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Integrating Artificial Intelligence in Smart Logistics: A Systematic Literature Research and Governance Framework

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Abstract

This study systematically examines the integration of Artificial Intelligence (AI) technologies into logistics and supply chain processes from a holistic, process-oriented perspective within the framework of Smart Logistics. A Systematic Literature Review (SLR) was conducted on 142 peer-reviewed studies indexed in the Web of Science (WoS) and Scopus databases and published between 2020 and 2026. The selected studies were analyzed using thematic content analysis to identify the principal operational benefits, implementation challenges, and governance requirements associated with AI adoption in logistics. The synthesized evidence indicates that AI applications are associated with reductions of 10%–30% in logistics operating costs, improvements of 15%–40% in delivery lead times, and increases of 20%–50% in inventory accuracy. The reviewed studies further report improvements of 20%–35% in demand forecasting accuracy, fuel-efficiency gains of 10%–25% through AI-supported vehicle-routing approaches, and increases of up to 30% in warehouse operational throughput. Despite these benefits, AI adoption is constrained by substantial initial investment requirements, inadequate data quality and standardization, cybersecurity vulnerabilities, fragmented and poorly integrated software systems, and shortages of specialized human expertise. Based on the synthesized findings, this study proposes a strategic roadmap and a hybrid Human-in-the-Loop (HITL) governance framework intended to support more coordinated, transparent, and responsible AI integration across logistics and supply chain operations.

Keywords: artificial intelligence, smart logistics, supply chain management, systematic literature review, human-in-the-loop governance, AI integration

1. INTRODUCTION

The continued globalization of production and distribution networks, rapid growth of e-commerce, and evolving customer expectations have substantially increased the complexity of contemporary logistics and supply chain operations [1]. Organizations are no longer concerned solely with coordinating the spatial and temporal movement of goods; they are also expected to reduce operating costs, improve resource utilization, enhance service responsiveness, and incorporate environmentally sustainable logistics practices [2]. Within this context, digital transformation has become an important driver of change in logistics systems. In particular, the integration of Artificial Intelligence (AI), big data analytics, the Internet of Things (IoT), cloud computing, and autonomous technologies is enabling logistics networks to become more connected, adaptive, and data-driven [3].

Recent advances in AI have expanded its application across the planning, execution, and control functions of logistics and supply chain management [4]. AI-based methods are increasingly applied to demand forecasting, vehicle routing, warehouse operations, inventory management, fleet scheduling, procurement, and multi-tier supply chain coordination [5]. In contrast to conventional decision-making approaches that depend largely on historical rules, predefined heuristics, and managerial experience, AI-enabled systems can process large volumes of heterogeneous and rapidly changing data to support predictive and prescriptive decision-making. These capabilities have the potential to improve operational efficiency, reduce decision-making delays, enhance resource allocation, and increase the responsiveness of logistics systems.

Despite the growing body of research on AI applications in logistics, much of the existing literature examines individual technologies or specific operational functions, such as vehicle-routing optimization, demand forecasting, warehouse automation, or inventory control [3]. Consequently, the broader implications of AI adoption across interconnected logistics processes remain insufficiently integrated within a common analytical framework. A process-oriented Smart Logistics perspective requires consideration of interactions among upstream procurement, inventory and warehousing, transportation and distribution, customer service, and reverse logistics. Evaluating these functions in isolation may overlook dependencies among technologies, organizational structures, data infrastructures, and operational decisions.

In addition to potential improvements in operational performance, the adoption of AI introduces a range of socio-technical and organizational challenges. These include limitations in data quality and interoperability, cybersecurity vulnerabilities, difficulties in integrating heterogeneous information systems, shortages of specialized expertise, limited algorithmic explainability, and the risks associated with algorithmic and automation bias. Accordingly, an assessment of AI-enabled logistics should consider not only reported performance improvements but also the organizational and governance conditions required for effective and responsible implementation. A balanced synthesis of these dimensions is particularly important because technological performance alone does not determine whether an AI application can be successfully integrated into a complex supply chain environment.

Against this background, the present study systematically synthesizes the literature on AI integration in logistics and supply chain management from a holistic, process-oriented Smart Logistics perspective. Rather than examining isolated technological applications, the study considers both the operational outcomes associated with AI adoption and the principal socio-technical, organizational, and governance challenges reported in the literature. The analysis is intended to provide an integrated understanding of how AI contributes to major logistics functions and to identify the conditions that may facilitate or constrain its effective implementation.

Accordingly, the study addresses the following research questions:

- **RQ1:** What operational and performance outcomes are associated with AI integration across major Smart Logistics processes, including warehousing, transportation, procurement, inventory management, and customer service?
- **RQ2:** What socio-technical risks, organizational constraints, and implementation barriers affect the effective integration of AI into logistics and supply chain operations?

By addressing these questions, the study seeks to consolidate a fragmented body of research and provide a structured foundation for the subsequent development of an integrated Human-in-the-Loop governance framework for AI-enabled logistics systems.

2. THEORETICAL FRAMEWORK: SMART LOGISTICS AND SMART SYSTEMS INTEGRATION (SSI)

Smart logistics extends traditional supply chain management by integrating digital technologies with physical logistics operations in a coordinated and process-oriented manner. Often associated with concepts such as "New Logistics" and Logistics 4.0, smart logistics is characterized by increasing digitalization, system interconnectivity, automation, data-driven decision-making, and adaptive operational control [3]. Rather than treating individual logistics functions as isolated activities, this perspective emphasizes the integration of information, technologies, and decision processes across the broader supply chain.

A central feature of smart logistics is the socio-technical integration of Artificial Intelligence (AI), the Internet of Things (IoT), and big data analytics [6]. These technologies enable organizations to collect, exchange, and analyze operational data in near real time and to use the resulting information to support predictive, prescriptive, and, in some cases, automated decision-making. Their role therefore extends beyond the digitization of conventional procedures. When effectively integrated, they can support more responsive and adaptive logistics systems capable of adjusting operational decisions to changing demand, inventory conditions, transportation constraints, and other environmental factors [7].

Logistics itself comprises interconnected material, information, and financial flows distributed across multiple organizations and operational functions. Although these flows have historically been managed through relatively separate functional units, digital integration increasingly enables their coordination within interconnected cyber-physical and information systems [8]. This enhanced connectivity can improve visibility and synchronization across procurement, warehousing, transportation, distribution, and customer-service activities. At the same time, greater interdependence can increase systemic exposure to disruptions, because failures in one technological or organizational component may affect other connected processes. Consequently, smart logistics requires governance mechanisms that address not only technological performance but also interoperability, resilience, security, accountability, and human oversight.

Smart Systems Integration (SSI) provides a complementary theoretical perspective for understanding this interconnected environment. The interdisciplinary literature presents different interpretations of the precise boundaries of SSI, but the concept generally concerns the coordinated integration of sensing, communication, data processing, actuation, energy management, and control functions within a unified system architecture [9]. Within this perspective, smart systems combine physical components with computational and communication capabilities in order to monitor operating conditions, exchange information, and support responsive control.

According to the framework associated with the European Technology Platform on Smart Systems Integration (EPoSS), smart systems integrate multiple technological functions, including sensing, data communication, energy management, actuation, and real-time control [10]. Applied to logistics and related industrial environments, SSI principles provide a basis for connecting intelligent devices, information systems, automated equipment, and decision-support mechanisms across operational processes. Such integration is particularly relevant to automated production environments, warehouses, transportation systems, and distribution networks, where coordinated information exchange can influence both operational decisions and managerial control [11].

In the context of this study, Smart Logistics and SSI are therefore treated as complementary concepts. Smart Logistics provides the process-oriented perspective through which AI applications are examined across logistics and supply chain functions, whereas SSI emphasizes the technological and organizational integration required to connect these applications within a coherent operational system. Together, these perspectives provide the theoretical basis for evaluating both the performance benefits of AI integration and the socio-technical risks and governance requirements examined in the subsequent sections.

3. METHODOLOGY

This study employs a Systematic Literature Review (SLR) methodology to identify, synthesize, and critically evaluate the reported operational effects, performance outcomes, and structural challenges associated with the integration of Artificial Intelligence (AI) into Smart Logistics and supply chain systems [12]. The review was designed to capture both the performance-related benefits of AI applications and the socio-technical and organizational constraints associated with their implementation.

3.1. LITERATURE SEARCH STRATEGY

The literature search was conducted using two major bibliographic databases, Web of Science (WoS) and Scopus. The review covered studies published between January 2020 and March 2026. The search strategy combined terms related to artificial intelligence, Smart Logistics, and supply chain management using Boolean operators.

The search expression was structured as follows:

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("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning")
AND ("smart logistics" OR "intelligent logistics" OR "logistics 4.0")
AND ("supply chain" OR "logistics management" OR "warehouse automation")
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This combination of search terms was intended to capture studies addressing AI-enabled decision-making and automation across a broad range of logistics and supply chain activities.

3.2. ELIGIBILITY CRITERIA

Studies were selected according to predefined inclusion and exclusion criteria.

Inclusion Criteria. Studies were considered eligible if they satisfied the following conditions:

1. the study was published as a peer-reviewed journal article between 2020 and 2026;
2. the full text was available in English;
3. the article was indexed in Web of Science (SSCI or SCI-E) or in a Q1/Q2 Scopus-indexed journal; and
4. the study reported empirical, quantitative, conceptual, or theoretical evidence concerning AI-related performance outcomes, operational applications, implementation challenges, or risks within logistics and supply chain contexts.

Exclusion Criteria. Studies were excluded when they met one or more of the following conditions:

1. the publication was a book review, editorial, conference proceeding, white paper, or other non-journal document;
2. the study examined AI applications outside the industrial logistics or supply chain domain, such as military operations or clinical healthcare; or
3. the publication was descriptive, non-peer-reviewed, or lacked sufficient evidence relevant to the operational performance or implementation of AI in logistics.

3.3. SCREENING AND STUDY SELECTION

The initial database search identified 840 potentially relevant publications. Following title and abstract screening, 310 articles were retained for further assessment. These studies were subsequently evaluated at the full-text stage against the predefined eligibility criteria. After completion of the full-text assessment, 142 studies satisfied the inclusion requirements and were retained for the final synthesis.

The study-selection process can therefore be summarized as follows:

$$840 \longrightarrow 310 \longrightarrow 142,$$

where 840 records were identified through database searching, 310 articles remained after title and abstract screening, and 142 studies were included after full-text eligibility assessment.

3.4. DATA EXTRACTION AND THEMATIC SYNTHESIS

The final set of 142 studies was subjected to qualitative content analysis and thematic coding. The extracted evidence was organized according to the major operational domains of Smart Logistics, including demand forecasting, inventory management, warehousing, transportation and routing, procurement, customer service, and broader supply chain governance.

The synthesis focused on two principal analytical dimensions corresponding to the research questions of the study. First, reported operational and performance outcomes associated with AI adoption were identified and grouped by logistics function. Second, the principal socio-technical, organizational, technological, and governance-related barriers to AI implementation were categorized thematically. The resulting evidence was subsequently organized into a structured analytical matrix to facilitate comparison across logistics processes, AI applications, reported performance outcomes, and implementation risks.

4. RESULTS AND DISCUSSION

The thematic synthesis of the reviewed literature indicates that the effects of AI integration in Smart Logistics can be organized into two broad dimensions. The first concerns operational and performance improvements across major logistics functions, including demand forecasting, inventory management, warehousing, transportation, and customer service. The second concerns socio-technical, organizational, and technological risks that may limit the effectiveness and sustainability of AI implementation. These two dimensions correspond directly to RQ1 and RQ2, respectively.

4.1. FUNCTIONAL AND PARAMETRIC ENHANCEMENTS OF AI INTEGRATION (RQ1)

Demand Forecasting, Inventory Management, and Procurement. AI-based forecasting methods have increasingly been applied to logistics environments characterized by non-linear demand patterns, multiple explanatory variables, and rapidly changing market conditions. Conventional time-series methods, including moving averages and Holt–Winters exponential smoothing, may be limited when such relationships are complex or highly dynamic. The reviewed literature indicates that deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, together with gradient-boosted methods such as XGBoost, can improve demand forecasting accuracy by approximately 20%–35% in the examined applications [13]. Improved forecasting accuracy can, in turn, support inventory planning and reduce information distortions across multi-echelon supply chains, thereby contributing to the mitigation of the Bullwhip Effect.

AI-based inventory management systems also combine computer vision, sensor technologies, and Radio-Frequency Identification (RFID) to improve the visibility and reconciliation of physical stock. Across the reviewed studies, such applications are associated with reported improvements of approximately 20%–50% in inventory accuracy. These technologies may additionally support procurement and replenishment decisions by providing more timely information on stock availability, consumption patterns, and anticipated demand.

Cyber-Physical Warehousing and Intelligent Warehouse Management Systems. AI integration has also contributed to the development of increasingly automated and data-driven warehouse environments. Within intralogistics operations, AI-supported Robotic Process Automation (RPA), Autonomous Guided Vehicles (AGVs), computer vision, and intelligent Warehouse Management Systems (WMS) have been associated with improvements in operational throughput of up to 30% [14].

Deep reinforcement learning and related optimization approaches can further support dynamic storage allocation, order-picking sequences, and warehouse slotting decisions. By continuously adjusting operational policies to changing inventory and order conditions, these methods can reduce unnecessary travel distances, improve space utilization, and shorten order-processing times. The literature also reports reductions in material-handling and picking errors, although the magnitude of these improvements varies according to warehouse configuration, technology maturity, and implementation context.

Freight Transportation, Last-Mile Distribution, and Routing Optimization. Transportation represents another major area in which AI-based optimization methods have been extensively investigated. Techniques such as Genetic Algorithms, Ant Colony Optimization, machine learning, and Deep Reinforcement Learning have been applied to Vehicle Routing Problems (VRPs), fleet allocation, and last-mile distribution planning.

These approaches can incorporate real-time traffic information, weather conditions, delivery requirements, vehicle capacities, and other operational constraints into routing decisions. The reviewed literature reports reductions of approximately 10%–25% in fuel consumption and associated CO_2 emissions in selected AI-supported routing applications [15]. Reported improvements in transportation and delivery lead times range from approximately 15% to 40%. The magnitude of these gains, however, depends on factors such as network structure, fleet characteristics, traffic conditions, optimization objectives, and the availability and quality of real-time data.

Customer Service and Relational Service Quality. Natural Language Processing (NLP), conversational AI systems, and Large Language Model (LLM)-based agents are increasingly being incorporated into logistics-related customer-service functions. These systems can automate routine inquiries, provide shipment-status information, support complaint handling, and improve the availability of customer assistance. Some applications report substantial reductions in response latency, including near-real-time or millisecond-level responses for automated queries [16].

Predictive Estimated Time of Arrival (ETA) models represent another important application of AI in customer-facing logistics operations. By integrating historical delivery data with traffic, weather, route, and vehicle information, such models can reduce uncertainty in estimated delivery times and improve communication with customers. More accurate ETA prediction may therefore contribute to improved service reliability and customer satisfaction in urban last-mile distribution [17].

Taken together, these findings suggest that AI can contribute to operational improvements across several logistics functions. Nevertheless, the reported performance gains should be interpreted in relation to the particular datasets, technological configurations, organizational settings, and evaluation methods used in the underlying studies.

4.2. SOCIO-TECHNICAL RISKS AND STRUCTURAL IMPEDIMENTS OF AI INTEGRATION (RQ2)

The operational benefits associated with AI adoption are accompanied by a range of socio-technical and organizational risks. The reviewed literature identifies cybersecurity exposure, limited algorithmic transparency, automation bias, fragmented system architectures, data-related bias, and inadequate organizational coordination as recurring challenges.

Cybersecurity and Cascading Vulnerabilities. Highly interconnected logistics environments increasingly depend on cloud-based platforms, IoT devices, enterprise information systems, and externally connected supply chain partners. Although this connectivity improves visibility and coordination, it also expands the potential cybersecurity attack surface

[18]. A security incident originating in a comparatively weak node, such as a subcontractor or legacy information system, may propagate through interconnected platforms and affect other components of the supply chain.

Such cascading vulnerabilities can compromise Enterprise Resource Planning (ERP), WMS, transportation-management, and data-sharing systems. Potential consequences include unauthorized data manipulation, operational disruption, loss of information integrity, and interruption of physical supply processes. Cybersecurity should therefore be treated as an integral component of AI-enabled logistics governance rather than as an isolated technical function.

Algorithmic Opacity and Automation Bias. The complexity of some advanced machine-learning and deep-learning models creates challenges for interpretation and explainability [19]. When operational personnel cannot understand how or why an AI system has generated a particular recommendation, two contrasting behavioral responses may emerge.

Algorithmic rejection occurs when users disregard potentially useful AI-generated recommendations because they lack confidence in the system or cannot interpret the reasoning underlying its outputs. In contrast, *automation bias* occurs when users place excessive confidence in automated recommendations and fail to exercise adequate human judgment or verification [20]. In logistics environments, either response can reduce the effectiveness of AI-assisted decision-making. Excessive rejection limits the practical value of intelligent systems, whereas excessive reliance may allow incorrect routing, inventory, procurement, or scheduling recommendations to propagate through operational processes.

The "Frankenstein Effect" and System Fragmentation. Another challenge concerns the fragmented adoption of AI technologies across different organizational units or supply chain partners. The literature describes situations in which procurement, warehousing, transportation, and fulfillment functions independently implement heterogeneous AI tools without a coordinated enterprise-level architecture [21]. This condition may be characterized as a "Frankenstein Effect," in which individually functional technologies collectively form an inefficient and poorly integrated information environment.

The resulting incompatibilities may generate isolated data repositories, inconsistent standards, duplicated functions, and difficulties in exchanging information across systems. Consequently, technological investment does not necessarily produce system-wide improvement unless individual AI applications are integrated through appropriate interoperability standards, data governance practices, and organizational coordination mechanisms.

Algorithmic Bias and Overfitting. AI systems trained on historical data may reproduce or amplify patterns, inefficiencies, and biases embedded in those datasets [22]. For example, historical differences in fulfillment performance across geographic regions, supplier groups, or customer segments may influence subsequent algorithmic recommendations if the underlying data are not adequately examined for systematic bias.

A related concern is model overfitting. Systems optimized primarily on historical observations may perform effectively under familiar conditions but respond poorly to structural changes, extreme disruptions, or previously unseen events. This limitation is especially relevant to logistics networks exposed to sudden demand shocks, supply interruptions, geopolitical events, natural disasters, or other low-frequency disruptions. Predictive models developed under relatively stable historical conditions may therefore exhibit reduced reliability when confronted with substantially different operating environments [23].

These findings demonstrate that the successful implementation of AI in logistics depends not only on algorithmic performance but also on data quality, system interoperability, cybersecurity, organizational readiness, human oversight, and governance arrangements. Accordingly, the benefits identified under RQ1 should be considered together with the risks and implementation constraints identified under RQ2.

Table 1. *Synthesis matrix*

Logistics Process Focus Area	Deployed AI Methodology / Algorithms	Parametric & Functional Performance Outcomes (RQ1)	Critical Risks, Constraints, & Structural Impediments (RQ2)	Core Literary Foundations
Demand Forecasting & Inventory Management	LSTM, XGBoost, Random Forest, DeepAR	• 20%–35% increase in demand forecasting accuracy. • 10%–30% reduction in holding costs. • Mitigation of the Bullwhip Effect.	• Epistemic overfitting on historical datasets. • Deficiencies in data governance/standardization. • Vulnerability to severe structural market shocks.	[13]
Cyber-Physical Warehousing (WMS)	Reinforcement Learning, Computer Vision, RPA	• Up to 30% inflation in operational throughput. • Drastic reductions in order picking cycle times. • Near-zero material handling error rates.	• Exorbitant initial capital expenditure (CapEx). • Kinetic/robotic constraints in dynamic, outdoor zones. • Scale-related technological barriers for SMEs.	[14, 24]
Freight Transportation & Fleet Allocation	Genetic Algorithms, Ant Colony Optimization, Deep Q-Networks	• 10%–25% reduction in fuel consumption & CO_2 metrics. • 15%–40% optimization in lead times.	• Distributed legal accountability matrix. • Regulatory/jurisdictional gaps for autonomous fleets. • High dependency on physical infrastructure.	[15]
Customer Relations & Reverse Logistics	NLP, LLM Architectures, Predictive ETA Analytics	• Asymmetric gains in customer satisfaction indices. • 24/7 autonomous query resolution and visibility. • Enhancements in relational service quality.	• The opaque "Black Box" interpretability deficit. • Erosion of customer trust due to loss of human touch. • Severe risk of systemic algorithmic bias.	[26]
Macro Supply Chain Governance	Cloud-Native Multi-Agent AI Ecosystems	• Maximization of multi-tier supply chain visibility. • Real-time, prescriptive risk management.	• The Frankenstein Effect (fragmented software integration). • Cascading cyber vulnerabilities across nodes. • Legal compliance boundaries (GDPR / Cross-border data).	[18, 21, 27]

4.3. PROCESS-BASED SYSTEMIC SYNTHESIS MATRIX

To consolidate the findings associated with RQ1 and RQ2, the reviewed evidence is organized into a process-based synthesis matrix (Table 1). The matrix relates the principal logistics functions to the AI methods applied within each domain, the reported operational and performance outcomes, the corresponding socio-technical and structural risks, and the supporting literature. This structure enables the potential benefits of AI integration to be considered alongside the implementation conditions and risks associated with each logistics process.

5. CONCEPTUAL MODEL PROPOSAL: HUMAN-IN-THE-LOOP (HITL) GOVERNANCE

Building on the operational benefits and socio-technical risks identified in the systematic review, this study proposes a Human-in-the-Loop (HITL) governance framework for AI-enabled logistics systems. The framework is intended to address three recurring challenges identified in the literature: limited algorithmic transparency associated with the "Black Box" phenomenon, excessive reliance on automated recommendations resulting from automation bias, and fragmented technological integration associated with the "Frankenstein Effect." Rather than relying on unrestricted machine autonomy, the proposed approach combines AI-supported decision-making with structured human supervision at critical stages of logistics and supply chain operations.

Within this socio-technical architecture, AI systems are responsible for computationally intensive and data-driven functions, including high-volume data processing, predictive analytics, multivariable optimization, anomaly detection, and routine prescriptive decision support. These capabilities enable AI to process large and heterogeneous datasets more rapidly than conventional manual approaches and to generate recommendations for operational activities such as routing, inventory allocation, demand forecasting, warehouse scheduling, and procurement planning.

Human managers and domain specialists, in contrast, perform supervisory and governance functions that require contextual interpretation, ethical judgment, organizational knowledge, and strategic evaluation. Their role is not to replace automated analysis but to assess whether AI-generated recommendations are operationally appropriate, consistent with organizational objectives, and compatible with relevant ethical, legal, and risk-management requirements. Human intervention is particularly important when algorithmic outputs involve high-impact decisions, unusual operating conditions, conflicting objectives, or circumstances in which the underlying data may be incomplete, biased, or unreliable.

The proposed HITL framework therefore establishes a complementary relationship between machine intelligence and human judgment. AI provides analytical speed, scalability, and computational capacity, whereas human oversight contributes contextual reasoning, accountability, and interpretive control. Maintaining human involvement at critical decision points can reduce the risk of uncritical acceptance of erroneous algorithmic outputs while also limiting unnecessary rejection of useful AI recommendations. This balance is particularly important in interconnected logistics environments, where an inappropriate decision in one operational function may propagate across other components of the supply chain.

From a governance perspective, the HITL model emphasizes three interconnected requirements: transparency, accountability, and system integration. Transparency requires that relevant AI-supported decisions can be interpreted and reviewed by responsible personnel. Accountability requires clear assignment of responsibility for decisions supported or generated by AI systems. System integration requires coordination among AI applications, enterprise information systems, and organizational units in order to reduce technological fragmentation and improve interoperability across logistics processes.

Accordingly, the proposed framework positions human oversight as an integral component of AI-enabled Smart Logistics rather than as an external corrective mechanism. By combining automated analytical capabilities with structured managerial supervision, organizations may improve the reliability, explainability, and organizational alignment of AI-assisted logistics decisions while retaining the operational advantages associated with intelligent automation.

6. CONCLUSIONS, MANAGERIAL IMPLICATIONS, AND FUTURE RESEARCH DIRECTIONS

The increasing digitalization of industrial and commercial activities associated with Industry 4.0 has strengthened the integration of physical operations, digital platforms, and data-driven decision-making across contemporary supply chains [28]. Within this broader transformation, the findings of the present systematic review indicate that Artificial Intelligence (AI) is becoming an important component of logistics planning, execution, and control. Its contribution extends beyond the implementation of individual information technologies, as effective AI adoption requires coordinated changes in organizational processes, data infrastructures, decision-making practices, and human–machine interaction.

The reviewed literature suggests that AI applications can contribute to improvements in demand forecasting, inventory accuracy, warehouse throughput, transportation efficiency, delivery performance, and customer-service responsiveness. At the same time, these benefits are not uniform across all operational contexts and should be interpreted in relation to the quality of the underlying data, the maturity of the deployed technologies, organizational readiness, and the methodological characteristics of the individual studies. Accordingly, the reported performance improvements should be understood as evidence of potential operational gains rather than as universally applicable effects.

The review also identifies several barriers that may constrain the successful implementation of AI in logistics and supply chain environments. These include inadequate data quality and standardization, limited interoperability among heterogeneous information systems, cybersecurity vulnerabilities, insufficient algorithmic transparency, automation bias, shortages of specialized expertise, and fragmented technology adoption across organizational units. These findings demonstrate that technological capability alone is insufficient to ensure successful AI integration. Effective implementation requires corresponding investments in governance, organizational coordination, data management, cybersecurity, and workforce capabilities.

From a managerial perspective, organizations considering AI adoption should therefore prioritize the development of reliable data infrastructures and common standards for information exchange across supply chain partners. Particular attention should be given to semantic interoperability, cybersecurity, model validation, and the integration of AI applications with existing enterprise systems. Organizations should also establish clearly defined responsibilities for the supervision of AI-supported decisions, especially in operational contexts in which inaccurate recommendations may have significant financial, service, safety, or supply continuity consequences.

The Human-in-the-Loop (HITL) governance framework proposed in this study provides one approach to addressing these requirements. Rather than pursuing unrestricted automation, the framework combines the analytical and computational capabilities of AI with human supervision at critical decision points. Such an approach may help organizations maintain accountability, contextual judgment, and interpretability while benefiting from the speed and scalability of AI-supported analysis. The effectiveness of this model, however, requires further empirical evaluation across different logistics environments.

The principal limitation of the present study is its reliance on secondary evidence retrieved from the Web of Science and Scopus databases. The findings are therefore dependent on the scope, methodological quality, and reporting practices of the studies included in the review. In addition, the reported quantitative performance ranges were synthesized from heterogeneous operational settings, technologies, datasets, and evaluation procedures. Direct comparison among these values should consequently be undertaken with caution.

Future research should validate the reported relationships and performance outcomes using primary empirical data collected across different supply chain configurations and industry contexts. Comparative studies involving business-to-business (B2B), business-to-consumer (B2C), and direct-to-consumer (D2C) logistics environments may provide a clearer understanding of the conditions under which AI generates measurable operational benefits. Quantitative approaches, including Structural Equation Modeling (SEM), longitudinal analysis, controlled field studies, and multi-case research designs, may also be employed to examine the relationships among AI capability, organizational readiness, governance mechanisms, and logistics performance.

Further research is also needed to evaluate the proposed HITL governance framework empirically, particularly with respect to decision accountability, algorithmic explainability, cybersecurity resilience, employee acceptance, and interoperability across organizational boundaries. Such investigations would help move the discussion beyond technological performance toward a more comprehensive understanding of the organizational and governance conditions required for responsible and sustainable AI integration in Smart Logistics.

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