

Article

Smart Industrial Robots, AI-Driven Autonomous Vehicles, and Drones in Warehouse Logistics

Alaa Eddine El Moussaoui ^{1,*} , Taoufiq El Moussaoui ^{2,*} , Najat Toufah ³  and Marc Ardizio ⁴

¹ EMIO, LIREEM Laboratory, Higher School of Technology, Nador, Mohammed First University, Oujda 60000, Morocco

² Polydisciplinary Faculty of Sidi Bennour, Chouaib Doukkali University, El Jadida 24000, Morocco

³ BIGOFE Laboratory, Faculty of Law, Economics and Social Sciences, Hassan II University, Casablanca 20250, Morocco; najat.toufah@univh2c.ma

⁴ CEREFIGE Research Center, IAE Metz School of Management, University of Lorraine, F-54000 Nancy, France; marc.ardizio@univ-lorraine.fr

* Correspondence: a.elmoussaoui@ump.ac.ma (A.E.E.M.); elmoussaoui.taoufiq@ucd.ac.ma (T.E.M.)

Abstract

Background: The rapid digitalization of warehouse logistics has accelerated the adoption of smart industrial robots, AI-driven autonomous vehicles, and drones to enhance operational coordination and supply chain performance. However, empirical evidence regarding the combined operational implications of these autonomous technologies within emerging-market logistics environments remains limited. This study examines the relationships between autonomous warehouse technologies and perceived warehouse operational performance in Morocco. **Methods:** A quantitative cross-sectional research design was employed using survey data collected from 1753 logistics professionals operating in warehouses connected to the SoftLogistics platform. Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM) were conducted to evaluate the proposed relationships and interaction effects among the study constructs. **Results:** The findings indicate that smart industrial robots, AI-driven autonomous vehicles, and drones are positively associated with perceived warehouse operational efficiency, operational accuracy, and warehouse resilience. The results further suggest that technological interoperability, workforce readiness, organizational adaptation, and AI-enabled coordination mechanisms may enhance the operational contribution of autonomous warehouse systems. **Conclusions:** Autonomous logistics technologies are associated with smart warehouse transformation and improved operational performance within emerging logistics environments. The findings also highlight the importance of organizational and socio-technical readiness for the implementation of autonomous warehouse technologies.

Keywords: industrial robots; smart logistics; artificial intelligence; autonomous warehouse systems; drones; warehouse operational performance



Academic Editor: Rameshwar Dubey

Received: 4 May 2026

Revised: 23 June 2026

Accepted: 23 June 2026

Published: 30 June 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

In recent years, the logistics industry has undergone significant transformations driven by rapid advances in automation, industrial robotics, and artificial intelligence (AI). Modern supply chains are increasingly complex due to rising customer expectations, stricter delivery schedules, and growing operational costs [1]. To maintain competitiveness, companies are adopting innovative technologies capable of supporting operational efficiency, minimizing human error, and improving real-time responsiveness within warehouse and distribution

operations. Industrial robots, autonomous vehicles, and drones have emerged as important technologies within modern logistics systems, not only automating repetitive tasks but also supporting intelligent coordination and data-driven decision-making across supply chain activities [2,3].

Within warehouses and distribution centers, industrial robots are commonly used for picking, sorting, packing, palletizing, and inventory handling operations with high levels of precision. Autonomous vehicles, including Automated Guided Vehicles (AGVs) and self-driving forklifts, facilitate internal goods transportation and material flow coordination, while drones support aerial monitoring and inventory inspection activities [4,5]. The integration of AI with these technologies further enables predictive scheduling, adaptive workflow coordination, anomaly detection, and real-time operational monitoring. This technological evolution reflects the broader transition toward Industry 4.0 and smart warehouse ecosystems characterized by interconnected, semi-autonomous, and data-driven logistics operations [6].

Despite the growing interest in autonomous logistics technologies, their implementation remains associated with several operational and organizational challenges. Previous studies indicate that infrastructure readiness, workforce adaptation, cybersecurity risks, implementation costs, and technological integration complexity may influence the successful deployment of autonomous warehouse systems, particularly within emerging logistics markets [7,8]. Consequently, the operational implications of autonomous technologies depend not only on technological capabilities but also on organizational readiness, workforce competencies, managerial support, and operational context.

The Moroccan logistics sector is experiencing a parallel evolution driven by the expansion of e-commerce activities, multinational operations, and increasing warehouse management complexity [9,10]. The SoftLogistics platform, hosting multiple warehouses operated by multinational firms, provides an illustrative setting for examining the deployment of smart industrial robots, autonomous vehicles, and drones within warehouse operations. The platform integrates warehouse coordination, inventory management, and logistics monitoring activities across multiple Moroccan warehouse facilities, providing an appropriate empirical context for investigating autonomous warehouse technologies within an emerging-market environment. This environment illustrates how technological innovation interacts with operational practices, workforce activities, and local infrastructure conditions [11]. Despite the increasing adoption of smart logistics technologies, empirical research examining their operational implications within the Moroccan logistics sector remains limited.

Although research on warehouse automation, AI-enabled logistics systems, and drone-supported operations has expanded considerably in recent years, several important gaps remain within the existing literature. First, much of the current literature focuses primarily on highly industrialized economies, while empirical evidence from emerging-market warehouse environments remains relatively limited. Second, previous studies often examine industrial robots, AI-enabled systems, or drones separately, despite the increasing operational integration of these technologies within smart warehouse ecosystems. Third, existing research provides limited empirical evidence regarding how autonomous logistics technologies are associated with perceived warehouse operational efficiency, operational accuracy, and warehouse resilience within contexts characterized by infrastructural and organizational constraints. In addition, implementation challenges related to workforce adaptation and operational readiness remain insufficiently explored in empirical smart warehouse studies.

Few studies have simultaneously examined the combined relationships among smart industrial robots, AI-enabled warehouse systems, and drones within warehouse operations

in an emerging-market logistics context using Structural Equation Modeling (SEM). Furthermore, previous studies often emphasize the technological potential of autonomous systems while giving comparatively less attention to implementation constraints and operational coordination challenges associated with smart warehouse transformation.

To address these gaps, this study employed a structured survey targeting 1753 logistics professionals, encompassing both managerial and operational perspectives across the SoftLogistics platform. Rather than measuring objective operational indicators directly, the study evaluates respondents' perceptions regarding the extent to which smart industrial robots, AI-enabled systems, and drones are associated with warehouse operational efficiency, operational accuracy, and warehouse resilience. The collected data provide insights into the adoption process, operational implications, and implementation challenges associated with autonomous warehouse technologies. SEM was employed to examine the relationships among the study constructs.

The study is theoretically grounded in the Technology–Organization–Environment (TOE) framework, Socio-Technical Systems Theory, and the Resource-Based View (RBV). These perspectives collectively suggest that the operational implications of autonomous logistics technologies depend on the interaction between technological capabilities, organizational readiness, workforce adaptation, and operational conditions.

The contributions of this research are fourfold. First, it provides empirical evidence regarding the adoption and perceived operational implications of autonomous warehouse technologies within an emerging-market logistics environment. Second, the study extends previous smart warehouse research by examining the combined relationships among industrial robots, AI-enabled systems, and drones rather than analyzing these technologies independently. Third, the study enriches the smart logistics literature by providing a multidimensional analytical perspective that combines technological, organizational, and operational factors within autonomous warehouse environments. Fourth, the findings offer practical insights for logistics managers and policymakers regarding workforce readiness, technological integration, infrastructure requirements, and implementation considerations associated with smart warehouse transformation initiatives.

Guided by these objectives, the primary research question is as follows:

RQ: How are smart industrial robots, AI-enabled warehouse systems, and drones associated with perceived warehouse operational efficiency, operational accuracy, and warehouse resilience within the Moroccan logistics context? The study examines whether interactions among autonomous warehouse technologies contribute to stronger perceived operational outcomes within warehouse environments. It evaluates the role of AI-powered autonomous technologies in relation to perceived warehouse operational performance and offers evidence-based recommendations regarding the implementation of intelligent systems within warehouse environments.

The remainder of the paper is structured as follows. Section 2 reviews the literature on smart industrial robots, AI-enabled warehouse systems, drones, and warehouse operational performance. Section 3 presents the theoretical framework and research hypotheses. Section 4 outlines the research methodology, including survey design, sampling procedure, questionnaire development, and analytical techniques. Section 5 presents the empirical findings and SEM results. Section 6 discusses the theoretical, practical, and policy implications of the findings, together with the study limitations and future research directions. Finally, Section 7 concludes the paper by summarizing the main findings and highlighting the study's contributions to the understanding of intelligent autonomous logistics systems in Morocco.

2. Literature Review

2.1. Smart Warehouse Technologies and Autonomous Logistics Systems

The adoption of industrial robots, autonomous vehicles, drones, and artificial intelligence (AI) has become a central component of modern warehouse logistics, particularly in operational environments requiring high efficiency, precision, and responsiveness [12]. Originally developed for manufacturing activities, industrial robots are increasingly deployed in warehouse operations to automate repetitive and labor-intensive tasks such as picking, packing, sorting, palletizing, and inventory handling [13,14]. These systems contribute to operational consistency, scalability, and workflow continuity across complex supply chain environments. When integrated with AI technologies, industrial robots acquire adaptive operational capabilities that support dynamic task allocation, predictive identification of bottlenecks, and real-time workflow adjustments [15]. Such capabilities may support warehouse coordination and responsiveness during periods of fluctuating demand or operational disruption [16,17].

Autonomous logistics vehicles, including Automated Guided Vehicles (AGVs) and autonomous forklifts, complement robotic systems by facilitating intra-warehouse transportation and reducing operational bottlenecks. Equipped with AI-based navigation and path-planning algorithms, these vehicles can dynamically adjust routes, avoid obstacles, and operate alongside human workers within warehouse environments, thereby enhancing operational continuity and material flow coordination [18]. According to [19], the integration of autonomous vehicles with industrial robots contributes to more coordinated and automated warehouse workflows and is often associated with greater operational continuity and improved workflow synchronization. Nevertheless, several previous studies have mainly examined autonomous logistics technologies within controlled or simulated environments, raising concerns regarding scalability, operational reliability, and coordination efficiency in real warehouse settings characterized by complex layouts and continuous human interaction [20].

Drones introduce additional operational capabilities within warehouse logistics, particularly for inventory monitoring, aerial inspection, rapid stock-taking, and operational surveillance activities. By enabling rapid assessment of large warehouse areas, drones provide real-time visibility that can support inventory management and warehouse coordination processes [21,22]. When integrated with AI technologies, drones can autonomously navigate operational environments, avoid obstacles, and coordinate activities with ground-based autonomous systems such as robots and AGVs [23]. Previous studies suggest that multi-agent coordination among drones, robots, and autonomous vehicles may contribute to inventory accuracy, operational continuity, and adaptive warehouse responsiveness [24,25]. This technological evolution reflects the broader transition toward Industry 4.0 and smart warehouse ecosystems characterized by interconnected, semi-autonomous, and data-driven logistics operations [26].

Artificial intelligence functions as a critical coordination mechanism connecting industrial robots, autonomous vehicles, and drones within intelligent logistics ecosystems [27,28]. AI techniques such as machine learning, deep learning, and reinforcement learning support predictive scheduling, anomaly detection, adaptive routing, and autonomous operational optimization through continuous analysis of real-time operational data [29]. These capabilities allow autonomous systems to adjust operational processes in response to demand variability, equipment constraints, and operational disruptions, thereby supporting operational efficiency, operational accuracy, and warehouse resilience [30]. The concept of smart logistics emphasizes the convergence of AI-enabled systems, industrial robots, autonomous vehicles, and drones to create interconnected, adaptive, and data-driven supply chain operations [31,32]. Smart warehouse environments rely on predictive analytics, real-time

monitoring, and coordinated decision-making processes to support operational continuity, responsiveness, and resilient warehouse management [33].

2.2. Operational and Organizational Challenges in Smart Logistics

Despite the increasing adoption of autonomous logistics technologies, several implementation challenges continue to affect operational deployment. Existing studies indicate that infrastructure readiness, technological interoperability, cybersecurity risks, implementation costs, workforce adaptation, and organizational resistance to change may influence the successful integration of autonomous systems within warehouse environments [2,14]. Organizational factors such as change management, cross-functional coordination, and organizational culture also influence the implementation and integration of smart logistics technologies [34].

From a theoretical perspective, the adoption and operational integration of autonomous warehouse technologies can be interpreted through the Technology–Organization–Environment (TOE) framework, the Resource-Based View (RBV), and Socio-Technical Systems Theory. The TOE framework emphasizes that technology adoption depends on the interaction between technological readiness, organizational capabilities, and environmental conditions [35]. Similarly, the RBV suggests that technological resources may contribute to operational advantages when effectively integrated with organizational competencies and logistics capabilities [36]. Socio-Technical Systems Theory further highlights that the operational effectiveness of autonomous systems depends on the alignment between technological infrastructure, operational workflows, and human participation within warehouse environments [37].

Consequently, workforce adaptation, employee training, safety considerations, and human–machine coordination become central elements influencing the successful implementation of industrial robots, autonomous vehicles, drones, and AI-enabled logistics systems. These human and organizational dimensions remain particularly important in emerging logistics markets where operational digitalization and automation capabilities are still evolving.

Many previous studies have been conducted within controlled or simulated environments, raising questions regarding scalability, operational reliability, and coordination efficiency in real-world warehouse operations characterized by complex layouts and continuous human interaction [38]. Practical deployment challenges associated with drones and AI-enabled systems also remain insufficiently explored within the literature. Regulatory compliance, navigation reliability, battery limitations, worker safety concerns, payload constraints, radio-frequency interference, and integration with warehouse management systems continue to influence operational implementation [21,22].

Artificial intelligence technologies also introduce additional operational complexities associated with data integration, algorithmic reliability, real-time coordination, and system interoperability [27,29]. Although AI-enabled logistics systems can support predictive scheduling, anomaly detection, and operational optimization, their effectiveness depends on infrastructure capabilities, data quality, organizational coordination, and workforce readiness. Several studies also emphasize that implementation failures may result from managerial optimism, insufficient employee acceptance, inadequate technological integration, or overreliance on automation systems without sufficient operational flexibility.

In addition, existing literature frequently emphasizes technological performance while giving comparatively less attention to operational risks, implementation constraints, and human-centered challenges associated with smart warehouse technologies. As a result, autonomous logistics systems should be evaluated not only from technological perspectives

but also from organizational, operational, and socio-technical perspectives capable of capturing the complexity of real warehouse environments.

Furthermore, much of the existing literature evaluates AI-enabled logistics systems within theoretical or simulated settings while providing limited empirical evidence from operational warehouse environments, particularly within emerging logistics markets such as Morocco. Empirical research examining how integrated autonomous technologies influence perceived warehouse operational performance dimensions, including efficiency, accuracy, and resilience, remains comparatively limited within operational logistics environments.

2.3. Research Gaps and Conceptual Positioning

Although research on warehouse automation and autonomous logistics technologies has expanded considerably, several important gaps remain within the existing literature. First, many previous studies examine industrial robots, autonomous vehicles, drones, or AI systems independently, despite the increasing operational integration of these technologies within smart warehouse ecosystems. Empirical evidence regarding the combined relationships among these autonomous technologies and perceived warehouse operational performance remains limited.

Second, the majority of existing studies focus primarily on highly industrialized economies and technologically mature logistics environments. Empirical evidence from emerging-market warehouse operations, particularly within North African logistics contexts, remains comparatively scarce. Consequently, the influence of contextual factors such as workforce readiness, organizational capabilities, infrastructure constraints, and operational coordination challenges remains insufficiently explored.

Third, several studies emphasize technological performance while giving comparatively less attention to implementation complexity, workforce adaptation, safety considerations, and human–technology interaction. Human–system interactions, including workforce adaptation, training requirements, and operational safety, are often underexplored despite their importance in achieving reliable and sustainable warehouse operations. Similarly, interaction effects among autonomous technologies, including the combined coordination between industrial robots, AI-enabled systems, autonomous vehicles, and drones, remain insufficiently examined in operational warehouse contexts.

Fourth, standardized performance measurement frameworks for next-generation autonomous logistics systems remain limited, thereby constraining comparative operational evaluation across studies. Existing studies also frequently rely on theoretical simulations or technical experiments while providing comparatively limited empirical evidence from operational warehouse environments characterized by organizational complexity and real-time operational constraints.

Finally, the literature provides limited empirical understanding regarding how autonomous warehouse technologies are associated with different dimensions of warehouse operational performance, particularly operational efficiency, operational accuracy, and warehouse resilience. This limitation is particularly important because warehouse performance is multidimensional and influenced by technological, organizational, operational, and human-centered factors simultaneously.

Addressing these gaps constitutes the primary motivation of the present study. By examining smart industrial robots, AI-enabled systems, autonomous logistics vehicles, and drones within the SoftLogistics platform, this research provides empirical insights into perceived operational implications, implementation challenges, and organizational dimensions associated with autonomous warehouse technologies in Morocco. Unlike previous studies that frequently examine isolated technologies or simulated environments, the present study adopts an integrated analytical perspective capable of examining the

combined relationships among autonomous logistics technologies and perceived warehouse operational performance within a real operational setting. These insights provide the foundation for the following section, which presents the theoretical framework and research hypotheses.

3. Theoretical Framework and Research Hypotheses

3.1. Theoretical Framework

Modern warehouse logistics increasingly depends on the integration of autonomous technologies capable of supporting operational coordination, workflow continuity, and adaptive decision-making within complex logistics environments. In contemporary warehouse systems, operational performance is no longer evaluated exclusively through productivity indicators but through multiple operational dimensions reflecting efficiency, accuracy, and resilience [39,40]. Operational efficiency refers to the ability of warehouse systems to optimize throughput, reduce operational delays, minimize cycle time, and improve resource utilization. Operational accuracy reflects the precision and reliability of warehouse activities such as picking, sorting, packing, inventory handling, and material tracking. Warehouse resilience represents the capacity of warehouse systems to maintain operational continuity, respond to disruptions, and adapt to changing operational conditions within dynamic supply chain environments [41,42].

The present study conceptualizes warehouse operational performance as a multidimensional construct composed of operational efficiency, operational accuracy, and warehouse resilience. This perspective responds to recent smart logistics literature emphasizing that autonomous warehouse systems should be evaluated through integrated operational dimensions rather than isolated productivity indicators alone.

The proposed framework focuses on three major autonomous logistics technologies: smart industrial robots, AI-driven autonomous vehicles, and drones. Smart industrial robots automate repetitive warehouse activities, autonomous logistics vehicles facilitate intelligent material transportation, and drones support aerial monitoring and real-time operational visibility. Rather than examining these technologies independently, the present study adopts an integrated perspective in which autonomous systems interact through AI-enabled coordination mechanisms within warehouse operations.

The theoretical foundation of the framework is informed by the Technology–Organization–Environment (TOE) framework, the Resource-Based View (RBV), and Socio-Technical Systems Theory. The TOE framework suggests that the operational adoption of autonomous technologies depends on technological readiness, organizational capabilities, and environmental conditions. The RBV further proposes that autonomous technologies may contribute to operational advantages when effectively integrated with logistics capabilities and organizational processes. In parallel, Socio-Technical Systems Theory emphasizes that operational outcomes depend on the alignment between technological systems, operational workflows, and human participation within warehouse environments. These perspectives collectively support the assumption that autonomous logistics technologies influence warehouse operational performance through both technological and organizational coordination mechanisms.

This integrated theoretical perspective is particularly relevant within emerging logistics markets such as Morocco, where warehouse digitalization, workforce readiness, and infrastructure capabilities continue to evolve simultaneously. Consequently, the operational implications of autonomous logistics technologies should be evaluated not only from technological perspectives but also from organizational and operational perspectives reflecting the complexity of real warehouse environments.

3.2. Direct Effect Hypotheses

3.2.1. Smart Industrial Robots and Operational Efficiency

Smart industrial robots (SIR) constitute a central component of warehouse automation because they support repetitive and labor-intensive activities such as order picking, palletizing, sorting, and packing operations. The integration of robotic systems within warehouse operations may reduce operational variability, improve task consistency, accelerate workflow execution, and reduce dependence on manual labor [43,44]. In addition, AI-enabled robotic systems may dynamically adjust operational tasks and coordinate workflows in response to changing operational conditions [45].

Previous studies indicate that robotic automation is associated with workflow continuity, operational scalability, and perceptions of greater warehouse operational efficiency [46,47]. Within emerging logistics environments characterized by increasing operational complexity and growing warehouse demand, smart industrial robots may support resource optimization and operational standardization while reducing workflow interruptions associated with manual handling activities. Based on these theoretical and operational considerations, the following hypothesis is proposed:

H1. *Adoption of smart industrial robots is positively associated with warehouse operational efficiency.*

3.2.2. AI-Driven Autonomous Vehicles and Operational Accuracy

AI-driven autonomous vehicles, including Automated Guided Vehicles (AGVs) and autonomous forklifts, support intelligent transportation and material handling activities within warehouse environments [18]. These systems rely on AI-enabled navigation, path-planning algorithms, and obstacle-avoidance mechanisms that allow for autonomous movement within dynamic operational settings. By reducing transport inconsistencies, coordination delays, and manual handling errors, autonomous logistics vehicles may contribute to more reliable and accurate warehouse operations [48].

The integration of autonomous vehicles with robotic systems may also support end-to-end operational coordination in which materials move efficiently between storage, picking, production, and dispatch areas with reduced human intervention. According to [49], such integration may support inventory tracking, reduce the likelihood of product misplacement, and strengthen operational reliability. AI-enabled autonomous vehicles may further contribute to operational visibility and process synchronization by supporting real-time coordination across warehouse activities characterized by continuous inventory movement and operational complexity. Consequently, the following hypothesis is formulated:

H2. *Adoption of AI-driven autonomous vehicles is positively associated with warehouse operational accuracy.*

3.2.3. Drones and Warehouse Resilience

Drones represent an additional dimension of autonomous warehouse systems by supporting aerial monitoring, stock verification, and real-time operational visibility. Equipped with AI capabilities, drones can autonomously navigate warehouse facilities, identify inventory discrepancies, and transmit operational information to warehouse personnel in real time [50]. These capabilities may support proactive operational responses, inventory coordination, and continuity management during operational disruptions.

Unlike ground-based automation systems, drones provide flexible and scalable operational monitoring capabilities that may be particularly valuable in large warehouses and operationally complex facilities [51]. Their contribution extends beyond monitoring because AI-enabled drones may also support predictive interventions, adaptive scheduling, and dynamic operational coordination. Previous studies further suggest that drones may

strengthen warehouse resilience by supporting disruption detection, inventory visibility, and adaptive response capabilities during periods of operational uncertainty. Based on these considerations, the following hypothesis is proposed:

H3. *Integration of drones with AI-enabled systems is positively associated with warehouse operational resilience.*

3.3. Interaction Effects Hypotheses

Autonomous logistics technologies rarely operate independently within modern warehouse systems. Instead, warehouse operational performance increasingly depends on coordinated interactions among robots, autonomous logistics vehicles, drones, and AI-enabled operational systems [7,52]. AI functions as a coordination layer supporting predictive scheduling, adaptive task allocation, anomaly detection, and real-time synchronization among autonomous technologies operating within warehouse environments.

Recent smart logistics literature suggests that the operational value of autonomous systems may emerge not only from individual technological capabilities but also from synergistic coordination among interconnected autonomous technologies. This integrated perspective is particularly relevant within complex warehouse environments where operational continuity depends on synchronized material handling, inventory visibility, and adaptive operational coordination.

The first interaction hypothesis examines the combined relationship between smart industrial robots and AI-driven autonomous vehicles with operational efficiency. The coordinated interaction between robotic systems and autonomous transport technologies may reduce idle time, strengthen workflow synchronization, and improve material flow continuity beyond the contribution of either technology independently.

H4. *The combined adoption of smart industrial robots and AI-driven autonomous vehicles is positively associated with warehouse operational efficiency beyond the individual effects of each technology.*

The second interaction hypothesis examines the combined relationship between AI-driven autonomous vehicles and drones with warehouse resilience. Multi-agent coordination between aerial monitoring systems and autonomous transport systems may support adaptive operational responses, disruption management, and real-time coordination capabilities within warehouse operations.

H5. *The combined adoption of AI-driven autonomous vehicles and drones is positively associated with warehouse operational resilience beyond the individual effects of each technology.*

3.4. Conceptual Model

The conceptual model derived from these hypotheses positions smart industrial robots, AI-driven autonomous vehicles, and drones as independent variables associated with operational efficiency, operational accuracy, and warehouse resilience as multidimensional operational performance outcomes. Interaction effects are explicitly incorporated to capture the coordinated relationships among autonomous technologies operating within smart warehouse systems.

Unlike previous studies that frequently examine isolated warehouse technologies or simulated operational settings, the proposed framework integrates direct effects, interaction effects, and multidimensional operational performance outcomes within a unified analytical model grounded in real warehouse operations.

The framework also recognizes the potential influence of contextual operational factors such as warehouse size, workforce experience, and managerial involvement, which may affect the implementation and perceived operational implications of autonomous logistics technologies. These contextual dimensions are particularly relevant within emerging logistics environments characterized by heterogeneous operational capabilities and varying levels of technological readiness.

The conceptual framework presented in Figure 1 therefore provides the analytical foundation for the Structural Equation Modeling (SEM) analysis conducted in this study.

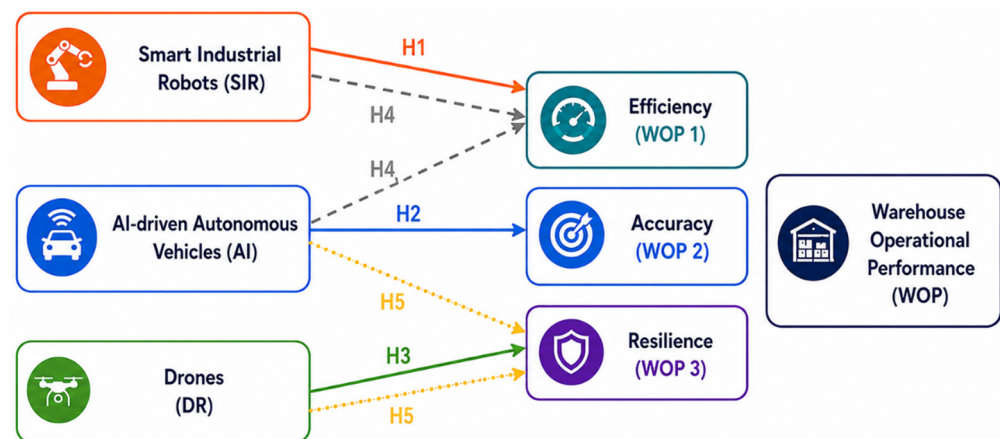


Figure 1. Conceptual Framework.

4. Research Methodology

4.1. Research Design

This study adopts a quantitative cross-sectional research design to examine the relationships between smart industrial robots, AI-driven autonomous vehicles, drones, and perceived warehouse operational performance within Moroccan warehouse environments. The quantitative approach was selected because it enables the systematic measurement of relationships among multiple latent constructs and supports the application of Structural Equation Modeling (SEM) for simultaneous assessment of measurement and structural relationships.

Unlike experimental or simulation-based studies frequently found in smart logistics research, the present study investigates autonomous logistics technologies within operational warehouse environments characterized by real organizational constraints, workforce interactions, and operational variability. This operational perspective is particularly relevant within emerging logistics environments where technology adoption remains heterogeneous across warehouse facilities.

The study was conducted within the SoftLogistics platform, a digital logistics ecosystem connecting multiple warehouses operated by multinational and local logistics companies in Morocco. The platform facilitates warehouse coordination, inventory management, transportation scheduling, and operational monitoring across participating warehouse facilities. The selected warehouses vary in operational size, automation maturity, and workforce structure, thereby providing a suitable context for examining autonomous logistics technologies under diverse operational conditions.

The study follows a cross-sectional design because each respondent completed the questionnaire once during the data collection period. Although the survey was administered during both peak and routine operational periods, the same respondents were not repeatedly measured over time. Consequently, the study does not constitute a longitudinal design.

The research design was developed in alignment with the conceptual framework presented in Section 3, ensuring that all constructs were operationalized consistently with the proposed theoretical relationships. The design further incorporates procedural mechanisms intended to strengthen measurement reliability, contextual relevance, and response quality, including questionnaire pretesting, respondent screening, and standardized survey administration procedures.

4.2. Sampling Procedure and Data Collection

The target population consisted of logistics professionals directly involved in warehouse operations across the SoftLogistics platform. Respondents included warehouse managers, operations supervisors, logistics coordinators, inventory specialists, process engineers, and operational employees working within participating warehouse facilities. This diversity of operational roles allowed the study to capture both managerial and operational perspectives regarding autonomous technology adoption and perceived warehouse performance.

A purposive sampling strategy was employed because the study specifically targeted respondents familiar with autonomous logistics technologies, including industrial robots, AI-enabled autonomous vehicles, and drones. Purposive sampling was considered appropriate because the research required respondents with operational exposure to warehouse automation systems rather than general logistics personnel without technological familiarity.

Data were collected from 18 warehouses affiliated with the SoftLogistics platform between 17 November 2025, and 19 January 2026. The participating facilities consisted of 5 small warehouses, 8 medium-sized warehouses, and 5 large warehouses operated by both multinational and local logistics companies. These warehouses were involved in warehousing, inventory management, order fulfillment, distribution activities, and e-commerce logistics operations, thereby providing a diverse operational context for examining autonomous logistics technologies. Survey invitations were distributed electronically through warehouse managers and operational coordinators responsible for participating warehouse facilities. A total of 2041 questionnaires were distributed, of which 1802 responses were received. Following data screening procedures, 49 questionnaires were excluded due to excessive missing values, incomplete responses, duplicate submissions, or response inconsistencies identified during the validation process. The remaining 1753 questionnaires were retained for analysis because they satisfied the predefined data quality criteria. Screening procedures included completeness verification, consistency checks, and the identification of anomalous response patterns. This resulted in a valid response rate of 85.9%.

Several respondents originated from the same warehouse facilities. However, because the study focused on individual perceptions regarding autonomous technology adoption and perceived operational performance, the unit of analysis remained the individual respondent rather than the warehouse itself.

The relatively large sample size is appropriate for Structural Equation Modeling and exceeds commonly recommended thresholds for SEM analysis involving latent constructs and interaction effects. In addition, post hoc statistical power analysis confirmed that the sample size was adequate for detecting medium and interaction effects within the proposed SEM model.

Demographic and professional information was also collected, including age, educational background, professional experience, warehouse role, and warehouse location. These variables were subsequently incorporated into moderation analysis to explore whether contextual and workforce characteristics influenced the relationships between autonomous technologies and perceived operational performance.

4.3. Questionnaire Design and Measurement Scales

The questionnaire was designed to capture all constructs included in the conceptual framework, including Smart Industrial Robots (SIR), AI-driven Autonomous Vehicles (AI), Drones (DR), and Warehouse Operational Performance (WOP). The questionnaire additionally included demographic and professional variables associated with moderation analysis.

The measurement items were adapted from previously validated scales used in logistics, warehouse automation, smart manufacturing, and supply chain management research. Because these scales were adapted to the Moroccan warehouse context, additional contextual modifications were introduced to ensure operational relevance and conceptual clarity.

The questionnaire was divided into four sections (Appendix A). The first section collected demographic and professional information. The second section evaluated the adoption and operational use of autonomous technologies. The third section measured perceived warehouse operational performance across three dimensions: operational efficiency, operational accuracy, and warehouse resilience. The fourth section explored contextual operational factors related to workforce readiness, organizational support, training adequacy, and infrastructure conditions.

Although Warehouse Operational Performance (WOP) was initially conceptualized as an overarching performance construct, the SEM analysis operationalized its three dimensions—operational efficiency, operational accuracy, and warehouse resilience—as distinct but related outcome dimensions. This approach was adopted to provide a more detailed assessment of how autonomous logistics technologies are associated with different aspects of perceived warehouse operational performance. Consequently, the structural model examined these dimensions separately while maintaining their conceptual integration within the broader warehouse performance framework.

All constructs were operationalized as reflective latent variables measured using five-point Likert scales ranging from “Strongly Disagree” to “Strongly Agree.” Reflective specification was considered appropriate because the observed measurement items were assumed to reflect underlying latent operational perceptions associated with autonomous technology adoption and perceived warehouse performance.

The questionnaire was pretested with 50 logistics professionals working in warehouse operations to evaluate item clarity, contextual relevance, and measurement consistency. Pilot participants included both managerial and operational employees to ensure that survey items remained understandable across heterogeneous warehouse roles. Minor wording adjustments were introduced following pilot feedback to improve contextual clarity and reduce ambiguity.

Table 1 presents the constructs, measurement items, and literature sources used in this study.

Table 1. Constructs and Measurement Items.

Construct	Item Code	Measurement Item	Scale/Response	References
Smart Industrial Robots (SIR)	SIR1	- The warehouse extensively uses robots for repetitive tasks such as picking, sorting, and packing.	5-point Likert (Strongly Disagree—Strongly Agree)	[14,53,54]
	SIR2	- Robots in the warehouse are capable of dynamically reallocating tasks in response to workflow changes.		
	SIR3	- Robots contribute to operational efficiency by reducing human errors in daily warehouse operations.		

Table 1. *Cont.*

Construct	Item Code	Measurement Item	Scale/Response	References
AI-driven Autonomous Vehicles (AI)	AI1	- AI-driven autonomous vehicles improve operational accuracy through predictive scheduling of warehouse transport tasks.	5-point Likert (Strongly Disagree—Strongly Agree)	[2,31,55]
	AI2	- AI-enabled autonomous vehicles help detect operational anomalies and adjust movements to prevent errors in warehouse operations.		
	AI3	- AI-powered autonomous vehicles facilitate real-time resource allocation by dynamically coordinating warehouse transport activities.		
Drones (DR)	DR1	- Drones are used for inventory monitoring and rapid stock-taking.	5-point Likert (Strongly Disagree—Strongly Agree)	[56,57]
	DR2	- Drones coordinate effectively with ground-based robots and AI-driven systems.		
	DR3	- Drones enhance warehouse operational resilience by providing real-time aerial oversight.		
Warehouse Operational Performance (WOP)	WOP1	- Warehouse operations achieve high efficiency in task completion, throughput, and cost reduction.	5-point Likert (Strongly Disagree—Strongly Agree)	[38,42,58,59]
	WOP2	- Warehouse operations maintain high accuracy in order fulfillment and inventory management.		
	WOP3	- Warehouse operations are resilient, maintaining continuity and adaptability during disruptions.		

4.4. Exploratory Factor Analysis and Measurement Validation

Because the measurement scales were adapted from multiple prior studies and applied within a new operational and cultural context, Exploratory Factor Analysis (EFA) was conducted prior to Confirmatory Factor Analysis (CFA). The purpose of EFA was to verify whether the observed variables naturally grouped into the proposed latent dimensions within the Moroccan warehouse context.

EFA was conducted using Principal Axis Factoring with Varimax rotation. The Kaiser–Meyer–Olkin (KMO) measure exceeded the recommended threshold of 0.70, while Bartlett’s Test of Sphericity was statistically significant, confirming the suitability of the dataset for factor analysis. The extracted factor structure supported the multidimensional structure proposed in the conceptual framework, with all retained items loading strongly on their intended constructs.

Following EFA, Confirmatory Factor Analysis (CFA) was conducted to validate the measurement model and assess construct reliability and validity. CFA was performed prior to structural model estimation to confirm the adequacy of the latent constructs and the relationships between observed variables and theoretical dimensions.

Reliability was assessed using Cronbach’s alpha and Composite Reliability (CR), with all constructs exceeding the recommended threshold of 0.70. Convergent validity was evaluated using Average Variance Extracted (AVE), with all AVE values exceeding the recommended threshold of 0.50. Discriminant validity was assessed using both the

Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT), confirming that all constructs remained empirically distinct.

Table 2 summarizes the SEM evaluation criteria and recommended threshold values for factor loadings, Cronbach’s alpha, Composite Reliability, AVE, CFI, TLI, RMSEA, and χ^2/df .

Table 2. SEM Evaluation Criteria and Recommended Threshold Values.

Evaluation Criterion	Recommended Threshold	Interpretation
Factor Loading	≥ 0.70	Indicates strong item reliability
Cronbach’s Alpha	≥ 0.70	Confirms internal consistency reliability
Composite Reliability (CR)	≥ 0.70	Confirms construct reliability
Average Variance Extracted (AVE)	≥ 0.50	Confirms convergent validity
Heterotrait–Monotrait Ratio (HTMT)	< 0.85	Confirms discriminant validity
Comparative Fit Index (CFI)	≥ 0.90	Indicates acceptable model fit
Tucker–Lewis Index (TLI)	≥ 0.90	Indicates acceptable model fit
Root Mean Square Error of Approximation (RMSEA)	≤ 0.08	Indicates acceptable approximation error
Standardized Root Mean Square Residual (SRMR)	≤ 0.08	Indicates acceptable residual fit
Chi-square/Degrees of Freedom (χ^2/df)	< 3.00	Indicates acceptable structural fit
Variance Inflation Factor (VIF)	< 5.00	Indicates absence of multicollinearity

4.5. Structural Equation Modeling

Structural Equation Modeling (SEM) was employed to simultaneously evaluate the measurement and structural models proposed in the conceptual framework. SEM was selected because it enables the estimation of direct effects, interaction effects, and moderation relationships among multiple latent constructs within a unified analytical framework.

The analysis was conducted using AMOS 29 software with Maximum Likelihood Estimation (MLE). Prior to SEM estimation, missing data, normality, and multicollinearity diagnostics were assessed. Missing values were limited and handled through expectation-maximization procedures. Skewness and kurtosis values remained within acceptable thresholds, supporting the use of MLE. Multicollinearity diagnostics confirmed that Variance Inflation Factor (VIF) values remained below recommended thresholds.

The structural model evaluated the hypothesized relationships between autonomous technologies and perceived warehouse operational performance dimensions. Path coefficients, significance levels, confidence intervals, and effect sizes were estimated for all hypothesized relationships.

Bootstrapping procedures with 5000 resamples were employed to assess the significance and robustness of structural relationships, including interaction effects. Confidence intervals were additionally examined to confirm parameter stability.

Interaction effects were estimated to examine whether combinations of autonomous technologies produced synergistic operational effects beyond individual technological contributions. Interaction terms were constructed using mean-centered variables to minimize multicollinearity risks prior to interaction estimation.

Moderation analysis was additionally conducted to examine whether workforce experience, managerial role, and warehouse size influenced structural relationships within the proposed model. These moderators were selected because prior smart logistics litera-

ture suggests that organizational characteristics and workforce capabilities may influence autonomous technology adoption and operational implications.

Model adequacy was evaluated using multiple goodness-of-fit indices, including the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), and Chi-square to degrees of freedom ratio (χ^2/df).

4.6. Common Method Bias and Robustness Procedures

Because both independent and dependent variables were collected from the same respondents, common method bias represented a potential methodological concern. Several procedural and statistical remedies were therefore implemented.

Procedurally, respondents were informed that participation was anonymous and confidential in order to reduce social desirability bias and evaluation apprehension. Questionnaire items were additionally organized to reduce response-pattern bias and common scale effects.

Statistically, Harman’s single-factor test was conducted to examine whether a single latent factor accounted for the majority of variance within the dataset. The results indicated that no single factor dominated the variance structure, suggesting that common method bias was unlikely to represent a severe threat to the study findings. A full-collinearity VIF assessment was additionally performed, with all values remaining below critical thresholds.

Additional robustness checks were conducted through alternative model estimations and subgroup comparisons to confirm the stability and consistency of the SEM results across operational categories.

5. Data Analysis and Results

5.1. Respondent Profile and Descriptive Statistics

A clear understanding of the respondent profile is essential for contextualizing the empirical findings and interpreting how autonomous logistics technologies are associated with perceived warehouse operational performance. The study collected responses from 1753 logistics professionals working across the SoftLogistics platform, representing warehouse facilities characterized by varying levels of operational complexity, technological maturity, and automation readiness. As presented in Table 3, the sample incorporates both managerial and operational perspectives. Specifically, 42% of respondents occupied managerial or supervisory positions, whereas 58% worked in operational functions, including inventory management, order processing, warehouse coordination, and logistics execution activities. This distribution is particularly relevant because the implementation of autonomous warehouse technologies depends on alignment between strategic decision-making and operational execution. Managers generally provide perspectives regarding investment priorities, organizational readiness, and technological integration, whereas operational employees provide insights regarding daily interaction with industrial robots, AI-enabled systems, and drone technologies.

The demographic profile further demonstrates the diversity and contextual relevance of the sample. Approximately 32% of respondents were between 31 and 40 years old, 28% between 25 and 30 years old, 18% between 41 and 50 years old, while 11% were between 18 and 24 years old and another 11% were above 50 years old. Educational levels also indicate a relatively strong professional profile, with 55% holding bachelor’s degrees, 30% possessing high school diplomas, and 15% holding postgraduate qualifications.

Professional experience among respondents remained relatively balanced across different career stages. Approximately 29% of respondents reported less than five years of professional experience, 25% between five and ten years, 21% between eleven and fifteen

years, and 25% more than fifteen years. This distribution allows the study to capture perceptions from both younger employees potentially more receptive to technological innovation and experienced professionals possessing broader operational knowledge regarding warehouse processes and operational coordination mechanisms.

Table 3. Demographic Profile of Respondents.

Variable	Category	Frequency	Percentage
Gender	Male	1017	58%
	Female	736	42%
Age	18–24	193	11%
	25–30	491	28%
	31–40	561	32%
	41–50	316	18%
	Above 50	192	11%
Education Level	High School	526	30%
	Bachelor Degree	964	55%
	Master/PhD	263	15%
Professional Experience	Less than 5 years	509	29%
	5–10 years	438	25%
	10–15 years	367	21%
	More than 15 years	439	25%
Job Role	Manager/Supervisor	736	42%
	Operational Staff	1017	58%
Warehouse Size	Small	438	25%
	Medium	879	50%
	Large	436	25%
Technology Exposure	Experience with Industrial Robots	1227	70%
	Experience with AI Systems	964	55%
	Experience with Drones	701	40%

From an operational perspective, respondents were distributed across warehouses of different sizes, thereby allowing the study to capture heterogeneity in technological adoption and operational complexity. Medium-sized warehouses represented the largest proportion of the sample (50%), while small and large warehouses each accounted for approximately 25% of respondents. In addition, respondents reported varying levels of technological exposure. Approximately 70% indicated operational familiarity with industrial robots, 55% with AI-enabled warehouse systems, and 40% with drone technologies.

The questionnaire was administered electronically through standardized survey administration procedures using five-point Likert scales ranging from “Strongly Disagree” to “Strongly Agree.” Prior to analysis, respondent screening and data screening procedures were conducted in order to eliminate incomplete and inconsistent questionnaires and strengthen data quality and response reliability.

The descriptive statistics of the principal constructs summarized in Table 4 indicate generally positive perceptions regarding autonomous warehouse technologies. Smart Industrial Robots (SIR) reported a mean score of 4.15 (SD = 0.62), AI-driven Autonomous Vehicles (AI) 4.08 (SD = 0.65), Drones (DR) 3.95 (SD = 0.68), and Warehouse Operational Performance (WOP) 4.12 (SD = 0.60). These values indicate that respondents generally perceived autonomous technologies as positively associated with warehouse operational activities. Nevertheless, the variability observed across responses also suggests differences

in operational maturity, technological readiness, infrastructure capabilities, workforce adaptation, and implementation conditions across warehouse facilities.

Table 4. Descriptive Statistics of Key Constructs.

Construct	Mean	SD	Min	Max
Smart Industrial Robots (SIR)	4.15	0.62	2.1	5.0
AI-driven Autonomous Vehicles (AI)	4.08	0.65	2.0	5.0
Drones (DR)	3.95	0.68	1.8	5.0
Warehouse Operational Performance (WOP)	4.12	0.60	2.2	5.0

Overall, the respondent profile confirms the presence of a technologically receptive but operationally heterogeneous workforce. This heterogeneity provides a relevant empirical foundation for subsequent SEM analysis examining how autonomous logistics technologies are associated with perceived warehouse operational efficiency, operational accuracy, and warehouse resilience within the Moroccan logistics context.

5.2. Exploratory Factor Analysis (EFA)

Because the measurement scales were adapted from multiple prior studies and applied within a new operational and cultural environment, Exploratory Factor Analysis (EFA) was conducted prior to Confirmatory Factor Analysis (CFA) in order to verify the dimensional structure of the proposed constructs within the Moroccan warehouse context.

EFA was performed using Principal Axis Factoring with Varimax rotation. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy reached 0.891, exceeding the recommended threshold of 0.70, while Bartlett’s Test of Sphericity was statistically significant ($\chi^2 = 4862.71, p < 0.001$), confirming the suitability of the dataset for factor analysis.

The EFA results reported in Table 5 confirm that all measurement items loaded strongly on their intended constructs. All factor loadings exceeded 0.70 without significant cross-loadings, thereby confirming the dimensional stability of the proposed constructs within the Moroccan logistics context.

Table 5. Exploratory Factor Analysis Results.

Construct	Item	Factor Loading
Smart Industrial Robots (SIR)	SIR1	0.81
	SIR2	0.84
	SIR3	0.79
AI-driven Autonomous Vehicles (AI)	AI1	0.83
	AI2	0.86
	AI3	0.80
Drones (DR)	DR1	0.78
	DR2	0.81
	DR3	0.79
Warehouse Operational Performance (WOP)	WOP1	0.85
	WOP2	0.82
	WOP3	0.83

5.3. Measurement Model Validation (CFA)

Confirmatory Factor Analysis (CFA) was subsequently conducted to validate the measurement model and assess construct reliability, convergent validity, and discriminant validity. The reliability and convergent validity results summarized in Table 6 confirm satisfactory internal consistency and construct validity across all latent variables. All Cronbach's Alpha and Composite Reliability (CR) values exceeded the recommended threshold of 0.70, thereby confirming satisfactory internal consistency reliability. Similarly, all Average Variance Extracted (AVE) values exceeded 0.50, supporting convergent validity.

Table 6. Reliability and Convergent Validity Assessment.

Construct	Cronbach's Alpha	CR	AVE
Smart Industrial Robots (SIR)	0.88	0.91	0.62
AI-driven Autonomous Vehicles (AI)	0.89	0.92	0.65
Drones (DR)	0.87	0.90	0.61
Warehouse Operational Performance (WOP)	0.91	0.93	0.66

Discriminant validity was assessed using both the Fornell–Larcker criterion and the Heterotrait–Monotrait Ratio (HTMT). The discriminant validity results presented in Tables 7 and 8 further confirm the empirical distinctiveness of the proposed constructs. All HTMT values remained below the recommended threshold of 0.85, confirming that the constructs were empirically distinct and conceptually independent.

Table 7. Fornell–Larcker Criterion.

Construct	SIR	AI	DR	WOP
SIR	0.788			
AI	0.41	0.806		
DR	0.36	0.39	0.781	
WOP	0.44	0.48	0.40	0.813

Table 8. Heterotrait–Monotrait Ratio (HTMT).

Construct	SIR	AI	DR	WOP
SIR	—	0.52	0.47	0.58
AI		—	0.49	0.61
DR			—	0.55
WOP				—

Note: “—” indicates diagonal elements (comparison of a construct with itself); therefore, HTMT values are not applicable.

Overall, the CFA results confirm that the measurement model demonstrates satisfactory reliability, convergent validity, discriminant validity, and overall SEM adequacy.

5.4. Common Method Bias and Robustness Checks

Because both independent and dependent variables were collected from the same respondents, common method bias represented a potential methodological concern. Several procedural and statistical remedies were therefore implemented to reduce this risk. Procedurally, respondents were informed that participation remained anonymous and

confidential in order to reduce evaluation apprehension and social desirability bias. Questionnaire items were additionally organized to minimize direct response pattern effects and reduce respondents' tendency toward consistency bias.

Statistically, Harman's single-factor test was conducted to examine whether a single latent factor accounted for the majority of variance within the dataset. The first factor explained 32.7% of total variance, remaining below the commonly accepted threshold of 50%, thereby suggesting that common method bias was unlikely to represent a severe threat to the study findings. The common method bias and collinearity diagnostics reported in Table 9 suggest that common method bias is unlikely to represent a severe methodological threat.

Table 9. Common Method Bias and Collinearity Diagnostics.

Diagnostic	Value	Threshold	Interpretation
Harman Single Factor Variance	32.7%	<50%	Acceptable
Maximum Full Collinearity VIF	2.84	<5.00	No multi-collinearity

Additional robustness procedures were also conducted through alternative model estimations, subgroup comparisons, and moderation stability analysis across warehouse size and professional categories. The structural relationships remained relatively stable across alternative estimations, thereby strengthening the robustness and consistency of the SEM findings.

Because subgroup comparisons were explored across managerial roles and warehouse size categories, measurement invariance considerations were also examined conceptually. However, full multi-group measurement invariance procedures were not comprehensively implemented within the present study. Consequently, the moderation findings should be interpreted cautiously and primarily as exploratory indications of contextual variation rather than definitive structural differences between respondent groups. The post hoc statistical power analysis summarized in Table 10 additionally confirms that the sample size was statistically adequate for detecting medium and interaction effects.

Table 10. Post hoc Statistical Power Analysis.

Parameter	Value
Sample Size	1753
Statistical Power	0.97
Effect Size	Medium
Significance Level	0.05

The post hoc power analysis confirmed that the sample size was sufficient for detecting medium and interaction effects within the SEM model. Nevertheless, because the study relies primarily on self-reported perceptual data collected through a cross-sectional survey design, the possibility of residual perceptual bias, managerial optimism, favorable organizational technology orientation, and social desirability effects cannot be completely excluded.

5.5. Structural Model Results and Hypothesis Testing

The structural model was estimated using Structural Equation Modeling (SEM) in AMOS 29 with Maximum Likelihood Estimation (MLE). Prior to estimation, missing data, normality, and multicollinearity diagnostics were examined. The normality diagnostics reported in Table 11 indicate acceptable skewness and kurtosis values for SEM estimation.

Table 11. Normality Diagnostics.

Construct	Skewness	Kurtosis
Smart Industrial Robots (SIR)	−0.84	0.92
AI-driven Autonomous Vehicles (AI)	−1.12	1.21
Drones (DR)	−0.73	0.81
Warehouse Operational Performance (WOP)	−0.65	−1.08

The skewness and kurtosis values remained within acceptable thresholds for Maximum Likelihood Estimation, thereby supporting acceptable univariate normality assumptions. As presented in Table 12, the structural model demonstrated satisfactory fit across all recommended SEM indices. Bootstrapping procedures with 5000 resamples additionally confirmed the stability of parameter estimates and confidence intervals.

Table 12. Structural Model Fit Indices.

Fit Index	Obtained Value	Recommended Threshold	Interpretation
CFI	0.961	≥ 0.90	Acceptable
TLI	0.953	≥ 0.90	Acceptable
RMSEA	0.042	≤ 0.08	Acceptable
SRMR	0.039	≤ 0.08	Acceptable
χ^2/df	2.15	< 3.00	Acceptable

The hypothesis testing results are summarized in Table 13, while the structural relationships and standardized path coefficients obtained from the SEM analysis are illustrated in Figure 2.

Table 13. SEM Path Coefficients and Hypothesis Testing.

Hypothesis	Path	β	SE	t-Value	p-Value	95% Confidence Interval	Result
H1	SIR $\rightarrow$ Efficiency	0.42	0.03	14.0	< 0.001	[0.36; 0.48]	Supported
H2	AI $\rightarrow$ Accuracy	0.46	0.04	11.5	< 0.001	[0.39; 0.52]	Supported
H3	Drones $\rightarrow$ Resilience	0.39	0.03	12.8	< 0.001	[0.33; 0.45]	Supported
H4	SIR*AI $\rightarrow$ Efficiency	0.18	0.02	6.9	< 0.01	[0.12; 0.24]	Supported
H5	AI*Drones $\rightarrow$ Resilience	0.15	0.02	5.8	< 0.01	[0.09; 0.20]	Supported

Note: * indicates an interaction effect between the corresponding constructs.

The model's explanatory power was also substantial. The R^2 values reached 0.48 for operational efficiency, 0.51 for operational accuracy, and 0.42 for warehouse resilience.

Overall, the empirical findings provide strong support for the conceptual framework proposed in this study. More specifically, Hypothesis H1 proposed that Smart Industrial Robots would be positively associated with perceived operational efficiency. The SEM results confirmed this relationship, suggesting that respondents perceive industrial robots as important contributors to workflow optimization, repetitive task automation, operational coordination, and process consistency within warehouse environments.

Hypothesis H2 proposed that AI-driven Autonomous Vehicles would be positively associated with perceived operational accuracy. The findings supported this relationship, indicating that AI-enabled systems are perceived as important mechanisms associated with

improved routing precision, inventory coordination, warehouse visibility, and operational decision-making quality.

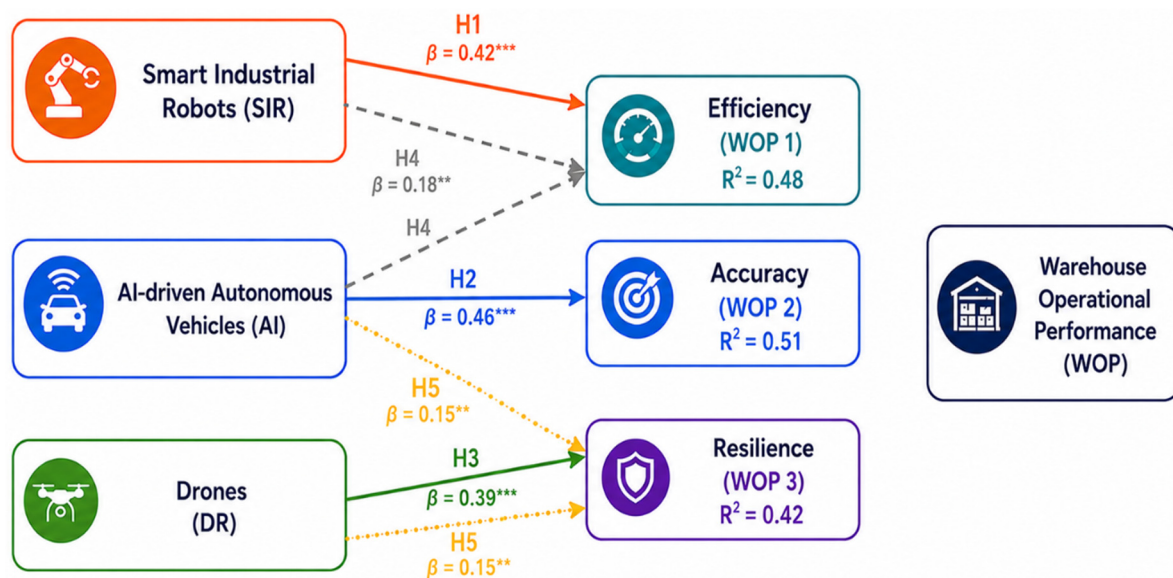


Figure 2. SEM Structural Model. Note: * indicates the statistical significance of the corresponding path coefficient (** $p < 0.01$; *** $p < 0.001$).

Hypothesis H3 predicted that drones would be positively associated with perceived warehouse resilience. The empirical results supported this hypothesis and suggest that drone technologies may contribute to adaptive warehouse monitoring, disruption detection, inventory visibility, and operational responsiveness during uncertain operational conditions.

Beyond the direct effects, the study additionally examined interaction effects among autonomous technologies. Hypothesis H4 proposed that the interaction between Smart Industrial Robots and AI-driven systems would strengthen perceived operational efficiency. The findings supported this hypothesis, suggesting that stronger operational implications emerge when robotics systems operate in coordination with AI-enabled decision and coordination mechanisms rather than through isolated technological implementation. Similarly, Hypothesis H5 proposed that the interaction between AI-enabled systems and drones would strengthen perceived warehouse resilience. The SEM results supported this relationship and suggest that coordinated interactions between predictive AI coordination systems and real-time drone monitoring technologies may be associated with stronger adaptive operational capabilities and disruption-management responsiveness within warehouse environments.

Collectively, these findings demonstrate that autonomous warehouse transformation is not limited to the adoption of individual technologies. Instead, the results suggest that perceived operational implications increasingly emerge from technological complementarities, organizational coordination, workforce adaptation, and integrated digital logistics architectures. Nevertheless, because the study relies primarily on perceptual survey data rather than objective warehouse operational indicators such as throughput rates, picking accuracy, inventory discrepancies, operational downtime, or disruption recovery time, the findings should not be interpreted as definitive evidence of causal operational improvement.

5.6. Moderation and Interaction Effects

The SEM analysis additionally examined interaction and moderation effects associated with workforce experience, managerial role, and warehouse size. These moderation vari-

ables were selected because previous smart logistics literature suggests that organizational characteristics, workforce capabilities, operational readiness, and infrastructure maturity may influence the implementation and perceived effectiveness of autonomous warehouse technologies within operational environments.

Interaction terms were estimated using mean-centered variables in order to reduce multicollinearity risks before interaction estimation. Product-indicator interaction procedures were subsequently incorporated into the SEM estimation process to evaluate synergistic relationships among autonomous technologies operating within warehouse environments.

The exploratory moderation effects summarized in Table 14 suggest that workforce experience, managerial role, and warehouse size may influence the perceived effectiveness of autonomous warehouse technologies.

Table 14. Moderation Effects of Experience, Role, and Warehouse Size.

Interaction	Moderator	Effect Size	t-Value	Significance
SIR*AI	Experience (>10 yrs)	0.21	5.3	$p < 0.01$
AI*Drones	Warehouse Size (Large)	0.18	4.9	$p < 0.01$
SIR → Efficiency	Job Role (Managerial)	0.19	4.6	$p < 0.01$

Note: * indicates an interaction effect between the corresponding constructs.

The interaction results demonstrated that the coordinated deployment of Smart Industrial Robots and AI-enabled systems generated stronger positive associations with perceived operational efficiency than isolated technological implementation. Similarly, the interaction between AI-enabled systems and drones was positively associated with perceived warehouse resilience.

These findings support the argument that autonomous warehouse technologies rarely operate independently within modern logistics systems. Instead, operational implications increasingly emerge from coordinated multi-agent interactions among robots, AI-enabled transport systems, drones, and real-time operational coordination mechanisms.

The moderation findings additionally indicate that contextual and human-centered dimensions remain important determinants of autonomous technology effectiveness. Experienced employees may possess stronger operational knowledge and greater ability to coordinate AI-enabled systems within complex warehouse activities.

At the same time, the findings also suggest that autonomous technology deployment may involve implementation complexity and organizational adaptation challenges. Workforce training requirements, cybersecurity concerns, infrastructure readiness, interoperability limitations, and resistance to operational change remain important operational considerations associated with autonomous warehouse transformation.

In addition, although moderation effects were identified across professional experience, managerial role, and warehouse size categories, the absence of full multi-group measurement invariance testing suggests that these moderation findings should be interpreted primarily as exploratory relationships. Future research should therefore implement comprehensive measurement invariance procedures before establishing definitive structural comparisons across operational groups. Nevertheless, these moderation and interaction effects should be interpreted cautiously because the study relies on cross-sectional perceptual data rather than longitudinal operational measurements.

6. Discussion

The present study investigated the relationships between Smart Industrial Robots (SIR), AI-driven Autonomous Vehicles (AI), Drones (DR), and perceived Warehouse Operational Performance (WOP) within the Moroccan logistics context. The empirical findings

indicate that autonomous warehouse technologies are positively associated with perceived operational efficiency, operational accuracy, and warehouse resilience. More importantly, the study suggests that stronger operational implications may emerge when these technologies operate through coordinated and integrated technological ecosystems rather than isolated implementations.

The findings reveal that Smart Industrial Robots exhibit the strongest association with perceived operational efficiency. This result aligns with previous studies by [12,14], which emphasized the ability of industrial robotics to automate repetitive warehouse tasks, reduce operational interruptions, strengthen workflow consistency, and improve logistics coordination mechanisms. However, while previous studies mainly focused on technologically mature logistics environments, the present findings extend this literature by suggesting that industrial robotics may also play a significant operational role within emerging-market logistics systems characterized by heterogeneous infrastructure quality and evolving digital maturity.

Similarly, AI-driven Autonomous Vehicles demonstrated the strongest association with perceived operational accuracy. This finding is consistent with previous research by [16,17], which highlighted the role of AI-enabled systems in improving warehouse visibility, predictive coordination, inventory synchronization, routing precision, and operational responsiveness. The findings therefore reinforce the argument that AI-enabled coordination systems increasingly constitute a central component of contemporary smart logistics architectures. At the same time, the Moroccan context reveals that the perceived effectiveness of AI-enabled systems remains strongly dependent on workforce readiness, digital infrastructure maturity, interoperability capabilities, and managerial support.

The findings additionally indicate that drones are positively associated with perceived warehouse resilience. This result extends previous warehouse automation literature that has traditionally focused primarily on productivity and operational efficiency while paying comparatively limited attention to resilience-oriented logistics capabilities. The present findings suggest that drones may contribute to adaptive warehouse monitoring, disruption detection, inventory visibility, operational continuity, and real-time responsiveness under uncertain operational conditions. Nevertheless, respondents also emphasized practical implementation constraints associated with drone deployment, including infrastructure limitations, cybersecurity concerns, navigation precision challenges, battery autonomy constraints, and operational integration difficulties with existing warehouse management systems.

One of the most important contributions of the study lies in the identification of interaction effects among autonomous technologies. While much of the previous literature evaluates robots, AI-enabled systems, and drones independently, the present findings suggest that stronger operational implications may emerge when these technologies operate through coordinated technological ecosystems. More specifically, the interaction between Smart Industrial Robots and AI-enabled systems was positively associated with perceived operational efficiency, whereas the interaction between AI-enabled systems and drones strengthened perceived warehouse resilience. These findings therefore support the argument that warehouse operational performance increasingly depends on technological complementarities, real-time coordination mechanisms, and integrated autonomous logistics architectures rather than isolated technological investments.

The findings additionally reinforce the socio-technical systems perspective developed in the theoretical framework. Autonomous warehouse transformation does not appear to result solely from technological acquisition. Instead, the findings suggest that workforce capabilities, organizational readiness, managerial coordination, operational adaptation, and infrastructure maturity are important factors associated with the perceived effectiveness of

autonomous systems. This interpretation is further supported by the moderation findings, which revealed that workforce experience, managerial role, and warehouse size significantly influenced several structural relationships within the SEM model.

The results also contribute to the Technology–Organization–Environment (TOE) framework by demonstrating that autonomous technology adoption alone remains insufficient unless accompanied by organizational alignment and operational readiness. Warehouses possessing stronger managerial support, digital infrastructure, workforce preparedness, and operational integration capabilities appear more likely to perceive positive operational implications from autonomous technologies. Conversely, organizations characterized by weaker infrastructure readiness or limited workforce digital competencies may face greater implementation complexity and lower operational integration capacity.

The findings additionally contribute to the Resource-Based View (RBV) and Dynamic Capability Theory. The identified interaction effects suggest that firms may generate stronger operational capabilities through the orchestration and integration of multiple autonomous systems rather than through isolated technological deployment. In this perspective, autonomous technologies may constitute strategic logistics resources whose operational value depends largely on complementary organizational capabilities, coordination mechanisms, workforce adaptation, and learning processes.

At the same time, the findings reveal that autonomous warehouse transformation involves substantial implementation complexity. Respondents emphasized the importance of workforce training, cybersecurity management, infrastructure readiness, operational interoperability, change-management practices, and human–technology coordination. These findings therefore nuance the frequently optimistic discourse surrounding autonomous logistics technologies by highlighting that digital transformation processes may generate organizational resistance, adaptation challenges, operational uncertainty, and technological dependency risks.

The Moroccan context additionally provides an important contribution to the emerging-market logistics literature. Most existing warehouse automation studies focus primarily on technologically mature economies characterized by advanced digital infrastructure and relatively standardized logistics systems. In contrast, the Moroccan logistics environment presents heterogeneous infrastructure quality, evolving digital transformation capabilities, operational variability, and unequal technological readiness across warehouse facilities. Consequently, the present findings provide a more context-sensitive understanding of how autonomous technologies are perceived and operationalized within emerging logistics ecosystems.

The findings additionally suggest that autonomous logistics transformation should not be interpreted exclusively through technological determinism perspectives. Although autonomous systems may support operational coordination and logistics responsiveness, their effectiveness appears strongly conditioned by organizational adaptation processes, workforce capabilities, institutional readiness, and strategic implementation choices. This interpretation is particularly important within emerging-market logistics systems where technological investment capacities, digital infrastructure quality, and workforce digital skills may vary substantially between firms and warehouse facilities.

Nevertheless, the findings should be interpreted cautiously. The study primarily measures respondents' perceptions regarding operational implications rather than objective warehouse performance indicators such as throughput rates, inventory accuracy, picking error rates, labor productivity, operational downtime, safety incidents, or disruption recovery time. Consequently, the results provide evidence of positive perceived associations between autonomous warehouse technologies and warehouse operational performance dimensions rather than direct evidence of objective operational improvement or causal superiority.

Furthermore, because the study relies on a cross-sectional survey design, causal relationships cannot be definitively established. The observed associations may partially reflect organizational technology orientation, managerial optimism, favorable attitudes toward digital transformation initiatives, or social desirability effects associated with technologically advanced logistics systems.

6.1. Implications for Theory

The study contributes to several theoretical streams related to smart logistics, autonomous systems, warehouse digitalization, and organizational transformation. First, the findings reinforce the relevance of socio-technical systems theory by demonstrating that warehouse operational performance emerges not only from technological deployment itself but also from the interaction between technological systems, workforce capabilities, organizational coordination, managerial support, and operational infrastructure. The findings therefore support the argument that autonomous warehouse transformation should be analyzed as a multidimensional socio-technical process rather than as a purely technological phenomenon.

Second, the study extends the Technology–Organization–Environment (TOE) framework by illustrating how organizational readiness, infrastructure maturity, managerial coordination, workforce experience, and operational adaptation influence the perceived effectiveness of autonomous warehouse technologies. The findings suggest that the operational implications of autonomous systems remain strongly dependent on organizational and environmental conditions surrounding technological implementation.

Third, the study contributes to the Resource-Based View (RBV) and Dynamic Capability Theory by highlighting the strategic importance of integrated autonomous logistics capabilities. The interaction effects identified between robots, AI-enabled systems, and drones suggest that firms may generate stronger logistics capabilities through coordinated technological complementarities rather than isolated technology adoption. Consequently, autonomous systems may represent strategic operational resources whose effectiveness depends on complementary organizational capabilities and learning processes.

Fourth, the study contributes to the limited literature examining autonomous logistics technologies within emerging-market environments. Existing warehouse automation research remains heavily concentrated on technologically mature economies. By focusing on Morocco, the present research extends theoretical understanding regarding how autonomous technologies are perceived under conditions characterized by evolving digital transformation processes, heterogeneous infrastructure quality, and operational variability.

Finally, the findings contribute to the growing literature concerning the multidimensional nature of warehouse operational performance. The results suggest that autonomous technologies may be associated differently with operational efficiency, operational accuracy, and warehouse resilience, highlighting the need to conceptualize warehouse operational performance as a multidimensional and context-dependent construct rather than a purely productivity-oriented outcome.

6.2. Implications for Practice and Policy

The findings provide several practical implications for warehouse managers, logistics operators, technology providers, and policymakers involved in logistics digital transformation initiatives. First, warehouse managers should avoid perceiving autonomous technologies as isolated operational solutions. The interaction effects identified in the study suggest that stronger operational implications emerge when robots, AI-enabled systems, and drones are deployed through coordinated logistics ecosystems characterized by interoperability, real-time coordination, and integrated operational management.

Second, workforce adaptation remains a critical determinant of successful autonomous warehouse transformation. Managers should therefore invest in workforce training, digital skills development, human-machine coordination capabilities, and organizational change-management programs. The findings suggest that operational resistance and workforce adaptation challenges may significantly influence the perceived effectiveness of autonomous systems.

Third, warehouse size and infrastructure maturity appear to influence autonomous technology effectiveness. Larger warehouses may possess stronger investment capacities, more advanced infrastructure, and greater operational flexibility for deploying integrated autonomous systems. In contrast, smaller warehouses may face resource limitations, technological integration challenges, and infrastructure constraints. Consequently, logistics digitalization strategies should be adapted to organizational size and operational context rather than implemented through standardized technological models.

Fourth, policymakers should strengthen logistics digital infrastructure, cybersecurity standards, interoperability frameworks, and workforce digital training initiatives in order to facilitate autonomous logistics transformation. Emerging-market logistics systems may require supportive institutional policies capable of reducing technological adoption barriers and improving digital readiness across warehouse ecosystems.

Fifth, the findings highlight the importance of cybersecurity governance and operational interoperability. Autonomous warehouse systems increasingly depend on interconnected digital infrastructures, AI-enabled coordination systems, and real-time operational data flows. Consequently, cybersecurity vulnerabilities, operational integration failures, and technological dependency risks may represent significant challenges for warehouse digital transformation.

Finally, the findings suggest that logistics digital transformation should be approached progressively rather than through large-scale immediate automation initiatives. Incremental implementation strategies integrating workforce adaptation, technological experimentation, operational learning, and infrastructure readiness may generate more sustainable and operationally coherent autonomous transformation processes.

6.3. Limitations of the Study and Future Research Directions

Despite its contributions, the study presents several limitations that should be acknowledged. First, the study relies primarily on self-reported perceptual data collected through survey responses. Although perceptual measures remain common within logistics and organizational research, future studies should integrate objective warehouse operational indicators such as throughput rates, inventory accuracy, picking error rates, labor productivity, operational downtime, safety incidents, disruption recovery metrics, and warehouse cycle times in order to strengthen empirical robustness.

Second, the study adopts a cross-sectional research design. Consequently, the findings identify perceived associations rather than causal relationships between autonomous technologies and warehouse operational performance. Future longitudinal studies could provide a more robust understanding of how autonomous warehouse transformation evolves over time and how operational implications develop during technology implementation processes.

Third, the study focuses specifically on the Moroccan logistics environment. Although this context provides valuable insights regarding autonomous technologies within emerging-market logistics systems, the findings may not be fully generalizable to other institutional or operational environments characterized by different technological maturity levels, regulatory systems, or infrastructure conditions.

In addition, the study employed a purposive sampling strategy targeting logistics professionals familiar with autonomous warehouse technologies. Although this approach was appropriate for capturing informed perceptions regarding industrial robots, AI-enabled systems, and drones, it may limit the generalizability of the findings to broader logistics populations or warehouse environments with lower levels of technological adoption. Future research could employ probability-based sampling techniques and include a wider range of logistics organizations to improve external validity and strengthen the generalizability of the findings.

Fourth, although robustness checks and common method bias procedures were conducted, residual perceptual bias, organizational optimism effects, and favorable technology orientation cannot be completely excluded. Future research could therefore combine perceptual survey data with operational performance datasets, observational analysis, or mixed-method approaches integrating qualitative interviews and case studies.

Fifth, although moderation effects were identified across workforce experience, managerial role, and warehouse size categories, the present study did not implement full multi-group measurement invariance procedures. Consequently, future studies should conduct comprehensive measurement invariance testing before establishing definitive structural comparisons across operational groups.

Finally, future research could further investigate emerging technological trajectories related to Industry 5.0, collaborative robotics, predictive warehouse intelligence, digital twins, deep learning systems, human-centered autonomous logistics ecosystems, and AI-enabled supply chain orchestration mechanisms.

7. Conclusions

This study examined the relationships between Smart Industrial Robots, AI-driven Autonomous Vehicles, Drones, and perceived Warehouse Operational Performance within the Moroccan logistics context. The findings suggest that autonomous warehouse technologies are positively associated with operational efficiency, operational accuracy, and warehouse resilience, particularly when deployed through coordinated and integrated technological ecosystems rather than isolated technological implementations.

The study makes several contributions to the literature on autonomous logistics and warehouse digitalization. First, it extends current knowledge by simultaneously examining the individual and interaction effects of multiple autonomous technologies within a single analytical framework. Second, it contributes empirical evidence from an emerging-market context, thereby enriching a literature that has largely focused on technologically mature economies. Third, the findings reinforce the relevance of socio-technical, TOE, RBV, and Dynamic Capability perspectives by demonstrating that the effectiveness of autonomous technologies depends not only on technological deployment itself but also on organizational readiness, workforce capabilities, managerial support, and operational integration.

Overall, the study highlights that the future of warehouse digital transformation is likely to depend on the successful integration of autonomous technologies with human, organizational, and operational capabilities. Consequently, autonomous warehouse transformation should be viewed not merely as a technological challenge but as a broader organizational and strategic process requiring coordinated technological and human development.

Author Contributions: Conceptualization, A.E.E.M. and T.E.M.; methodology, A.E.E.M., T.E.M., N.T. and M.A.; software, A.E.E.M., T.E.M. and N.T.; validation, T.E.M. and M.A.; formal analysis, A.E.E.M., T.E.M. and N.T.; investigation, A.E.E.M., T.E.M., N.T. and M.A.; resources, A.E.E.M. and N.T.; data curation, T.E.M. and M.A.; writing—original draft preparation, A.E.E.M., T.E.M., N.T. and M.A.; writing—review and editing, A.E.E.M. and T.E.M.; visualization, A.E.E.M., T.E.M., N.T. and M.A.; supervision, A.E.E.M. and T.E.M.; project administration, A.E.E.M., T.E.M., N.T. and M.A.; funding

acquisition, A.E.E.M., T.E.M., N.T. and M.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: This study was waived for ethical review by the Institutional Committee of the Faculté des Sciences Juridiques, Économiques et Sociales-Aïn Chock, Université Hassan II de Casablanca, as the study was conducted exclusively in the fields of management sciences, logistics, and supply chain management based on an anonymous questionnaire survey, with voluntary participation, no collection of personal identification information, and no biomedical intervention (Waiver Reason: Moroccan Law No. 28-13 exempts non-clinical, anonymous, questionnaire-based research from formal ethics committee approval). An Ethical Declaration and Confidentiality Statement was signed by the Vice-Dean in charge of Scientific Research on 21 May 2026.

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

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to confidentiality restrictions.

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

Appendix A. Questionnaire Structure and Measurement Items

Dear Participant,

This questionnaire is part of an academic research study examining the impact of smart industrial robots, artificial intelligence systems, and drones on warehouse operational performance. Your responses are anonymous and will be used only for academic purposes. Please answer honestly based on your professional experience.

All measurement items were evaluated using a five-point Likert scale:
☐ 1 = Strongly Disagree ☐ 2 = Disagree ☐ 3 = Neutral ☐ 4 = Agree ☐ 5 = Strongly Agree.

Appendix A.1. Section 1: Demographic and Professional Information

1. **Gender** ☐ Male ☐ Female
2. **Age** ☐ 18–24 ☐ 25–30 ☐ 31–40 ☐ 41–50 ☐ Above 50
3. **Educational Background** ☐ High School ☐ Bachelor Degree ☐ Master Degree ☐ PhD
4. **Professional Experience** ☐ Less than 5 years ☐ 5–10 years ☐ 11–15 years
☐ More than 15 years
5. **Job Role** ☐ Manager ☐ Operational Staff ☐ Warehouse Coordinator ☐ Logistics Technician
6. **Warehouse Size** ☐ Small ☐ Medium ☐ Large
7. **Familiarity with Autonomous Technologies**
 - * Industrial Robots ☐ Very Low ☐ Low ☐ Moderate ☐ High ☐ Very High
 - * AI-driven Autonomous Vehicles ☐ Very Low ☐ Low ☐ Moderate ☐ High ☐ Very High
 - * Drone Technologies ☐ Very Low ☐ Low ☐ Moderate ☐ High ☐ Very High

Appendix A.2. Section 2: Autonomous Logistics Technologies

Smart Industrial Robots (SIR)

- * The warehouse extensively uses robots for repetitive operational activities such as sorting, picking, and packing. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * Industrial robots dynamically adapt to operational workflow variations within warehouse activities. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * Industrial robots contribute to reducing operational errors and improving warehouse coordination. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

AI-driven Autonomous Vehicles (AI)

- * AI-driven autonomous vehicles improve operational accuracy through predictive coordination of warehouse transport activities. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * AI-driven autonomous vehicles facilitate anomaly detection and operational adjustment within warehouse processes. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * AI-driven autonomous vehicles improve real-time resource allocation and warehouse operational synchronization. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Drones (DR)

- * Drones are used for inventory monitoring and warehouse inspection activities. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * Drones coordinate effectively with AI-driven autonomous vehicles and ground-based warehouse technologies. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * Drone technologies contribute to warehouse operational resilience through real-time monitoring and rapid operational visibility. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Appendix A.3. Section 3: Warehouse Operational Performance (WOP)

- * Autonomous technologies contribute to improving overall warehouse operational efficiency. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * Autonomous technologies contribute to improving warehouse operational accuracy and coordination. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * Autonomous technologies contribute to strengthening warehouse operational resilience during disruptions. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Appendix A.4. Section 4: Additional Contextual and Exploratory Questions

(The following exploratory questions were included to better contextualize respondents' perceptions regarding autonomous warehouse implementation and operational readiness. These items were used for contextual interpretation purposes and were not incorporated as latent constructs within the SEM model).

- * **Workforce Readiness:** Employees are adequately prepared to work with autonomous warehouse technologies. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * **Organizational Support:** The organization strongly supports warehouse digital transformation initiatives. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * **Infrastructure Readiness:** The warehouse possesses adequate technological infrastructure for autonomous systems integration. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * **Operational Interoperability:** Autonomous systems interact effectively with existing warehouse management systems. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * **Cybersecurity Preparedness:** The warehouse possesses adequate cybersecurity measures for autonomous logistics operations. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * **Human–Technology Coordination:** Employees coordinate effectively with autonomous warehouse systems. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5
- * **Training Adequacy:** Employees receive sufficient training regarding autonomous warehouse technologies. ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

References

1. Grover, V.; Dogra, M.M.; Sahu, M.D.; Nandal, M.; Gnaguly, A. Supply chain management strategy and practices: Traditional vs. advanced. In *Blockchain, IoT, and AI Technologies for Supply Chain Management: Apply Emerging Technologies to Address and Improve Supply Chain Management*; Apress: Berkeley, CA, USA, 2024; pp. 1–43.
2. Gu, C.; Reefke, H.; Yates, N. Autonomous vehicle adoption and supply chain social sustainability: Delphi study and expert interviews. *Int. J. Phys. Distrib. Logist. Manag.* **2025**, *55*, 275–306. [CrossRef]

3. Rainer, R.K., Jr.; Richey, R.G., Jr.; Chowdhury, S. How robotics is shaping digital logistics and supply chain management: An ongoing call for research. *J. Bus. Logist.* **2025**, *46*, e70005. [[CrossRef](#)]
4. El Moussaoui, A.E.; El Moussaoui, T.; Benbba, B.; Jaegler, A.; El Andaloussi, Z. Understanding the choice of collection & delivery point by the E-consumer via a machine learning model: Moroccan case study. *Procedia Comput. Sci.* **2022**, *210*, 204–211.
5. Telikani, A.; Sarkar, A.; Du, B.; Santoso, F.; Shen, J.; Yan, J.; Yong, J.; Yap, E.W. Autonomous Aerial Vehicles-Aided Intelligent Transportation Systems: Vision, Challenges, and Opportunities. *IEEE Commun. Surv. Tutor.* **2025**, *27*, 3772–3819. [[CrossRef](#)]
6. Tsarouhas, P. Intelligent Logistics and Supply Chain Systems Based on Industry 4.0/5.0. *Appl. Sci.* **2026**, *16*, 2617. [[CrossRef](#)]
7. Rodríguez-García, M.; Kembro, J.H.; Betts, K.; Ponce-Cueto, E. Managing technology-related disruptions and vulnerabilities in highly automated warehouse systems: An integrative review and research agenda. *Int. J. Prod. Res.* **2026**, *64*, 1676–1708.
8. Tran, M.C.; Nguyen, L.C.; Pham, P.L.; Hoang, P.M.; Dinh, H.G.; Truong, H.Q.; Duong, A.T.B. Digital transformation in logistics: A framework for Industry 4.0 in developing countries. *Compet. Rev. Int. Bus. J.* **2026**, *36*, 24–41. [[CrossRef](#)]
9. El Moussaoui, T.; Chakir, L.; El Moussaoui, A.E. Exploring Information Technology (IT) Acceptance among Supply Chain Stakeholders in Morocco's Pharmaceutical Industry. In *Ecological and Human Dimensions of AI-Based Supply Chain*; IGI Global Scientific Publishing: Palmdale, PA, USA, 2025; pp. 245–270.
10. Bourriche, A.; Souaf, M. Comparative analysis of e-commerce infrastructure: A study of Morocco and the USA. *J. Electron. Bus. Digit. Econ.* **2026**, *5*, 180–204. [[CrossRef](#)]
11. El Moussaoui, A.E.; El Moussaoui, T.; Benbba, B.; Chakir, L.; Jaegler, A.; El Andaloussi, Z. Sustainable effects of information sharing between distribution logistics actors: A qualitative case study. *Environ. Dev. Sustain.* **2025**, *27*, 12305–12323.
12. Ferreira, B.; Reis, J. A systematic literature review on the application of automation in logistics. *Logistics* **2023**, *7*, 80. [[CrossRef](#)]
13. El Moussaoui, A.E.; Benbba, B.; Jaegler, A.; El Moussaoui, T.; El Andaloussi, Z.; Chakir, L. Consumer perceptions of online shopping and willingness to use pick-up points: A case study of Morocco. *Sustainability* **2023**, *15*, 7405. [[CrossRef](#)]
14. Pessot, E.; Zangiacomi, A.; Marchiori, I.; Fornasiero, R. Empowering supply chains with Industry 4.0 technologies to face megatrends. *J. Bus. Logist.* **2023**, *44*, 609–640. [[CrossRef](#)]
15. Gabsi, A.E.H. Integrating artificial intelligence in industry 4.0: Insights, challenges, and future prospects—A literature review. *Ann. Oper. Res.* **2024**, 1–28. [[CrossRef](#)]
16. Modgil, S.; Singh, R.K.; Hannibal, C. Artificial intelligence for supply chain resilience: Learning from COVID-19. *Int. J. Logist. Manag.* **2022**, *33*, 1246–1268.
17. Löffel, M.; Diehlmann, F.; Zienau, A.; Lüttenberg, M.; Wiens, M.; Wagner, S.M.; Schultmann, F. Improving disaster preparedness through public-private collaboration—dual-use warehouses for food supply. *Prod. Plan. Control* **2026**, *37*, 771–795. [[CrossRef](#)]
18. Garikapati, D.; Shetiya, S.S. Autonomous vehicles: Evolution of artificial intelligence and the current industry landscape. *Big Data Cogn. Comput.* **2024**, *8*, 42. [[CrossRef](#)]
19. Abosuliman, S.S.; Almagrabi, A.O. Routing and scheduling of intelligent autonomous vehicles in industrial logistics systems. *Soft Comput.* **2021**, *25*, 11975–11988. [[CrossRef](#)]
20. Kosmidis, M.; Antoniou, S.; Balaska, V.; Kansizoglou, I.; Gasteratos, A. Towards warehouse 5.0: A framework of human-centered technologies. In *2024 IEEE International Conference on Imaging Systems and Techniques (IST)*; IEEE: Piscataway, NJ, USA, 2024; pp. 1–6.
21. Malang, C.; Charoenkwan, P.; Wudhikarn, R. Implementation and critical factors of unmanned aerial vehicle (UAV) in warehouse management: A systematic literature review. *Drones* **2023**, *7*, 80. [[CrossRef](#)]
22. Ali, S.S.; Khan, S.; Fatma, N.; Ozel, C.; Hussain, A. Utilisation of drones in achieving various applications in smart warehouse management. *Benchmarking Int. J.* **2024**, *31*, 920–954.
23. Sapkota, R.; Roumeliotis, K.I.; Karkee, M. UAVs meet agentic AI: A multidomain survey of autonomous aerial intelligence and agentic UAVs. *arXiv* **2025**, arXiv:2506.08045.
24. Hua, M.; Qi, X.; Chen, D.; Jiang, K.; Liu, Z.E.; Sun, H.; Zhou, Q.; Xu, H. Multi-agent reinforcement learning for connected and automated vehicles control: Recent advancements and future prospects. *IEEE Trans. Autom. Sci. Eng.* **2025**, *22*, 16266–16286. [[CrossRef](#)]
25. Ekechi, C.C.; Elfouly, T.; Alouani, A.; Khattab, T. A survey on UAV control with multi-agent reinforcement learning. *Drones* **2025**, *9*, 484. [[CrossRef](#)]
26. Kalsoom, T.; Ahmed, S.; Rafi-Ul-Shan, P.M.; Azmat, M.; Akhtar, P.; Pervez, Z.; Imran, M.A.; Ur-Rehman, M. Impact of IoT on manufacturing industry 4.0: A new triangular systematic review. *Sustainability* **2021**, *13*, 12506. [[CrossRef](#)]
27. Nikitas, A.; Michalakopoulou, K.; Njoya, E.T.; Karampatzakis, D. Artificial intelligence, transport and the smart city: Definitions and dimensions of a new mobility era. *Sustainability* **2020**, *12*, 2789. [[CrossRef](#)]
28. El Moussaoui, T.; Loqman, C.; El Moussaoui, A.E. Adoption of artificial intelligence in smart cities: Literature review and bibliometric analysis. *Gener. AI Cybersecur. Priv.* **2025**, 103–125. [[CrossRef](#)]
29. Bharathiyar, M.; Veeraiyan, E.A.; Murugesan, P.; Natesan, P.T. Leveraging machine learning and artificial intelligence for advanced mobile network systems. In *Transforming Healthcare*; CRC Press: Boca Raton, FL, USA, 2025; pp. 305–327.

30. Rashid, A.; Rasheed, R. Supply chain cognitive resilience through AI-powered risk mitigation and autonomous resilience. *Supply Chain Manag. Int. J.* **2026**, *31*, 222–237. [\[CrossRef\]](#)
31. Rai, D. AI Driven Optimization in Specific SCM Domains: Warehousing, Logistics, Transport. *J. Comput. Sci. Technol. Stud.* **2025**, *7*, 612–618.
32. Abror, K.; Turaev, D.; Ashirova, A.; Smitha, M.J.; Urozboev, K.; Berisbayevna, A.A.; Raghu, N. Integration of Artificial Intelligence and IoT for Future Smart System Applications. In *Intelligent Systems and Sustainable Solutions for AIOT-Powered Environmental Monitoring*; IGI Global Scientific Publishing: Palmdale, PA, USA, 2026; pp. 1–28.
33. Arvind, V.R.; Shrinidhi, R.M.; Deepa, T.; Maheedhar, M. Intelligent Warehousing: A Machine Learning and IoT Framework for Precision Inventory Optimization. *IEEE Access* **2025**, *13*, 169381–169414. [\[CrossRef\]](#)
34. Cichosz, M.; Wallenburg, C.M.; Knemeyer, A.M. Digital transformation at logistics service providers: Barriers, success factors and leading practices. *Int. J. Logist. Manag.* **2020**, *31*, 209–238. [\[CrossRef\]](#)
35. Awa, H.O.; Ojiabo, O.U.; Orokor, L.E. Integrated technology-organization-environment (TOE) taxonomies for technology adoption. *J. Enterp. Inf. Manag.* **2017**, *30*, 893–921. [\[CrossRef\]](#)
36. Lyu, G.; Chen, L.; Huo, B. Logistics resources, capabilities and operational performance: A contingency and configuration approach. *Ind. Manag. Data Syst.* **2019**, *119*, 230–250.
37. Sony, M.; Naik, S. Industry 4.0 integration with socio-technical systems theory: A systematic review and proposed theoretical model. *Technol. Soc.* **2020**, *61*, 101248. [\[CrossRef\]](#)
38. Tulli, S.K.C. Warehouse Layout Optimization: Techniques for Improved Order Fulfillment Efficiency. *Int. J. Acta Inform.* **2023**, *2*, 138–168.
39. Mohammed, A.; Rahman, M.; Demir, G.; Shah, B.; Alaya, A. When warehouses dream: A systems-informed exploration of Industry 5.0 principles in warehousing performance management. *Int. J. Syst. Sci. Oper. Logist.* **2025**, *12*, 2559257. [\[CrossRef\]](#)
40. Peng, E.Y.; Zhang, D.; Xie, Y.; Linderman, K. Top management incentives and supply chain efficiency: A tournament theory perspective. *Int. J. Oper. Prod. Manag.* **2026**, *46*, 821–845.
41. Castellucci, T.; Moretti, E.; Tappia, E.; Melacini, M. Synchronizing material flows in logistics systems: Conceptual framework and research opportunities. *Prod. Plan. Control* **2026**, *37*, 665–690.
42. Colabianchi, S.; Bernabei, M.; Costantino, F.; Romano, E.; Falegnami, A. MARLIN method: Enhancing warehouse resilience in response to disruptions. *Logistics* **2023**, *7*, 95. [\[CrossRef\]](#)
43. Li, X.; Hua, G.; Cheng, T.C.E.; Liu, S. Human-Centric Order Batching and Allocation When Picking with Robot Teammates in the Warehouse. *Int. J. Prod. Econ.* **2026**, *296*, 109999. [\[CrossRef\]](#)
44. Addula, S.R.; Tyagi, A.K. Future of computer vision and industrial robotics in smart manufacturing. In *Artificial Intelligence-Enabled Digital Twin for Smart Manufacturing*; Wiley: Hoboken, NJ, USA, 2024; pp. 505–539.
45. Sharma, R. AI-Powered Robotics and Automation: Revolutionizing Industries. In *Artificial Intelligence and Machine Learning Algorithms for Engineering Applications*; CRC Press: Boca Raton, FL, USA, 2025; pp. 246–267.
46. Pramod, D. Robotic process automation for industry: Adoption status, benefits, challenges and research agenda. *Benchmarking Int. J.* **2022**, *29*, 1562–1586.
47. Mishras, D.; Rath, K.C.; Tripathy, S.K.; Rocha, A.; Darwish, D. Enhancing Productivity and Workflows in Smart Industry Through Robotics Process Automation. In *Engineering, Technology and Management: Practices for Sustainable Manufacturing Industry*; Springer Nature: Cham, Switzerland, 2025; Volume 1, pp. 147–173.
48. Sharma, N.; Cupek, R. Real-time control and optimization of internal logistics systems with collaborative robots. *Procedia Comput. Sci.* **2023**, *225*, 248–258. [\[CrossRef\]](#)
49. Willems, L. Understanding the impacts of autonomous vehicles in logistics. In *The Digital Transformation of Logistics: Demystifying Impacts of the Fourth Industrial Revolution*; Wiley: Hoboken, NJ, USA, 2021; pp. 113–127.
50. Shandilya, S.K.; Ortiz-Rodriguez, F.; Shandilya, S.; Romero, G. (Eds.) *AI, Cybersecurity and Data Science for Drone and Unmanned Aerial Vehicles: Real-Life Applications and Case Studies*; CRC Press: Boca Raton, FL, USA, 2025.
51. Poma, A.; Sojo, A.; Maza, I.; Ollero, A. Ground Control Station for Multi-UAV Systems in Infrastructure Inspection and Environmental Monitoring Applications. *J. Intell. Robot. Syst.* **2025**, *111*, 109. [\[CrossRef\]](#)
52. Kumar, I.; Maitri, V. *Smart Freight Logistics: Intelligent Transport Systems and Emerging Technologies*; Taylor & Francis: Abingdon, UK, 2026.
53. Bolu, A.; Korçak, Ö. Adaptive task planning for multi-robot smart warehouse. *IEEE Access* **2021**, *9*, 27346–27358. [\[CrossRef\]](#)
54. Jie, C.X.; Hui, T.K.; Hoong, B.S.; Yang, J.C.K.; Yusof, H. The implementation of robotics and automation in improving warehouse efficiency among logistics operators in Malaysia. *Technol. Educ.* **2023**, *163*, 163–179.
55. Mohsen, B.M. AI-driven optimization of urban logistics in smart cities: Integrating autonomous vehicles and IoT for efficient delivery systems. *Sustainability* **2024**, *16*, 11265.

56. Baytur, B.; Özceylan, E. Unmanned Aerial Vehicles in Inventory Management: An Overview of Current Research and Applications. In *International Conference on Science, Engineering Management and Information Technology*; Springer Nature: Cham, Switzerland, 2024; pp. 361–374.
57. Thangamani, R.; Suguna, R.K.; Kamalam, G.K. Drones and autonomous robotics incorporating computational intelligence. In *Computational Intelligent Techniques in Mechatronics*; Wiley: Hoboken, NJ, USA, 2024; pp. 243–296.
58. Seetharaman, K.M.R. Analysing the role of inventory and warehouse management in supply chain agility: Insights from retail and manufacturing industries. *Int. J. Curr. Eng. Technol.* **2022**, *12*, 583–590. [[CrossRef](#)]
59. Epe, M.; Azmat, M.; Islam, D.M.Z.; Khalid, R. Use of smart glasses for boosting warehouse efficiency: Implications for change management. *Logistics* **2024**, *8*, 106. [[CrossRef](#)]

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.