.

No.	Indicator	Abbreviation	Unit	Recommended Value	Source
1	Temperature (light work)	T	°C	18–26	National labour regulations
2	Relative humidity	RH	%	40–60	PN-EN ISO 7730 [46]
3	Absolute humidity	AH	g/m ³	—	—
4	Noise exposure	—	dB(A)	85 (daily exposure limit)	Directive 2003/10/EC
5	Carbon dioxide concentration	CO ₂	ppm	<1000	WHO indoor air quality guidelines
6	Illuminance	—	lx	300–1000	PN-EN 12464-1 [47]
7	Particulate matter (PM _{2.5})	PM _{2.5}	µg/m ³	15 (24 h WHO guideline)	WHO Air Quality Guidelines (2021)
8	Particulate matter (PM ₁₀)	PM ₁₀	µg/m ³	45 (24 h WHO guideline)	WHO Air Quality Guidelines (2021)

Comments: indicators are limited to the area of machine work. The PM₁ and PM₄ parameters are not included due to the lack of recommended values. The WHO indicates indicative values that an organization can adopt as limit values.

Table 3. Selected values of environmental quality parameters and work comfort.

No.	Indicator (Abbreviation)	Indicator Description	Range				
			I	II	III	IV	V
1	Mental comfort (MC)	Subjective feeling of pressure related to work pace, workload, and deadlines	No pressure; full psychological comfort	Slight pressure occasionally experienced	Moderate and noticeable pressure affecting comfort	High pressure causing stress and discomfort	Very high pressure causing severe psychological discomfort and tension
2	Preparation/competence for entrusted tasks (P/C)	Subjective perception of preparedness, competence, and confidence in task execution	Fully prepared and confident in all assigned tasks	Mostly prepared with only minor uncertainties	Moderate confidence; occasional need for assistance or clarification	Low confidence and noticeable difficulties in task execution	Very low competence perception; inability to perform tasks independently
3	Sense of security in the use of machinery and equipment (SoS)	Emotional tension and perceived safety related to operating machinery and equipment	Complete sense of safety and control	Minor concerns but generally safe feeling	Moderate sense of risk and occasional stress	High level of stress and insecurity during operation	Very high fear and lack of safety when operating machinery
4	Subjective tiredness/drowsiness (T/D)	Self-assessment of physical and mental fatigue during work	Fully alert and rested	Slight fatigue with no impact on work	Moderate tiredness affecting comfort and efficiency	High fatigue causing reduced performance and attention	Extreme fatigue or drowsiness impairing work ability
5	Level of concentration/distraction (C/D)	Ability to maintain attention and focus on work tasks	Full concentration and focus maintained	Minor distractions with negligible impact	Moderate distraction affecting task continuity	Frequent loss of concentration and reduced attention	Very low concentration with inability to maintain focus
6	Emotional well-being (EW-B)	Overall emotional state, mood, interpersonal relations, and work atmosphere	Very positive mood and supportive atmosphere	Generally positive emotional state	Neutral emotional condition with occasional tension	Negative emotional state and frequent stress	Very poor emotional well-being and strong negative emotions
7	Comfort of work and space (CoWaS)	Assessment of workplace ergonomics, spatial arrangement, and workstation comfort	Very comfortable and ergonomic workspace	Mostly comfortable with minor inconveniences	Moderate comfort with noticeable ergonomic limitations	Uncomfortable workspace affecting task performance	Very poor ergonomic conditions causing discomfort and difficulty
8	Availability of support (AoS)	Availability of organisational, technical, and interpersonal support during work	Immediate and comprehensive support available	Support generally available when needed	Limited support causing occasional difficulties	Insufficient support in many work situations	Lack of support significantly hindering work performance

3.3. Fuzzy Analytic Hierarchy Process (FAHP)

Among MCDA techniques, the AHP, introduced by Saaty, is one of the most widely used methods for deriving criteria weights through structured pairwise comparisons [48]. AHP has been successfully applied in numerous domains, including risk assessment, environmental management, infrastructure planning, and engineering decision problems, often in combination with Geographic Information Systems (GIS) and other optimisation tools. However, despite its broad applicability, classical AHP operates under the assumption of precise numerical judgments (typically using a fixed 1–9 scale), which limits its ability to explicitly capture uncertainty, vagueness, and subjectivity inherent in expert evaluations [49].

To overcome these limitations, the FAHP was developed by integrating AHP with fuzzy set theory [50]. FAHP extends the classical framework by allowing decision-makers to express pairwise comparisons using fuzzy numbers and linguistic variables instead of crisp values. This enables a more realistic representation of human reasoning in situations where judgments are imprecise or uncertain. As a result, FAHP improves the robustness of weight estimation by explicitly modelling uncertainty in expert assessments and allowing aggregation of group expert opinions, as well as analysis of variability in derived criteria weights. In FAHP-based approaches, uncertainty is not treated as a limitation but as an intrinsic characteristic of the decision problem. The method also supports the assessment of consistency in expert judgments and can be combined with simulation techniques, such as Monte Carlo analysis, to evaluate the stability of results under small perturbations of input data. Consequently, FAHP has been widely applied in complex decision environments, including facility location selection, environmental risk assessment, machine tool evaluation, landfill site selection, and infrastructure and energy systems planning.

The FAHP method employs a linguistic scale and triangular fuzzy numbers to represent the uncertainty and ambiguity inherent in expert judgments [51]. Linguistic scale and triangular fuzzy numbers applied in the FAHP analysis presents Table 4.

Table 4. Linguistic scale and triangular fuzzy numbers applied in the FAHP analysis.

Linguistic Assessment	Saaty Scale Equivalent	Triangular Fuzzy Number (TFN)	Interpretation in Occupational Safety Assessment
Equal importance	1	(1, 1, 1)	Both indicators have the same influence on occupational safety and ergonomic conditions
Weak importance	2	(1, 2, 3)	One indicator is slightly more important than another in the assessment of work safety
Moderate importance	3	(2, 3, 4)	One indicator has a noticeable influence on safety performance compared to another
Moderate to strong importance	4	(3, 4, 5)	The importance of one indicator is clearly higher and regularly affects occupational risk
Strong importance	5	(4, 5, 6)	One indicator strongly influences work safety and operational reliability
Strong to very strong importance	6	(5, 6, 7)	The indicator has a dominant role in shaping workplace safety conditions
Very strong importance	7	(6, 7, 8)	One criterion is considered critically important compared to another
Very strong to extreme importance	8	(7, 8, 9)	The indicator almost completely dominates the comparative assessment
Extreme importance	9	(8, 9, 9)	One indicator is absolutely more important in occupational safety evaluation

Based on the review of MCDA methods, it was concluded that the FAHP method would be used to build the assumed methodology of risk assessment in machine processes. The fuzzy method was considered to be a good method due to the subjective nature of the data, which requires expert evaluation. The use of the FAHP method through the use of fuzzy logic is the preferred method for gradual evaluation of values instead of a strict comparison of values, e.g., true/false [52]. As indicated by the literature, FAHP permits decision-makers to express their opinions in a more natural and intuitive way [53]. In the case of the developed set of qualitative indicators presented in Table 3, where there are terms such as “medium comfort”, the FAHP method allows for formal modelling of such a determination, thus indicating its better fit in the proposed approach than in the case of the AHP method. In addition, the FAHP method makes it possible to build a system based on the aggregation of quantitative and qualitative data, taking into account the uncertainty and opinion of experts, which is particularly important in a dynamic industrial environment.

Finally, we propose the new approach to analyse the work safety that incorporates both quantitative and qualitative parameters characterizing the working environment of employees involved in machining processes (Figure 2).

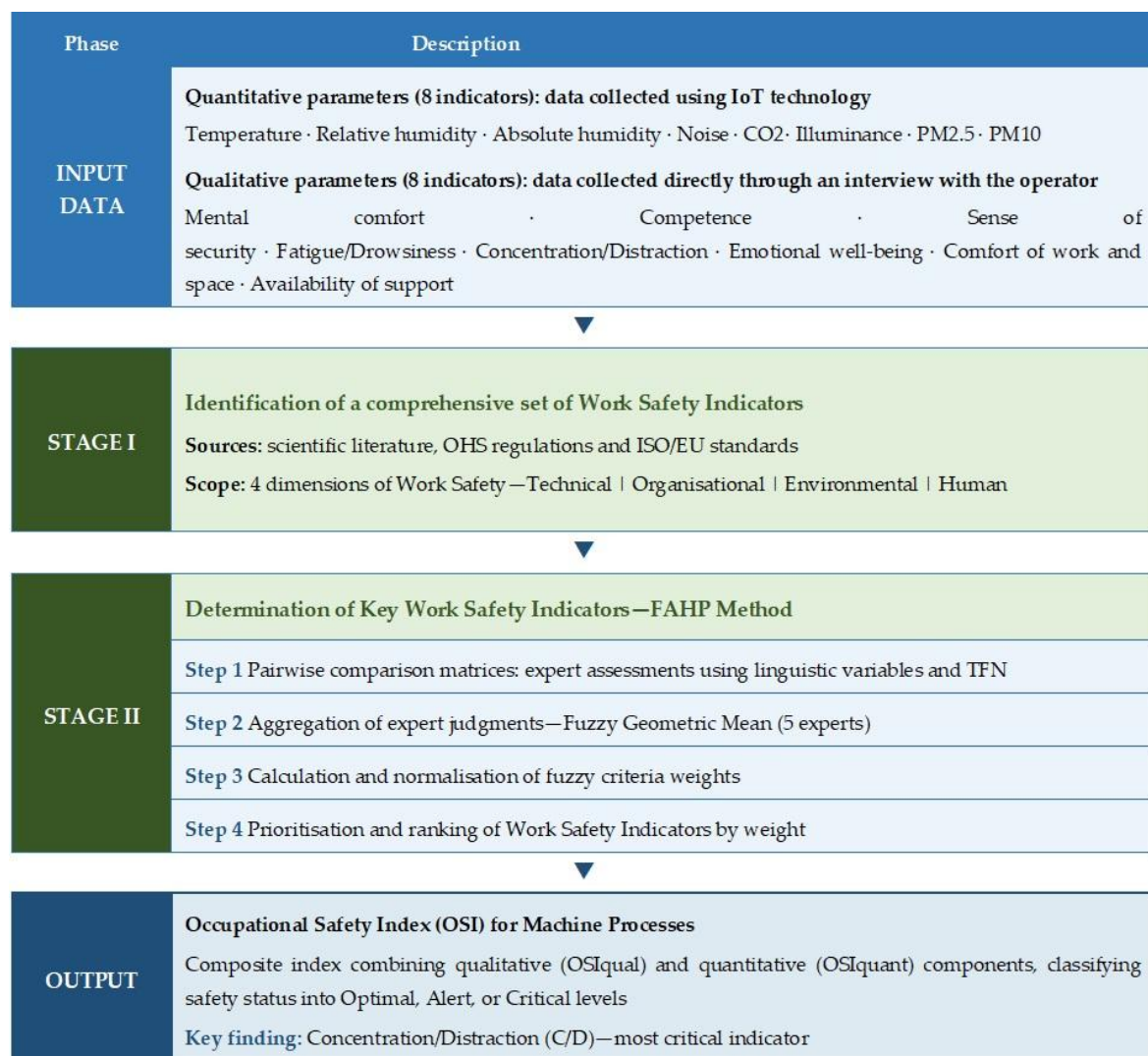


Figure 2. Proposed approach for Work Safety Assessment in Machine Processes using FAHP.

4. Research Results

4.1. FAHP Analysis

Answering RQ2, the FAHP analysis was performed using pairwise comparison matrices developed by five experts representing both industrial and academic environments. Expert judgments were expressed using linguistic variables corresponding to triangular fuzzy numbers (TFNs), as presented in Table 4. The adopted linguistic scale enabled experts to formulate assessments under conditions of uncertainty, subjectivity, and incomplete information, which is particularly relevant in the evaluation of qualitative occupational safety indicators in machining environments. The selection of experts was based on their professional experience and competencies in occupational safety, ergonomics, and industrial risk assessment. The panel included five specialists with extensive backgrounds in both industrial practice and academic research. Expert 1 represents an industrial occupational safety specialist with 10 years of professional experience in occupational health and safety (OHS). He works as an external OHS consultant for companies operating in various industrial and service sectors. His responsibilities include the development and implementation of occupational safety management systems, conducting occupational risk assessments, and ensuring compliance with safety regulations. He holds a higher education degree in occupational health and safety and has extensive experience in hazard identification, workplace environmental assessment, and the organization of safe work systems. Expert 2 is an occupational safety practitioner with extensive experience in manufacturing environments. His expertise includes occupational risk assessment, analysis of workplace environmental conditions, and the implementation of safety improvements in machine-based processes. He has participated in safety audits, near-miss event analysis, and the continuous monitoring of environmental factors influencing operator safety and ergonomics. Expert 3 represents the academic community. He has been an academic lecturer for more than 15 years, specializing in occupational health and safety (OHS), with particular expertise in the technical safety of machinery and equipment. His teaching and research activities focus on machine safety, risk assessment methodologies, safety management systems, and compliance with occupational safety regulations. He has extensive experience in educating future OHS professionals, supervising research projects, and participating in scientific studies related to workplace safety and accident prevention. Expert 4 is also an active academic lecturer with many years of experience in teaching occupational health and safety. Expert 5 is an occupational health and safety (OHS) specialist with five years of professional experience in the industrial sector. He has practical experience in applying OHS management principles in manufacturing environments and promoting a proactive safety culture within organizations. The participation of expert practitioners in the development of the proposed approach is in line with recommendations [54] emphasizing that the development of procedures should be undertaken in close cooperation with artisans and supervisors.

The general structure of the FAHP pairwise comparison matrix for qualitative occupational safety indicators is presented in Table A1. To verify the reliability of the expert judgments, a consistency analysis was performed following the classical Analytic Hierarchy Process (AHP) procedure proposed by Saaty. Since pairwise comparisons were initially expressed using triangular fuzzy numbers (TFNs), the consistency analysis was conducted on the defuzzified comparison matrices. A consistency test was chosen, which is commonly used in studies using the FAHP method [55–58].

Step I. Construction of the fuzzy pairwise comparison matrix.

The experts evaluated the relative importance of the criteria using linguistic variables represented by triangular fuzzy numbers (TFNs). Consequently, the fuzzy pairwise comparison matrix was defined as:

$$\tilde{A} = \begin{pmatrix} (1, 1, 1) & \tilde{a}_{12} & \tilde{a}_{1n} \\ \tilde{a}_{21} & (1, 1, 1) & \tilde{a}_{2n} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & (1, 1, 1) \end{pmatrix} \quad (1)$$

where:

$$\tilde{a}_{ij} = (l, m, u).$$

is a triangular fuzzy number describing the relative importance of criterion i over criterion j , while the reciprocal comparisons satisfy:

$$\tilde{a}_{ij} = \left(\frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}} \right) \quad (2)$$

Step II. Defuzzification of the fuzzy matrix.

The consistency analysis cannot be performed directly on fuzzy values. Therefore, each triangular fuzzy number was converted into a crisp value using the Centre of Gravity (COG) method:

$$a_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3} \quad (3)$$

As a result, the fuzzy comparison matrix was transformed into the crisp matrix:

$$A = [a_{ij}] \quad (4)$$

which was subsequently used for consistency verification.

Step III. Determination of the priority vector and the maximum eigenvalue.

The normalized priority vector was determined by solving the eigenvalue problem

$$A_w = \lambda_{\max} w \quad (5)$$

Step IV. Consistency Index.

The Consistency Index (CI) was determined from:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (6)$$

where n —the number of criteria (6).

Step V. Consistency Ratio.

The Consistency Ratio (CR) was calculated according to:

$$CR = \frac{CI}{RI} \quad (7)$$

where RI —denotes Saaty's Random Index (7).

In our research, the RI for the 8 criteria is 1.41.

The consistency of expert judgments was evaluated according to the following criterion:

- $CR < 0.10$ —the pairwise comparison matrix is considered consistent;
- $CR \geq 0.10$ —the expert judgments should be revised.

The consistency analysis was carried out for the judgments provided by all five experts. The obtained values are presented in Table 5.

Table 5. Consistency of expert assessment.

Expert	$\lambda_{\max}$	CI	CR	Decision
1	8.234	0.033	0.024	Consistent
2	8.611	0.087	0.062	Consistent
3	8.206	0.029	0.021	Consistent
4	8.450	0.064	0.046	Consistent
5	8.206	0.029	0.021	Consistent

Since all obtained CR values were below the threshold of 0.10, the expert judgments were considered sufficiently consistent and suitable for further FAHP calculations. Although all five expert matrices satisfied the $CR < 0.10$ consistency criterion, some variation in judgment consistency and emphasis can be observed. Expert 2 ($CR = 0.062$) and Expert 4 ($CR = 0.046$) exhibited comparatively less consistent judgments than Experts 1, 3, and 5 ($CR \approx 0.02$ – 0.03), reflecting a wider spread in the relative weights they assigned to C/D and Sense of Safety (SoS) compared to the other criteria. Nevertheless, all five experts—irrespective of their industrial or academic background—consistently ranked C/D and SoS among the two most important qualitative indicators, while AoS was consistently rated as the least influential.

Table 6 presents the results based on Equations (8) and (9) [59].

$$\tilde{a}_{ij} = \left(\prod_{k=1}^K l_{ij}^{(k)} \right)^{1/K}, \left(\prod_{k=1}^K m_{ij}^{(k)} \right)^{1/K}, \left(\prod_{k=1}^K u_{ij}^{(k)} \right)^{1/K} \quad (8)$$

$$a_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3} \quad (9)$$

where:

$\tilde{a}_{ij}$ —aggregated triangular fuzzy number representing the pairwise comparison between criteria i and j ;

a_{ij} —defuzzified value of the aggregated triangular fuzzy number;

i, j —indices of the compared criteria;

K —total number of experts participating in the evaluation;

$l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)}$ —lower, modal, and upper values of the triangular fuzzy number assigned by expert k for the comparison of criteria i and j , where $k = 1, \dots, K$;

$\prod$ —product operator;

$1/K$ —exponent corresponding to the geometric mean used to aggregate expert judgments.

Table 6. The aggregated pairwise comparison matrix.

Criteria	MC	P/C	SoS	T/D	C/D	EW-B	CoWaS	AoS
MC	1.587	0.933	0.362	0.707	0.313	1.000	1.129	1.316
P/C	2.756	1.000	0.631	1.168	0.686	1.000	1.587	2.419
SoS	3.659	1.587	1.000	2.000	1.000	1.587	2.080	2.782
T/D	1.587	0.857	0.500	1.000	0.588	0.812	1.147	1.290
C/D	3.659	1.587	1.000	1.698	1.000	1.587	2.340	2.782
EW-B	1.587	1.000	0.631	1.147	0.631	1.000	1.587	2.080
CoWaS	0.933	0.631	0.481	0.707	0.480	0.631	1.000	1.587
AoS	0.631	0.414	0.302	0.631	0.362	0.481	0.631	1.000

Although Equations (1) and (2) are formulated in their classical form for the pairwise aggregation of two expert judgments, in the present study they were applied iteratively to aggregate the assessments of all five participating experts: for each pairwise comparison, the corresponding fifth root of the product of the five expert-specific triangular fuzzy numbers was calculated, generalizing the square-root geometric mean shown below to $n = 5$ experts.

The evaluation made it possible to identify priority quality indicators (Table 7).

Table 7. Ranking of quality indicators based on expert assessment.

Ranking Position	Indicator	Priority Weight
1	SoS	0.2024
2	C/D	0.2007
3	P/C	0.1391
4	EW-B	0.1258
5	T/D	0.1029
6	MC	0.0907
7	CoWaS	0.0767
8	AoS	0.0616

The aggregated pairwise comparison matrix (Table 6) was derived using the geometric mean of judgments provided by five experts representing industrial and academic environments. This approach enabled the integration of diverse perspectives on work safety determinants in machining processes, ensuring that both operational and research-oriented viewpoints were reflected in the final evaluation. The results of the aggregation indicate a clear differentiation in the perceived importance of the analysed criteria. Among all evaluated dimensions, safety-related and cognitive performance factors exhibit the highest relative importance, particularly the criterion sense of security in the use of machinery and equipment (SoS) and Level of concentration/distraction (C/D). These indicators consistently received high comparative values across expert groups, reflecting their critical role in ensuring safe machine operation. In the aggregated matrix, SoS demonstrates strong dominance over most criteria (e.g., $MC = 3.659$; $EW-B = 1.587$), while C/D also maintains consistently high values (e.g., against $MC = 3.659$; $CoWaS = 2.340$), confirming its central position in the decision structure. Environmental and organisational factors, represented by MC, EW-B, and CoWaS, exhibit moderate importance. Their values in the aggregated matrix remain close to unity in several comparisons, indicating a balanced but not dominant influence on overall work safety. This suggests that, while regulatory and technical aspects of machine operation are well established in industrial practice, their marginal contribution to variability in safety perception is lower compared to human-related factor. In contrast, the lowest relative importance is observed for AoS, which consistently shows lower comparative values across the matrix (e.g., $MC = 0.631$; $C/D = 0.362$). This indicates that, within the expert judgment structure, organisational support mechanisms were perceived as less influential in determining immediate safety outcomes in machining processes compared to cognitive and environmental stressors.

The C/D indicator reflects an operator's ability to maintain sustained attention on task-related activities while resisting both internal and external stimuli that may interfere with safe and effective machine operation. The obtained results are consistent with both expert opinions and findings reported in the literature, which identify sustained attention and vigilance as key determinants of human reliability in industrial environments. Empirical studies have shown that attentional failures are among the leading causes of workplace accidents and safety incidents, whereas the ability to maintain continuous focus is essential for safe and stable operation in complex and dynamic work systems [60,61]. In

machining processes, the operator functions as a real-time supervisor of the technological process and is required to respond to unexpected events such as equipment malfunctions, process deviations, or safety alarms. These situations often occur under time pressure and in environments characterized by multiple sensory stimuli. Under such conditions, even short-term lapses in attention may lead to operational errors, delayed hazard recognition, or incorrect responses to warning signals. This explains the dominant position of the C/D criterion in the FAHP results. The aggregated results also highlight the strong role of SoS (Sense of Safety), which reflects the operator's perceived level of control and safety during machine operation. The relatively high weights associated with SoS indicate that perceived safety is not only an emotional construct but also a functional determinant of operational performance. Operators who perceive higher levels of safety tend to demonstrate improved decision-making accuracy and lower cognitive stress, which directly influences their ability to maintain concentration. The prominence of C/D within the FAHP model can further be explained by its strong interdependencies with other evaluated criteria. The literature indicates that operator concentration is directly influenced by environmental conditions such as noise, temperature, air quality, and illumination [62,63]. Prolonged exposure to adverse environmental conditions contributes to increased psychophysical fatigue, reduced cognitive performance, and impaired perceptual abilities. Consequently, concentration should be interpreted as an integrative indicator reflecting the combined effects of environmental (MC, EW-B), organisational (CoWaS), and human-related factors (SoS, AoS) on occupational safety. At the same time, the aggregated matrix shows that technical and organisational factors (MC and EW-B) maintain a moderate level of importance, indicating their stabilizing role in the overall safety system. Although these factors are strongly regulated in industrial practice, their marginal influence on variability in safety perception is lower compared to cognitive and perceptual dimensions. In contrast, AoS and CoWaS received relatively lower importance values, suggesting that, in the context of machining processes, they are perceived as indirect rather than immediate determinants of operational safety. Overall, the results confirm that occupational safety in machining processes is primarily driven by human-centered factors, with concentration/distraction and perceived safety forming the core determinants of risk variation. This highlights the need to treat cognitive performance not as a secondary variable, but as a central component of safety assessment frameworks. The concept presented in the paper is the basis for the calculation of the occupational safety index (OSI).

4.2. The New OSI-Based Framework

The calculation of the OSI requires the following steps:

- (1) Normalization of quantitative indicators (Table 2), in which the measured data are transformed to a 0–5 scale according to their impact on occupational safety. Values exceeding the reference limits result in a lower occupational safety rating.

It was assumed that, in an industrial environment focused on technological development in accordance with the Industry 4.0/5.0 paradigm, the quantitative indicators (Table 2) would be measured using the IoT infrastructure deployed on the shop floor. These parameters are recorded in real time and provide a direct representation of the physical working conditions at the machining workstation. It should be emphasized that the quantitative indicators constitute the fundamental environmental parameters in real industrial conditions and provide the basis for occupational safety assessment.

- (2) Application of the FAHP method to determine the weights of qualitative criteria.

The results obtained from the experts, in the form of the aggregated pairwise comparison matrix developed using the FAHP method, enable the determination of the relative importance of the adopted qualitative criteria by calculating their corresponding weights.

- (3) Aggregation of quantitative and qualitative indicator assessments into a single OSI.

OSI is derived from the combination of two groups of indicators. The qualitative indicators (Table 3) are assessed using a five-point scale ranging from 1 to 5, whereas the quantitative indicators (Table 2) are normalized to the same 1–5 scale, where a value of 1 represents a fully safe (optimal) condition and a value of 5 corresponds to a critical condition.

At the same time, the qualitative indicators reflect the operator's perception and psychophysical state, with the 1–5 scale describing the level of subjective comfort and workload. The proposed framework also incorporates indicator priorities. The weights assigned to the qualitative indicators are based on the expert evaluations obtained using the FAHP method, whereas all quantitative indicators are assumed to have equal importance. The relative importance of the indicators constitutes an integral component of the final occupational safety assessment.

The assessment scale adopted for the qualitative indicators is presented in Table 3, while their corresponding weights are given in Table 7. The qualitative indicators are rated on a five-point scale (1–5), with each score representing the value reported directly by the operator during the assessment. For the quantitative indicators, a five-level rating scale was developed to reflect graduated deviations from the reference values (Table A2). Level 1 corresponds to the recommended range, ensuring a high level of operator comfort and appropriate working conditions, whereas Level 5 represents a critical condition in which the parameter values may adversely affect the operator's health, well-being, and work performance.

Due to the absence of a clearly established regulatory or legal reference value for AH, the reference range adopted for Level 1 (6–12 g/m³) is based on commonly accepted indoor environmental comfort guidelines rather than on a binding standard. This range was retained within the equally weighted set of quantitative indicators to ensure methodological consistency and should be re-evaluated once a task-specific normative reference value becomes available.

Therefore, the OSI is developed:

$$OSI = OSI_{\text{qual}} + OSI_{\text{quant}} \quad (10)$$

OSI quality:

$$OSI_{\text{qual}} = \sum_{i=1}^8 w_i \cdot Q_i \quad (11)$$

where:

w_i —weight of this criterion i ($\sum w_i = 1$).

Q_i —evaluation of this criterion assigned from the decision matrix i ($Q_i \in \{1, 2, 3, 4, 5\}$).

$$OSI_{\text{quant}} = \frac{1}{8} \sum_{j=1}^8 N_j \quad (12)$$

where:

N_j —normalized to a scale of 1–5 the value of the j -th measurement j ($N_j \in [1, 5]$).

To keep OSI within the same 1–5 range as its two components, and consistent with the Optimal/Alert/Critical thresholds defined below, the two sub-indices are aggregated as an average rather than a direct sum: $OSI = (OSI_{qual} + OSI_{quant})/2$. This preserves the equal-contribution principle described above while ensuring that OSI remains bounded within the interval [1, 5]. On the basis of the OSI, the level of occupational safety is defined on the following scale:

- Optimal level ($1.00 \leq OSI \leq 2.00$): the working conditions are stable. The operator shows optimal psychophysical readiness. No action required.
- Alert level ($2.01 \leq OSI \leq 4.00$): conditions have deteriorated. Working conditions should be checked and changes made.
- Critical level ($4.01 \leq OSI \leq 5.00$): imminent risk of an accident or extreme operator fatigue.

If safety systems can be adapted, it is recommended to automatically initiate process stop procedures or force supervisory intervention if a critical level is detected.

The workstation in machining processes described in Section 3.1 was used to demonstrate the application of the proposed OSI-based framework as a tool supporting managers in their decision-making processes. In the example the weights from Table 7 (w_i for the qualitative indicators, 0.125 for each quantitative indicator) are applied. So, for the task: preparation of the workstation for the machining process it is assumed: sample ratings (1 = safe/favorable, 5 = critical/unfavorable): qualitative – MC = 2, P/C = 1, SoS = 1, T/D = 2, C/D = 2, EW-B = 2, CoWaS = 2, AoS = 2; quantitative – T = 1, RH = 1, AH = 1, Noise = 1, CO₂ = 1, Illuminance = 2, PM2.5 = 1, PM10 = 1. $OSI_{qual} = \sum(w_i \cdot Q_i) \approx 1.66$; $OSI_{quant} = (1/8) \cdot \sum N_j = 9/8 = 1.13$. $OSI = (1.66 + 1.13) / 2 \approx 1.39$, which falls within the Optimal level ($1.00 \leq OSI \leq 2.00$): working conditions are stable and the operator shows optimal psychophysical readiness before the machining process begins. Next, for the task: supervision of the machining process and machine operation OSI is calculated. After several hours of continuous operation, the qualitative ratings shift toward increasing fatigue and reduced concentration: MC = 3, P/C = 2, SoS = 3, T/D = 4, C/D = 4, EW-B = 3, CoWaS = 3, AoS = 2; the quantitative readings are T = 2, RH = 2, AH = 1, Noise = 3, CO₂ = 3, Illuminance = 2, PM2.5 = 2, PM10 = 2. $OSI_{qual} = \sum(w_i \cdot Q_i) \approx 3.10$; $OSI_{quant} = (1/8) \cdot \sum N_j = 17/8 \approx 2.13$. $OSI = (3.10 + 2.13) / 2 \approx 2.61$, which falls within the Alert level ($1.81 \leq OSI \leq 3.50$): conditions have deteriorated—driven mainly by the increase in C/D and T/D, the two highest-weighted or most safety-critical qualitative indicators—and working conditions should be checked and preventive measures (e.g., a scheduled break or task rotation) implemented before the risk of operational error increases further.

The proposed OSI-based framework (Section 4.2) serves as an integral component of decision-support systems that integrate environmental, organizational, and psychophysical data into a unified occupational health and safety assessment model.

5. Discussion

The conducted study confirms that occupational safety in machining processes should be analyzed from a holistic perspective, taking into account not only technical and organizational aspects but also environmental parameters and human-related factors. Contemporary industrial environments are characterized by highly dynamic working conditions; therefore, traditional approaches to safety assessment, primarily based on regulatory compliance and the analysis of individual hazards, are becoming increasingly insufficient. The proposed approach, based on the FAHP, enables the incorporation of uncertainty and subjectivity inherent in expert judgments, which is particularly important when evaluating qualitative occupational safety factors. The OSI thresholds proposed in Section 4 (Optimal, Alert,

Critical) offer a direct, actionable decision rule: an Alert-level OSI should trigger a review of working conditions, while a Critical-level OSI should trigger an automatic process stop or mandatory supervisory intervention, as illustrated by the numerical example in Section 4. In terms of limitations, the proposed weights reflect the judgments of five experts and the specific machining workstation described in Section 3.1; validating the framework across additional workstations, industries, and larger expert panels, together with a formal sensitivity analysis of the FAHP weights, remains an important direction for future research.

Looking at the research results summarized in Table 1, the proposed approach complements the existing literature in the area of safety and risk assessment, where the FAHP is applied to support risk evaluation. A significant advantage of the proposed model is the integration of environmental parameters into occupational safety assessment. Recent studies increasingly indicate that the quality of the working environment directly affects operators' cognitive performance, concentration levels, and the frequency of operational errors. The added value of the proposed approach (Figure 1) lies in the development of an integrated framework that combines both quantitative and qualitative indicators for the assessment of work safety in the machine process.

Unlike many existing studies that focus primarily on either technical risk factors or selected occupational safety aspects, the proposed approach enables a more comprehensive evaluation by incorporating technical, organizational, environmental, and human-related factors within a assessment structure.

Particular attention should be given to factors such as noise levels, temperature, air quality, and airborne particulate matter concentrations. Despite the growing body of research on indoor environmental quality, these parameters are still relatively rarely incorporated into risk assessment models for machining processes. The results indicate that environmental factors may indirectly influence occupational safety through their impact on workers' psychophysical condition. Prolonged exposure to excessive noise, inadequate thermal conditions, or elevated CO₂ concentrations may lead to reduced concentration, increased fatigue, and impaired decision-making capabilities. In practical terms, this implies that even a properly designed and safeguarded technological process may generate elevated operational risk if environmental conditions are not adequately monitored and controlled. It is worth emphasizing that the proposed approach aligns with current developments in occupational safety systems based on real-time environmental monitoring. Environmental sensors and automated data acquisition systems are increasingly being deployed to continuously assess workplace conditions. The integration of such data with multicriteria decision-making methods may provide valuable support for safety management and decision-making processes. Therefore, the proposed framework extends the current application of FAHP in safety assessment by providing a holistic method for evaluating work safety in the machine process.

As highlighted in the literature on workplace safety technologies [64], the collection of well-being-related data (e.g., fatigue levels after the sixth hour of a work shift), combined with incident and safety-performance data, allows managers to make dynamic decisions regarding break scheduling, task allocation, and job rotation. Consequently, integrating human-factor indicators with operational safety data may significantly improve the effectiveness of risk management and contribute to the prevention of workplace accidents in industrial environments. So, the proposed solution enables the identification of the actual dominant risk factors affecting operator safety.

However, several limitations of the proposed model should be acknowledged. First, the analysis is based on expert evaluations, which—despite the application of fuzzy logic retain a degree of subjectivity. Consequently, the results may vary depending on the experts' experience and the specific characteristics of the analyzed industrial environment.

Another research gap concerns the limited number of studies integrating environmental parameters, psychophysical factors, and multicriteria decision-making methods within a unified occupational safety assessment framework. To date, most studies have focused separately on workplace ergonomics, conventional risk assessment, or environmental condition monitoring. The proposed approach represents an attempt to combine these areas within a single decision-support model.

Future research may extend the model by incorporating data obtained from real-time sensor systems and by applying artificial intelligence techniques to support dynamic risk assessment. Another promising direction involves the development of adaptive safety models that account for variations in environmental conditions as well as the current psychophysical state of machine operators during machining operations. Such advancements could contribute to more proactive, data-driven, and resilient occupational safety management systems in modern manufacturing environments. Next, future research will also focus on validating the proposed OSI-based framework through its application in real-world settings, for instance, using an approach similar to the case study presented in [65].

Contribution to Sustainability

The proposed framework directly supports the implementation of SDG 3 Good health and well-being by integrating continuous monitoring of workplace environmental conditions with the assessment of operators' psychophysical state. Unlike conventional occupational safety approaches, which primarily focus on compliance with environmental regulations or technical safety measures, the proposed methodology combines quantitative environmental indicators with qualitative human-related factors within a unified OSI. This integrated approach enables a comprehensive assessment of occupational safety by simultaneously considering the physical working environment together with the operator's cognitive, emotional, and psychophysical condition. The quantitative component of the framework relies on the real-time acquisition of workplace environmental parameters using an IoT-based monitoring infrastructure. Continuous measurements of temperature, humidity, noise, illuminance, carbon dioxide concentration, and particulate matter (PM_{2.5} and PM₁₀) enable the early identification of deviations from recommended values before they adversely affect employees' health, cognitive performance, or operational safety. Consequently, preventive actions can be implemented promptly, reducing workers' exposure to harmful physical and chemical factors and improving overall workplace conditions.

The importance of continuous environmental monitoring is further supported by recent findings published by the EEA. According to the EEA report [66], long-term exposure to fine PM_{2.5} was responsible for approximately 239,000 premature deaths in Europe, while ozone exposure contributed to around 70,000 deaths and nitrogen dioxide (NO₂) exposure to approximately 48,000 deaths. These findings highlight the need for systematic monitoring of workplace environmental conditions, particularly in industrial environments where employees may be exposed to elevated concentrations of airborne pollutants.

While environmental conditions constitute a fundamental component of occupational health, the operator's psychological and cognitive state is equally important for ensuring safe work performance. For this reason, the proposed framework incorporates qualitative indicators describing mental comfort, fatigue, concentration, emotional well-being, perceived safety, task preparedness, workplace comfort, and the availability of organizational support. These human-related factors are integrated with objective environmental measurements through the FAHP-based decision model, enabling a holistic assessment of occupational safety and facilitating the early identification of situations in which deteriorat-

ing environmental conditions may negatively affect human performance and increase the likelihood of operational errors or workplace accidents.

The importance of including psychosocial factors in occupational safety management is emphasized by international organizations. The WHO states that mental health directly influences productivity, work ability, occupational safety, accident occurrence, and long-term employment stability, making the promotion of psychological well-being an essential component of healthy workplaces [67]. Similarly, the European Agency for Safety and Health at Work (EU-OSHA) highlights that favourable psychosocial working conditions improve employees' health, well-being, and work performance, whereas chronic work-related stress contributes to poorer health outcomes, increased absenteeism, reduced productivity, and a higher risk of occupational accidents [68]. Overall, the proposed framework supports a proactive approach to occupational health management by combining continuous environmental monitoring with the assessment of operators' psychophysical readiness. Through the early detection of both environmental and psychosocial risk factors, the methodology contributes to healthier, safer, and more sustainable workplaces, thereby directly supporting the achievement of SDG 3.

Next, it supports the implementation of SDG 9 Industry, Innovation and Infrastructure by integrating Industry 4.0 technologies, IoT sensors, and multicriteria decision-making methods into occupational safety management. The continuous acquisition and analysis of environmental and psychophysical indicators enable real-time monitoring of machining processes, early detection of hazardous situations, and data-driven decision-making. Such an approach contributes to the development of intelligent and resilient industrial infrastructure by supporting predictive safety management instead of reactive accident prevention. Furthermore, the integration of IoT technologies with the FAHP decision-support model promotes digital transformation of manufacturing systems and increases the efficiency, reliability, and sustainability of industrial operations. These assumptions are consistent with the Industry 5.0 concept, where human-centered digital technologies improve both production performance and worker safety. Previous studies indicate that digitalization, smart monitoring systems, and IoT-based data analytics constitute key enablers of sustainable industrial innovation and resilient infrastructure, directly supporting the achievement of SDG 9 [69–71].

Finally, the proposed methodology also contributes to SDG 12 Responsible consumption and production by improving the efficiency and sustainability of manufacturing processes through continuous monitoring of workplace conditions and human performance. Early identification of adverse environmental conditions and operator-related risk factors reduces the likelihood of production errors, machine failures, defective products, and process interruptions. Consequently, the proposed OSI supports more efficient use of raw materials, energy, and manufacturing resources by minimizing waste generated through human errors and unplanned downtime. Moreover, the integration of environmental monitoring with occupational safety assessment enables organizations to optimize production processes while simultaneously protecting employees and reducing the environmental impact associated with inefficient manufacturing. This holistic approach is consistent with sustainable production principles, which emphasize resource efficiency, waste prevention, and environmentally responsible industrial management as fundamental components of SDG 12. Recent studies indicate that Industry 4.0 technologies, IoT systems, and data-driven decision-support tools play an increasingly important role in achieving responsible production by improving process efficiency, reducing resource consumption, and supporting circular economy practices [72,73].

6. Conclusions

The conducted study demonstrated that occupational safety in machining processes should be assessed comprehensively, taking into account technical, organizational, environmental, and human-related factors. The application of the FAHP enabled the incorporation of uncertainty and expert knowledge into the evaluation process, particularly with respect to qualitative safety indicators that are difficult to measure directly. The results indicate that environmental parameters, including noise levels, air quality, temperature, and airborne particulate matter concentrations, have a significant impact on operators' psychophysical condition and may indirectly influence operational safety performance.

Specifically, the FAHP analysis showed that SoS and C/D obtained the highest weights among the eight qualitative indicators (0.2024 and 0.2007, respectively; Table 7), identifying operator concentration and perceived safety—rather than purely technical or organizational factors—as the dominant determinants of work safety in the analysed machining process. Availability of organizational support (AoS) obtained the lowest weight (0.0616), suggesting it plays a comparatively secondary, indirect role.

The proposed approach facilitates the prioritization of safety indicators and supports decision-making processes related to occupational safety management in machining operations. Furthermore, the study highlights the need for continued research on integrating real-time environmental monitoring data with multicriteria decision-support methods. Future work should focus on validating the proposed model in real industrial environments and extending it with dynamic risk assessment mechanisms capable of accounting for changing workplace conditions.

From a practical standpoint, these results imply that safety managers should prioritize interventions that protect operator concentration and perceived safety—such as structured break scheduling after prolonged machine supervision, task rotation to limit sustained attentional load, noise and lighting control at the workstation, and targeted training that reinforces confidence in machine operation—ahead of measures aimed solely at organizational support mechanisms, which the FAHP results identify as comparatively less critical.

Author Contributions: Conceptualization, J.P.-M. and H.Ł.; methodology, J.P.-M., M.S. and H.Ł.; software, H.Ł. and M.S.; validation, J.P.-M. and H.Ł.; formal analysis, J.P.-M., H.Ł. and M.S.; investigation, J.P.-M., H.Ł. and M.S.; resources, J.P.-M., H.Ł. and M.S.; data curation, H.Ł. and M.S.; writing—original draft preparation, J.P.-M., H.Ł. and M.S.; writing—review and editing, J.P.-M.; visualization H.Ł. and M.S.; supervision, J.P.-M.; project administration, J.P.-M.; funding acquisition, J.P.-M. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by a program of the Polish Ministry of Science under the title 'Regional Excellence Initiative', project no. RID/SP/0050/2024/1.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are not openly available due to reasons of sensitivity and are available from the corresponding author upon request. Data are located in controlled access data storage at University of Zielona Góra, Poland.

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

Appendix A

Table A1. General structure of the FAHP pairwise comparison matrix for qualitative occupational safety indicators.

Criteria	MC	P/C	SoS	T/D	C/D	EW-B	CoWaS	AoS
Expert 1: Industrial environment								
MC	1	1/3	1/3	1/2	1/5	1/2	1	3
P/C	3	1	1	2	1/3	1/2	3	5
SoS	3	1	1	2	1/3	1/2	3	5
T/D	2	1/2	1/2	1	1/4	1/3	2	4
C/D	5	3	3	4	1	2	5	7
EW-B	2	2	2	3	1/2	1	4	6
CoWaS	1	1/3	1/3	1/2	1/5	1/4	1	3
AoS	1/3	1/5	1/5	1/4	1/7	1/6	1/3	1
Expert 2: Industrial environment								
MC	4	2	1/2	1/4	1/2	1/2	1/3	1
P/C	6	4	1	1/3	1	1	1	3
SoS	6	4	1	1/2	1	1	1	3
T/D	5	3	1/2	1/3	1	1	1	2
C/D	8	6	2	1	3	2	3	5
EW-B	6	4	1	1/2	2	1	1	2
CoWaS	2	1	1/4	1/6	1/3	1/4	1/4	1/2
AoS	1	1/2	1/6	1/8	1/5	1/6	1/6	1/4
Expert 3: Academic environment								
MC	1	1/2	1/5	3	1/3	2	3	4
P/C	2	1	1/3	4	1/2	3	4	5
SoS	5	3	1	7	2	4	5	6
T/D	1/3	1/4	1/7	1	1/5	1/3	1/2	1/2
C/D	3	1/2	1/2	5	1	3	4	5
EW-B	1/2	1/3	1/4	3	1/3	1	2	3
CoWaS	1/3	1/4	1/5	2	1/4	1/2	1	2
AoS	1/4	1/5	1/6	2	1/5	1/3	1/2	1
Expert 4: Academic environment								
MC	1	1/3	1/5	1/3	1/3	1/3	1/3	1/4
P/C	3	1	1/3	1/2	1/2	1/3	1/3	1/4
SoS	5	3	1	1/2	1/2	1/3	1/3	1/3
T/D	3	2	2	1	1/2	1/2	1	1/2
C/D	3	2	2	2	1	1	1	1/2
EW-B	3	3	3	2	1	1	1/2	1/2
CoWaS	3	3	3	1	1	2	1	1/2
AoS	4	4	3	2	2	2	2	1
Expert 5: Industrial environment								
MC	1	1/2	1/4	1/2	1/2	2	2	3
P/C	2	1	1/2	1	2	2	3	4
SoS	4	2	1	2	3	4	4	5
T/D	2	1	1/2	1	2	3	3	4
C/D	2	1/2	1/3	1/2	1	2	3	3
EW-B	1/2	1/2	1/4	1/3	1/2	1	2	2
CoWaS	1/2	1/3	1/4	1/3	1/3	1/2	1	2
AoS	1/3	1/4	1/5	1/4	1/3	1/2	1/2	1

Table A2. Assessment Levels for Quantitative Indicators and the Adopted Priority Weights.

Crtiteria _{quant}	1	2	3	4	5	Priority
T	18–26	16–<18 or >26–28	14–<16 or >28–30	12–<14 or >30–32	<12 or >32	0.125
RH	40–60	30–<40 or >60–70	20–<30 or >70–80	10–<20 or >80–90	<10 or >90	0.125
AH	6–12	4–<6 or >12–14	3–<4 or >14–16	2–<3 or >16–18	<2 or >18	0.125
Noise	≤70	70–<80	80–<85	85–<90	≥90	0.125
CO ₂	<800	800–<1000	1000–<1500	1500–<2000	≥2000	0.125
Illuminance	300–1000	200–<300 or >1000–1200	150–<200 or >1200–1500	100–<150 or >1500–2000	<100 or >2000	0.125
PM _{2.5}	≤15	15–<25	25–<35	35–<50	≥50	0.125
PM ₁₀	≤45	45–<75	75–<100	100–<150	≥150	0.125

References

1. AS/NZS 4024.1:2019; Safety of Machinery—General Principles for Design, Risk Assessment and Risk Reduction. Standards Australia: Sydney, Australia; Standards New Zealand: Wellington, New Zealand, 2019.
2. Ståhl, C.; Lundqvist, D.; Reineholm, C. Improving work environments through regulation: A literature review on the influence of regulation, inspection practices and organizational conditions in European workplaces. *Saf. Sci.* **2025**, *191*, 106917. [CrossRef]
3. ISO 12100; Safety of Machinery—General Principles for Design—Risk Assessment and Risk Reduction. International Organization for Standardization (ISO): Geneva, Switzerland, 2010.
4. ISO 26262; Road Vehicles—Functional Safety—Part 1: Vocabulary. International Organization for Standardization (ISO): Geneva, Switzerland, 2018.
5. Zang, T.; Awada, M.; Becerik-Gerber, B.; Roll, S.C.; Lucas, G.; Narayanan, S. Does your office make you feel worse? Linking environmental exposure and temporal factors to cognitive symptoms. *Indoor Environ.* **2026**, *3*, 100171. [CrossRef]
6. Aksüt, G.; Eren, T.; Alakaş, H.M. Using wearable technological devices to improve workplace health and safety: An assessment on a sector base with multi-criteria decision-making methods. *Ain Shams Eng. J.* **2024**, *15*, 102423. [CrossRef]
7. Simeone, A.; Grant, R.; Ye, W.; Caggiano, A. A human-cyber-physical system for Operator 5.0 smart risk assessment. *Int. J. Adv. Manuf. Technol.* **2023**, *129*, 2763–2782. [CrossRef]
8. Štilić, A.; Puška, A. Integrating multi-criteria decision-making methods with sustainable engineering: A comprehensive review of current practices. *Eng* **2023**, *4*, 1536–1549. [CrossRef]
9. Forcina, A.; Silvestri, L.; De Felice, F.; Falcone, D. Exploring Industry 4.0 technologies to improve manufacturing enterprise safety management: A TOPSIS-based decision support system and real case study. *Saf. Sci.* **2024**, *169*, 106351. [CrossRef]
10. Del Giudice, M.E.; Sharafkhani, M.; Di Nardo, M.; Murino, T.; Leva, M.C. Exploring safety of machineries and training: An overview of current literature applied to manufacturing environments. *Processes* **2024**, *12*, 684. [CrossRef]
11. ISO 45001:2018; Occupational Health and Safety Management Systems—Requirements with Guidance for Use. International Organization for Standardization (ISO): Geneva, Switzerland, 2018.
12. Stefan, E.; Paltrinieri, N. Harmonizing the Assessment of Occupational and Process Safety Risks. *Chem. Eng. Trans.* **2020**, *82*, 31–36. [CrossRef]
13. Wang, X.; Chen, H.; Liu, B.; Yang, M.; Long, Q. Safety Assessments at the Organizational Level: A Systematic Review. *Front. Public Health* **2020**, *8*, 81. [CrossRef] [PubMed]
14. Reason, J. *Managing the Risks of Organizational Accidents*; Ashgate: Aldershot, UK, 1997.
15. Zhu, X.; Wang, A.; Zhang, K.; Hua, X. A deep learning method to mitigate the impact of subjective factors in risk estimation for machinery safety. *Appl. Sci.* **2024**, *14*, 4519. [CrossRef]
16. Viswanathan, K.; Johnson, M.S.; Toffel, M.W. Do safety management system standards indicate safer operations? Evidence from the OHSAS 18001 occupational health and safety standard. *Saf. Sci.* **2024**, *171*, 106383. [CrossRef]
17. Rautiala, S.; Liukkonen, T.; Korenius, P.; Salmi, K.; Isokääntä, P.; Hirvonen, M. Measured and perceived indoor environmental quality in process control rooms and offices of production facilities. *Indoor Environ.* **2025**, *2*, 100142. [CrossRef]
18. Derdowski, L.A.; Mathisen, G.E. Psychosocial factors and safety in high-risk industries: A systematic literature review. *Saf. Sci.* **2023**, *157*, 105948. [CrossRef]
19. Kheiri, S.K.; Vahedi, Z.; Sun, H.; Megahed, F.M.; Cavuoto, L.A. Human reliability modeling in occupational environments toward a safe and productive Operator 4.0. *Int. J. Ind. Ergon.* **2023**, *97*, 103479. [CrossRef]
20. Bianchini, F.; Calamo, M.; Marinacci, M.; Rossi, J.; Mecella, M. SETTE: A human-centric framework for operator safety monitoring in Industry 5.0. *Procedia Comput. Sci.* **2026**, *277*, 3800–3809. [CrossRef]
21. European Agency for Safety and Health at Work (EU-OSHA). Climate Change and Occupational Safety and Health. Available online: <https://osha.europa.eu/en/themes/climate-change-and-occupational-safety-and-health> (accessed on 7 July 2026).

22. Ishizaka, A.; Siraj, S. Are multi-criteria decision-making tools useful? An experimental comparative study of three methods. *Eur. J. Oper. Res.* **2018**, *264*, 462–471. [\[CrossRef\]](#)
23. Ashour, M.; Mahdiyar, A. A comprehensive state-of-the-art survey on the recent modified and hybrid analytic hierarchy process approaches. *Appl. Soft Comput.* **2024**, *150*, 111014. [\[CrossRef\]](#)
24. Liao, H.; He, Y.; Wu, X.; Wu, Z.; Bausys, R. Reimagining multi-criterion decision making by data-driven methods based on machine learning: A literature review. *Inf. Fusion* **2023**, *100*, 101970. [\[CrossRef\]](#)
25. Yatsalo, B.; Radaev, A.; Haktanir, E.; Skulimowski, A.M.J.; Kahraman, C. A family of fuzzy multi-criteria sorting models FTOPSIS-Sort: Features, case study analysis, and the statistics of distinctions. *Expert Syst. Appl.* **2024**, *237*, 121486. [\[CrossRef\]](#)
26. Saputro, T.E.; Figueira, G.; Almada-Lobo, B. Hybrid MCDM and simulation-optimization for strategic supplier selection. *Expert Syst. Appl.* **2023**, *219*, 119624. [\[CrossRef\]](#)
27. Suleiman, A.M. Exploring work environment management boundaries using work domain analysis. *Saf. Sci.* **2023**, *157*, 105922. [\[CrossRef\]](#)
28. Gul, M.; Lo, H.W.; Yucesan, M. Fermatean fuzzy TOPSIS-based approach for occupational risk assessment in manufacturing. *Complex Intell. Syst.* **2021**, *7*, 2635–2653. [\[CrossRef\]](#)
29. Laal, F.; Komeili, A.; Alboghobeish, A.; Ansari, A. Prioritizing leading and lagging safety and health indicators using fuzzy-AHP and TOPSIS methods. *Theor. Issues Ergon. Sci.* **2025**, *27*, 19–37. [\[CrossRef\]](#)
30. Muthusamy, K.; David, J.S.J.; Nair, S.D.S.; Ainarappan, N. OSH hazards risk assessment using AHP technique: A case study of an electronics manufacturing company. In Proceedings of the Second Asia Pacific International Conference on Industrial Engineering and Operations Management, Surakarta, Indonesia, 14–16 September 2021.
31. Kulaç, S.; Kiraz, A. An integrated ergonomic risk assessment framework based on fuzzy logic and IVSF-AHP for optimising ergonomic risks in a mixed-model assembly line. *Ergonomics* **2024**, *67*, 2009–2029. [\[CrossRef\]](#) [\[PubMed\]](#)
32. Seker, S.; Zavadskas, E.K. Application of fuzzy DEMATEL method for analyzing occupational risks on construction sites. *Sustainability* **2017**, *9*, 2083. [\[CrossRef\]](#)
33. Kaya, T.; Kahraman, C. Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. *Expert Syst. Appl.* **2011**, *38*, 6577–6585. [\[CrossRef\]](#)
34. Tabor, J. Fuzzy TOPSIS in occupational risk management assessment. *Sci. Pap. Silesian Univ. Technol. Organ. Manag. Ser.* **2024**, *207*, 591–601. [\[CrossRef\]](#)
35. Marttunen, M.; Lienert, J.; Belton, V. Structuring problems for multi-criteria decision analysis in practice: A literature review of method combinations. *Eur. J. Oper. Res.* **2017**, *263*, 1–17. [\[CrossRef\]](#)
36. Behzadian, M.; Kazemzadeh, R.; Albadvi, A.; Aghdassi, M. PROMETHEE: A comprehensive literature review on methodologies and applications. *Eur. J. Oper. Res.* **2010**, *200*, 198–215. [\[CrossRef\]](#)
37. Gül, M.; Ak, M.F.; Guneri, A.F. Pythagorean fuzzy VIKOR-based approach for safety risk assessment in mine industry. *J. Saf. Res.* **2019**, *69*, 135–153. [\[CrossRef\]](#) [\[PubMed\]](#)
38. Comberti, L.; Demichela, M. Customised risk assessment in manufacturing: A step towards the future of work safety management. *Saf. Sci.* **2022**, *154*, 105809. [\[CrossRef\]](#)
39. Merlo, E.; Lamon, E.; Fusaro, F.; Lorenzini, M.; Carfi, A.; Mastrogiovanni, F.; Ajoudani, A. An ergonomic role allocation framework for dynamic human–robot collaborative tasks. *J. Manuf. Syst.* **2023**, *67*, 111–121. [\[CrossRef\]](#)
40. Macdonald, W.; Oakman, J. The problem with “ergonomics injuries”: What can ergonomists do? *Appl. Ergon.* **2022**, *103*, 103774. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Claeys, A.; Hoedt, S.; Domken, C.; Aghezzaf, E.-H.; Claeys, D.; Cottyn, J. Methodology to integrate ergonomics information in contextualized digital work instructions. *Procedia CIRP* **2022**, *106*, 168–173. [\[CrossRef\]](#)
42. Reiman, A.; Kaivo-oja, J.; Parviainen, E.; Takala, E.-P.; Lauraeus, T. Human Factors and Ergonomics in Manufacturing in the Industry 4.0 Context—A Scoping Review. *Technol. Soc.* **2021**, *65*, 101572. [\[CrossRef\]](#)
43. Jha, P.R.; Di Pasquale, V.; Saleem, J.J.; Wang, X. Taxonomy of Performance Shaping Factors in Manufacturing: A Systematic Literature Review. *Hum. Factors Ergon. Manuf. Serv. Ind.* **2024**, *34*, 367–385. [\[CrossRef\]](#)
44. ISO 6385:2016; Ergonomics Principles in the Design of Work Systems. International Organization for Standardization (ISO): Geneva, Switzerland, 2016.
45. PN-N-18002:2011; Occupational Health and Safety Management Systems—General Guidelines for Occupational Risk Assessment. Polish Committee for Standardization (PKN): Warsaw, Poland, 2011.
46. PN-EN ISO 7730; Ergonomics of the Thermal Environment—Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria. Polish Committee for Standardization (PKN): Warsaw, Poland, 2026.
47. PN-EN 12464-1; Light and Lighting—Lighting of Work Places—Part 1: Indoor Work Places. Polish Committee for Standardization (PKN): Warsaw, Poland, 2022.

48. Carpitella, S.; Kratochvíl, V.; Pištěk, M. Multi-criteria decision making beyond consistency: An alternative to AHP for real-world industrial problems. *Comput. Ind. Eng.* **2024**, *198*, 110661. [\[CrossRef\]](#)
49. Vinogradova-Zinkevič, I.; Podvezko, V.; Zavadskas, E.K. Comparative assessment of the stability of AHP and FAHP methods. *Symmetry* **2021**, *13*, 479. [\[CrossRef\]](#)
50. Haque, M.F. Predicting Seismic Sustainability for a Complex CHESST Interaction by AHP Using LWST. *J. Saf. Sustain.* **2024**, *1*, 181–188. [\[CrossRef\]](#)
51. Borovička, A. New approach for estimation of criteria weights based on the linguistic evaluation. *Expert Syst. Appl.* **2019**, *125*, 100–111. [\[CrossRef\]](#)
52. Fantozzi, I.C.; Colleluori, L.; Schiraldi, M.M. A quali-quantitative analysis model integrating fuzzy analytical hierarchy process and cost–benefit analysis for optimizing KPI implementation: Insights from a practical case study application. *Eng* **2025**, *6*, 56. [\[CrossRef\]](#)
53. Rane, N.L.; Choudhary, S.P. Fuzzy AHP and fuzzy TOPSIS as an effective and powerful multi-criteria decision-making (MCDM) method for subjective judgements in selection process. *Int. Res. J. Mod. Eng. Technol. Sci.* **2023**, *5*, 4. [\[CrossRef\]](#)
54. Gonyora, M. When More Becomes Less: Re-Examining Permit-to-Work, Procedures, and Communication as Risk-Management Controls. *J. Saf. Sustain.* **2026**, *in press*, corrected proof. [\[CrossRef\]](#)
55. Liu, Y.; Eckert, C.M.; Earl, C. A Review of Fuzzy AHP Methods for Decision-Making with Subjective Judgements. *Expert Syst. Appl.* **2020**, *161*, 113738. [\[CrossRef\]](#)
56. Zhu, C.; Sun, S.; Chen, T.; Zhong, Q.; Liu, H.; Li, J.; He, D. Risk Assessment of Equipment Research Project Costs Based on FAHP–CRITIC Combined Weights for Two-Dimensional Cloud Model. *Discret. Dyn. Nat. Soc.* **2024**, *2024*, 6515118. [\[CrossRef\]](#)
57. Mohd Zaki, N.H.; Bidin, J.; Sharif, N.; Akil, K.A.K.; Nayan, S. Fuzzy Analytic Hierarchy Process (FAHP) in Analyzing Mathematical E-Learning Success Factors. *J. Comput. Res. Innov.* **2024**, *9*, 2. [\[CrossRef\]](#)
58. Chen, C.-Y.; Huang, J.-J. Deriving Fuzzy Weights from the Consistent Fuzzy Analytic Hierarchy Process. *Mathematics* **2022**, *10*, 3499. [\[CrossRef\]](#)
59. Buckley, J.J. Fuzzy Hierarchical Analysis. *Fuzzy Sets Syst.* **1985**, *17*, 233–247. [\[CrossRef\]](#)
60. Anderson, B.A.; Kim, N.; Gregoire, L.; Yan, N.; Ahn, C.R. Attention failures cause workplace accidents: Why workers ignore hazards and what to do about it. *Policy Insights Behav. Brain Sci.* **2024**, *11*, 24–33. [\[CrossRef\]](#)
61. Sharpe, B.T.; Tyndall, I. The sustained attention paradox: A critical commentary on the theoretical impossibility of perfect vigilance. *Cogn. Sci.* **2025**, *49*, e70061. [\[CrossRef\]](#) [\[PubMed\]](#)
62. Al Horr, Y.; Arif, M.; Kaushik, A.; Mazroei, A.; Katafygiotou, M.; Elsarrag, E. Occupant productivity and office indoor environment quality: A review of the literature. *Build. Environ.* **2016**, *105*, 369–389. [\[CrossRef\]](#)
63. Zakerian, S.A.; Yazdanirad, S.; Gharib, S.; Azam, K.; Zare, A. The effect of increasing the illumination on operators' visual performance in the control-room of a combined cycle power plant. *Ann. Occup. Environ. Med.* **2018**, *30*, 56. [\[CrossRef\]](#) [\[PubMed\]](#)
64. National Safety Council. Fatigue Monitoring and Wearables. Available online: <https://www.nsc.org/workplace/safety-topics/work-to-zero/safety-technologies/fatigue-monitoring-and-wearables> (accessed on 7 July 2026).
65. Burlet-Vienney, D.; Beaugrand, S.; Gonella, M.; Galy, B.; Ledoux, E. If only pickups and vans could fly: Vehicle maintenance and the challenge of safely lifting large vehicles on a two-post lift. *J. Saf. Sustain.* **2026**, *3*, 37–49. [\[CrossRef\]](#)
66. European Environment Agency (EEA). *Air Quality in Europe 2022*; EEA: Copenhagen, Denmark, 2022.
67. World Health Organization (WHO). *Guidelines on Mental Health at Work*; WHO: Geneva, Switzerland, 2022.
68. European Agency for Safety and Health at Work (EU-OSHA). *Guidance for Workplaces on Supporting Individuals Experiencing Mental Health Problems*; EU-OSHA: Bilbao, Spain, 2024.
69. Costa, E. Industry 5.0 and SDG 9: A Symbiotic Dance Towards Sustainable Transformation. *Sustain. Earth Rev.* **2024**, *7*, 4. [\[CrossRef\]](#)
70. Singh, R.; Akram, S.V.; Gehlot, A.; Buddhi, D.; Priyadarshi, N.; Twala, B. Energy System 4.0: Digitalization of the Energy Sector with Inclination Towards Sustainability. *Sensors* **2022**, *22*, 6619. [\[CrossRef\]](#) [\[PubMed\]](#)
71. Díaz-Martínez, M.A.; Román-Salinas, R.V.; Fuentes-Rubio, Y.A.; Morales-Rodríguez, M.A.; Cervantes-Zubirias, G.; Rivera-García, G.E. IoT-Driven Pathways Toward Corporate Sustainability in Industry 4.0 Ecosystems: A Systematic Review. *Sustainability* **2026**, *18*, 1052. [\[CrossRef\]](#)
72. United Nations Environment Programme (UNEP). Available online: <https://www.unep.org> (accessed on 7 July 2026).
73. United Nations Industrial Development Organization (UNIDO). Available online: <https://www.unido.org> (accessed on 7 July 2026).

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.