# Artificial Intelligence in Supply Chain Management: Perspectives for Integration within the Physical Internet Paradigm

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***Abstract:*** *This study conducts a scoping literature review to examine the application of Artificial Intelligence (AI) in Supply Chain Management (SCM) and explores its potential integration within the Physical Internet (PI) paradigm. Analyzing 48 empirical articles published between 2020 and 2025, the review identifies five thematic clusters: demand forecasting, transportation optimization, terminal operations, risk management, and urban logistics. Results demonstrate that although AI enhances efficiency and decision-making across supply chains, current implementations are predominantly siloed and lack the interoperability required for PI adoption. The articulation between SCM, AI, and PI is made explicit by highlighting how modular, scalable, and decentralized logistics infrastructures demand intelligent systems. The study reveals critical research opportunities to develop modular, explainable, and sustainable AI models aligned with PI principles, thereby paving the way for autonomous, hyperconnected, and environmentally responsible logistics networks.*

***Keywords:*** *Artificial Intelligence, Supply Chain Management, Physical Internet, Optimization, Sustainability, Scoping Literature Review.*

***Physical Internet (PI) Roadmap Fitness****: Select the most relevant area(s) for your paper according to the PI roadmaps adopted in Europe and Japan: ☐ PI Nodes (Customer Interfaces, Logistic Hubs, Deployment Centers, Factories), ☐ Transportation Equipment, ☐ PI Networks, ☐ System of Logistics Networks, ☐ Vertical Supply Consolidation, ☐ Horizontal Supply Chain Alignment, ☒ Logistics/Commercial Data Platform, ☒ Access and Adoption, ☐ Governance.*

***Targeted Delivery Mode-s****: ☒ Paper, ☐ Poster, ☐ Flash Video, ☐ In-Person presentation*

## 1 Introduction

The Artificial intelligence (AI) has emerged as a transformative agent in the field of supply chain management (SCM), significantly reshaping the operations that take place in supply chains globally. AI technologies, such as machine learning, predictive analytics, autonomous systems, and natural language processing, are progressively being integrated into SCM processes for the purpose of optimizing operations, improving decision making, and increasing efficiency (Cannas et al., 2024; Singh Chadha & Venkatadri, 2024). Numerous studies have reported successful applications of AI in SCM in various tasks, such as demand forecasting, inventory management, purchasing, logistics, and risk management, achieving significant improvements in operational efficiency and cost reductions (Gedam et al., 2023; Shahzadi et al., 2024). In this context, the integration of AI into SCM is no longer perceived merely as a passing trend, but as a strategic imperative for organizations to remain competitive in today's dynamic environments (Gedam et al., 2023).

Despite these advances and benefits, the widespread adoption of AI faces structural barriers in traditional supply chains. There are persistent challenges related to data quality, technological complexity, cybersecurity, and organizational resistance to change (Hangl et al., 2023). Legacy and rigid technology infrastructures, in particular, make it difficult to integrate AI solutions with existing systems, creating friction when incorporating new digital tools (Shrivastav, 2022). In addition, it has been observed that data is often siloed within organizational departments, making it difficult to access and integrate information (Pan et al., 2021). The fragmented and multi-actor nature of traditional logistics networks implies disparate and poorly interoperable data sources (Delgado et al., 2025). This lack of interoperability, resulting from inconsistent technology standards and heterogeneous systems, impedes the flow of information along the chain and makes it difficult to fully leverage AI capabilities. These structural barriers, imposed by the very nature of traditional logistics networks, constitute a significant obstacle to AI-driven transformation in the context of conventional SCM (Shrivastav, 2022). This challenge underscores the need to rethink the architecture of supply chains to facilitate the effective integration of AI into logistics management. These limitations highlight the need for a more adaptive logistics infrastructure, leading to the emergence of the Physical Internet (PI) paradigm.

In this context, the PI paradigm emerges as a disruptive vision with the potential to overcome the structural limitations of current supply chains (Cortes-Murcia et al., 2022; Safwen & Németh, 2021). The PI proposes an open, hyper-connected, and modular logistics system, inspired by the Internet's operational principles (Montreuil, Ballot, et al., 2012). In this paradigm, goods are transported and stored through interoperable networks using standardized containers and common protocols. According to Montreuil et al., (2012) PI is defined as "an open global logistics system based on physical, digital and operational interconnectivity through encapsulation, interfaces, and protocols." The underlying philosophy of hyperconnectivity is predicated on the universal integration of all actors, facilities, and means within the supply chain. The concept of modularity, on the other hand, is exemplified by the implementation of interchangeable standard containers and components, thereby facilitating logistics systems that are more efficient and flexible, akin to the plug-and-play functionality of the Internet (Meller et al., 2012). This paradigm aspires to create logistics networks that are as seamless and transparent as the digital Internet, thereby enabling the frictionless exchange of goods and information across multiple organizations.

At a conceptual level, the PI's principles align closely with the requirements of AI in SCM. The proposed hyper-connected and open logistics ecosystem would generate substantial volumes of integrated data and end-to-end visibility, which are ideal conditions for applying machine learning algorithms and predictive analytics to optimize network-wide decisions. The modularity and standardization of IP would simplify the integration of autonomous systems (e.g., intelligent vehicles or robots) operating in a coordinated manner at different nodes of the chain (Gumzej, 2023). The integration of AI with a PI-style infrastructure holds great promise in enhancing the intelligence, agility, and comprehensive optimization of supply chains. This convergence unites the capabilities of digital intelligence with a physical network designed for interoperability. However, it is important to acknowledge that academic research integrating AI into the PI framework in a consolidated manner is still in its infancy.

Recent contributions, as Singh Chadha & Venkatadri, (2024) and (Münch et al., 2024), have initiated the exploration of the intersection between AI and PI. Singh Chadha and Venkatadri provided systematic analysis focusing exclusively on AI applications within the PI framework. Similarly, Münch et al. offered a comprehensive bibliometric mapping of the PI research landscape, highlighting the emergence of AI among other enabling technologies but without performing an in-depth analysis of AI’s operational integration into PI systems. While these studies represent important milestones, they approach AI either as a direct contributor to PI implementation without broader SCM context (Singh Chadha and Venkatadri), or as one technological trend among many without detailed articulation of its transformative mechanisms.

This paper aims to bridge this gap by conducting a Scoping Literature Review to map the current landscape of AI applications in SCM and to explore how these developments align with, and can support, the implementation of the PI paradigm. While prior literature explores AI and the PI independently, this paper aims also to synthesize both domains through a systematic review, identifying synergies and future research opportunities.

The remainder of this paper is organized as follows: Section 2 outlines the key concepts related to AI in SCM and the PI framework. Section 3 details the methodology used to conduct the systematic review. Section 4 presents and analyzes the results. Section 5 discusses the implications of the findings. Finally, Section 6 concludes the paper and suggests avenues for future research.

## 2 Key concepts

This section introduces two foundational concepts, Supply Chain Management and the PI, that underpin the integration of artificial intelligence into next-generation logistics systems.

### 2.1 Evolution Supply Chain Management (SCM)

In recent decades, Supply Chain Management (SCM) has transitioned from a linear, functionally isolated discipline to a dynamic and system-wide coordination mechanism that governs the flow of goods, information, and value across interconnected global networks (Ivanov, 2022; Fang, Fang, Hu, & Wan, 2022). This evolution reflects a paradigmatic shift in how firms conceptualize and operationalize their logistics and production systems, moving from cost-centered, reactive models to proactive, resilient, and customer-responsive architectures (Büyüközkan & Göçer, 2018; Núñez-Merino, Maqueira-Marín, Moyano-Fuentes, & Castaño, 2022). SCM now encompasses the integration of strategic planning, real-time execution, and continuous adaptation across diverse actors, from raw material suppliers to end-users, within a complex, and often geographically dispersed, ecosystem (Kajba, Jereb, & Obrecht, 2023).

Modern SCM is not only concerned with operational efficiency but also with the alignment of supply chain activities with broader business goals, including sustainability, agility, and digitalization. This requires the orchestration of upstream and downstream processes, such as demand forecasting, procurement, production scheduling, transportation management, inventory control, and reverse logistics (Ma, Zhang, You, & Tian, 2025). The growing volatility of global markets, together with environmental and geopolitical disruptions, has revealed the limitations of rigid, siloed supply chains and has underscored the urgency of developing intelligent, interconnected systems capable of autonomous response and systemic resilience (Bui et al., 2021; Ivanov, 2022).

While modern SCM emphasizes integration, agility, and digital transformation, it remains constrained by traditional logistics infrastructures. The PI emerges as a potential solution to these constraints.

### 2.2 Physical Internet paradigm

The Physical Internet (PI) constitutes a transformative logistics paradigm inspired by the digital Internet's architecture and principles. Initially conceptualized by Montreuil, Ballot, et al., (2012) the PI reimagines the movement and management of physical goods through open, standardized, and interconnected networks. It seeks to overcome the inefficiencies of conventional logistics systems, which are often siloed, rigid, and asset-centric. Instead, the PI proposes an infrastructure where modular logistics units (π-containers) move seamlessly across interoperable networks (π-nodes and π-handlers), coordinated through universal routing protocols and real-time data synchronization, mirroring how data packets circulate through the Internet.

At the heart of the PI is a commitment to systemic modularity, decentralization, and dynamic orchestration. Its operational logic is rooted in standardized physical elements, such as PI-transporters, conveyors, and containers, interconnected through intelligent hubs and governed by protocols that enable continuous flow optimization. This structural logic fosters asset-sharing, multimodal transport efficiency, and collaborative logistics, while supporting objectives such as environmental sustainability and economic resilience. Rather than functioning as isolated supply chains, PI-based systems operate as open, distributed ecosystems capable of self-organization and adaptive reconfiguration.

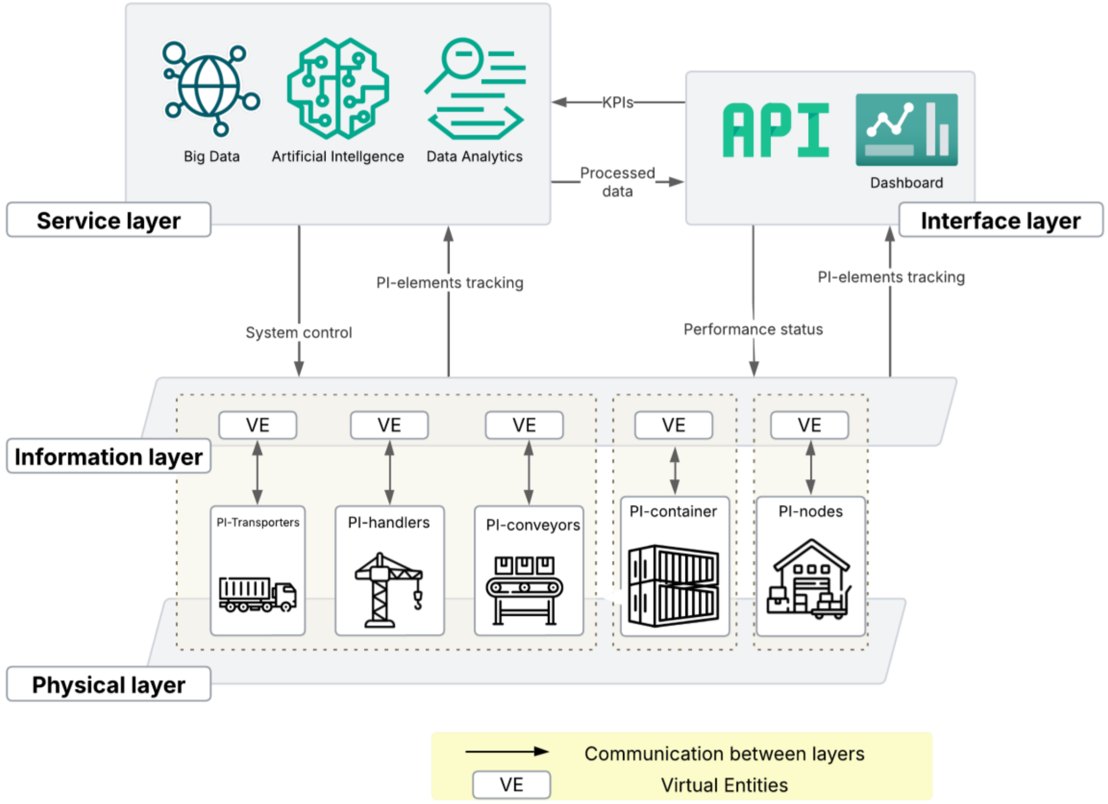

*Figure 1:Functional architecture of PI*

A defining feature of the PI is its layered architecture, which mirrors the protocol stack of the digital Internet and enables separation of concerns between physical operations and intelligent services (see Figure 1). The four core layers include: (1) the Physical Layer, where tangible logistics entities operate; (2) the Information Layer, which encapsulates these physical components as Virtual Entities (VEs) and ensures traceability and control; (3) the Service Layer, where advanced functions—such as AI-driven forecasting, system control, and data analytics—are executed; and (4) the Interface Layer, which mediates access through APIs and dashboards for human and machine agents. Within this layered model, AI plays a transversal role, particularly in the Service Layer, by enabling cognitive automation, optimization of routing and scheduling, and real-time orchestration across the network. The Interface Layer standardizes the interaction with external stakeholders and supports transparency, monitoring, and real-time decision-making. Together, these layers enable a flexible, intelligent, and scalable logistics network where physical and digital elements are fully synchronized.

## 3 Scoping Literature Review

To address the objectives of this study, a Scoping Literature Review was conducted. This methodological approach is particularly suited for emerging and interdisciplinary fields, as it allows for the systematic mapping of existing research, the identification of conceptual boundaries, and the recognition of knowledge gaps (Arksey & O'Malley, 2005). In this case, the scoping review method was selected to capture the breadth and diversity of AI applications in SCM and to explore how these applications intersect with the principles of the PI. Given the exploratory nature of the topic and the fragmented state of current literature linking AI and PI, this approach supports synthesis that responds directly to the three guiding research questions: (1) What are the main AI applications in SCM? (2) How do these applications align with PI principles? and (3) What challenges and gaps exist in AI adoption for PI-enabled supply chains? The scoping review provides a foundation for identifying both established practices and emerging research directions to guide the design and implementation of intelligent, modular, and sustainable logistics systems aligned with the PI paradigm.

To ensure the relevance and thematic coherence of the literature reviewed, the scoping study employed a structured Boolean query approach. The query was designed by clustering key terms, as shown in Table 1, into three conceptual domains: (1) AI techniques, (2) supply chain processes, and (3) operational applications. This structure allowed the search to capture a wide but thematically consistent body of research at the intersection of AI and SCM. By combining clusters using logical "AND" operators, the query retrieved only those articles that addressed all three dimensions simultaneously. Additional filters were applied to restrict the results to peer-reviewed journal articles published in English between 2020 and 2025 and within relevant disciplines.

| Cluster | Keywords Included |
|---|---|
| **1. AI Techniques** | "artificial intelligence", "AI", "machine learning", "deep learning", "neural network*", "computational intelligence" |
| **2. Supply Chain Scope** | "supply chain*", "supply chain management", "SCM", "supply chain", "logistics", "procurement", "distribution", "Physical Internet" |
| **3. Operational Functions** | "optimization", "management", "forecasting", "planning", "automation", "use case*", "implementation", "adoption", "integration" |

*Table 1: Search terms*

A clearly defined set of inclusion and exclusion criteria was applied throughout the review process. Studies were considered eligible if they explicitly defined or empirically evaluated an AI application and focused on one or more core supply chain functions, such as procurement, logistics, inventory, or distribution. Articles were excluded if they were editorials, conference proceedings, or tertiary reviews, or if they lacked a clear methodological foundation, adopted a non–supply chain perspective, presented opinion-based arguments without empirical grounding, or treated AI as a secondary or peripheral topic. This filtering strategy ensured the selection of literature that directly addressed the central research questions of the study

The selection process was carried out in two stages. In the first stage, titles, abstracts, and keywords of all retrieved articles were screened and categorized as included, excluded, or "uncertain" based on the predefined criteria. In the second stage, the full texts of all articles marked as included or uncertain were thoroughly reviewed. At this point, each study was reassessed to confirm its eligibility, and a definitive inclusion decision was made. Studies without accessible full texts were excluded from the final selection. This two-step screening process ensured consistency and transparency in the identification of relevant contributions to the field. Figure 2 provides a visual summary of the article selection procedure, following the structure of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework.

# 4 Results and analysis

After applying the selection filters, the final dataset of relevant studies was systematically analyzed. The following section presents the results and key patterns derived from this literature, organized thematically. The systematic literature review underpinning this study was conducted across two major scientific databases, Scopus and IEEE Xplore. After applying defined inclusion and exclusion criteria a total of 48 articles were retained for detailed analysis.

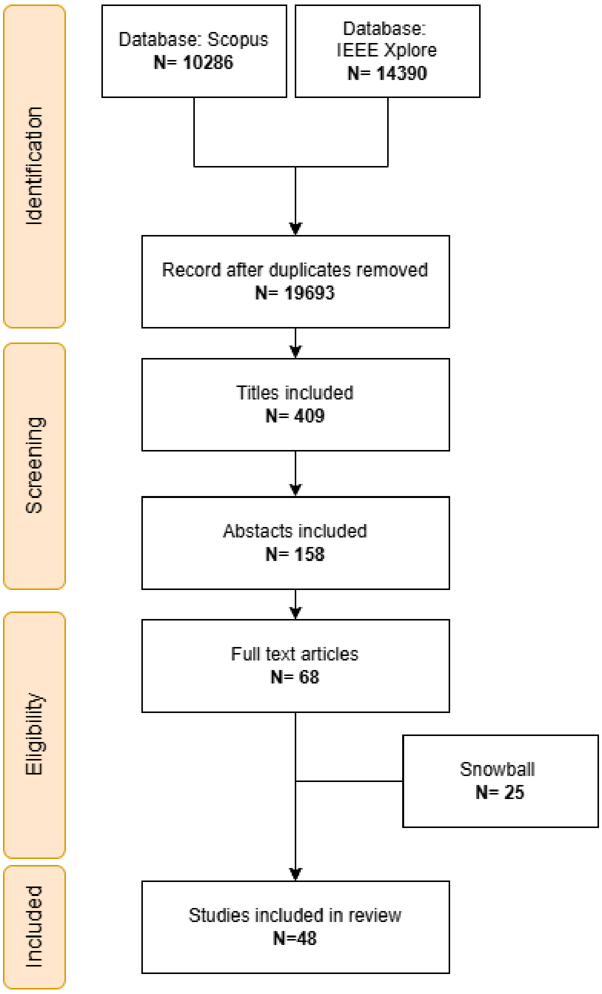

*Figure 2: Literature review process*

The following sections are organized around the three research questions guiding this review. Section 4.1 identifies and categorizes the main AI applications in SCM into thematic clusters. Section 4.2 evaluates how these applications align with the core principles of the PI, such as modularity, decentralization, and interoperability. Section 4.3 discusses the key challenges and research gaps that hinder AI's integration into PI-enabled supply networks.

## 4.1 RQ1: What are the Main AI Applications in SCM?

To map the AI applications in SCM, the literature was analyzed and organized into five major thematic clusters:

- Demand and Throughput Forecasting, encompassing predictive models for flow estimation and capacity planning;
- Transportation and Route Optimization, focused on AI-driven routing, scheduling, and multi-modal coordination;
- Terminal and Warehouse Operations, covering applications related to stacking, congestion control, and facility-level decision-making;
- Disruption and Risk Management, which includes models for predictive maintenance, delay propagation, and safety analytics; and

- Urban Mobility and Facility Identification, reflecting studies that apply AI to urban transport dynamics, commuting patterns, and logistics infrastructure mapping.

The next subsections go into further explanation about the debate areas.

### 4.1.1 Demand Forecasting and Predictive Analytics

AI is increasingly applied in SCM to enhance demand forecasting and throughput estimation. Machine learning (ML) and deep learning (DL) models have demonstrated superior predictive accuracy compared to traditional methods, particularly in dynamic and time-sensitive operational contexts. Ribeiro et al., (2022) apply ensemble learning models, such as XGBoost and random forests, to forecast short-term warehouse energy consumption, improving inventory and energy management responsiveness. Similarly, Mamede et al., (2023) show that Long Short-Term Memory (LSTM) networks outperform classical ARIMA models in predicting transportation demand across Brazilian distribution centers.

Beyond short-term operational gains, AI forecasting is also supporting strategic decision-making. De Nailly et al., (2024) employ deep probabilistic models to estimate pedestrian flows in multimodal hubs, while Cuong et al., (2022) integrate ARIMA with artificial neural networks (ANN) to model seaport throughput variations post-COVID-19.

### 4.1.2 Transportation & Route Optimization

DL and reinforcement learning (RL) models dominate recent developments, enabling more effective route planning and rescheduling compared to traditional heuristics. For instance, Ding et al., (2023) propose a deep RL model for disruption recovery in airline operations, while Guo et al., (2022) apply a convolutional neural network (CNN)-BiLSTM architecture to predict freight train travel times with high temporal accuracy. Aljanabi et al., (2024) further enhance multimodal travel time estimation by combining singular value decomposition with CNNs and recurrent neural networks, and Pineda-Jaramillo, (2023)demonstrates the utility of gradient boosting models like CatBoost in identifying delay causes in European freight rail networks.

In parallel, AI is increasingly supporting strategic infrastructure forecasting. Asadi et al., (2024) compare physical models such as SWAT+ with ML approaches, including support vector regression and neural networks, for streamflow forecasting, contributing to resource-aware transport planning. Ensemble methods (Aljanabi et al., 2024) and transfer learning strategies (Guo et al., 2024) are also gaining attention to enhance prediction performance under cross-domain and data-scarce conditions.

### 4.1.3 Terminal and Warehouse Operations

The application of AI to terminal and warehouse operations has become a prominent stream within SCM, focusing on optimizing spatial layout, operational efficiency, and infrastructure sustainability in containerized environments. ML and optimization models are increasingly used to support decision-making in container stacking, berth scheduling, and yard resource allocation. Ambrosino & Xie, (2024) propose a hybrid approach integrating spectral clustering with tactical optimization to reduce yard congestion and container rehandling. Similarly, Zhang, (2023) introduces a hybrid architecture combining dynamic programming with self-attention-based neural networks to enhance stacking decisions, achieving superior performance over classical heuristics. In the domain of congestion management, Jahangard et al., (2025) develop an integrated ML-optimization framework to forecast port congestion and improve container flow management, while Yasuda et al., (2024) apply real-time tracking data within ML models to support operational decision-making.

### 4.1.4 Disruption and Risk Management

Managing risk and disruption has become a frontier AI application in modern, interconnected supply chains. Recent research increasingly emphasizes predictive models and robust optimization frameworks as essential tools for anticipating failures, supporting contingency planning, and ensuring operational continuity during crises. or instance, Wang et al., (2022) employ gradient boosting techniques to forecast broken rail incidents in U.S. freight networks, providing a basis for predictive maintenance planning. In high-speed rail systems, Huang, Lessan, et al., (2020) develop a Bayesian network model capable of forecasting delay propagation with over 90% accuracy, supporting proactive disruption management.

AI applications are also enhancing operational safety and situational awareness. Atak and Arslanoğlu, (2022) propose supervised ML models to predict marine terminal accidents using operational and contextual datasets, enabling improved risk classification for port authorities. Similarly, Alvarellos et al., (2021) develop an ML-based model to forecast moored ship movements under varying environmental conditions, providing early warnings to prevent collisions and structural damage.

#### *4.1.5 Urban Mobility and Facility Identification*

In the context of last-mile delivery and transport node design have become important areas for AI applications in SCM. Recent models focus on forecasting travel times, analyzing commuter flows, and reorganizing spatial infrastructure to enhance logistics performance. Nejadshamsi et al., (2025) propose a hybrid Graph Convolutional Network–Graph Attention Network model to predict commuting flows across urban networks, improving the adaptability of last-mile logistics. De Beer & Joubert, (2024) utilize GNSS-vehicle data and supervised learning to map the evolution of freight facility locations, offering insights into urban logistics infrastructure dynamics. Pei & Yu, (2023) introduce the PAC algorithm to reconfigure public transport station placements based on mobility patterns, achieving over 20% improvement in accessibility and modular layout efficiency. Having mapped the current landscape of AI applications in SCM, the next subsection evaluates how these innovations align with the core principles of the PI.

### 4.2 RQ2: How do Current AI Applications Align with Physical Internet Principles?

The PI paradigm is built on four foundational operational principles: modularity, interoperability, decentralization, and openness. To realize PI, logistics systems must be able to function through standardized, modular units; enable real-time information and asset sharing across independent actors; operate via decentralized control mechanisms; and foster open, network-wide collaboration. Certain AI applications demonstrate strong potential to support key PI principles, particularly in enhancing responsiveness and system reactivity. AI-driven forecasting models (de Nailly et al., 2024; Ribeiro et al., 2022) significantly improve real-time demand prediction and throughput estimation, contributing to the dynamic adaptability needed in modular, hyperconnected logistics systems. Similarly, advances in facility reconfiguration, such as the PAC algorithm for transport node optimization (Pei & Yu, 2023), embody modular thinking by enabling infrastructure elements to adapt dynamically to changing mobility patterns. These developments align well with PI's emphasis on modular, flexible network operations.

However, despite these promising areas, the majority of current AI applications exhibit only partial alignment with the full operational vision of the PI paradigm. Transportation and routing optimization models (Ding et al., 2023; Guo et al., 2022) improve operational efficiency under dynamic conditions, reinforcing adaptability at the network level. However, these models often rely on centralized control structures and full system visibility, conflicting with PI's decentralization objectives. Similarly, container terminal optimization frameworks (Ambrosino & Xie, 2024; Jahangard et al., 2025) enhance local modular performance but typically optimize isolated facilities without standardizing interfaces for cross-terminal collaboration, limiting interoperability across the broader logistics network. While some AI applications support core

PI principles, significant challenges and gaps must be addressed to fully enable PI-driven supply networks.

### 4.3 RQ3: What challenges and gaps exist in AI adoption for PI-enabled supply chains?

Thematic clusters examined in Section 4.1 exhibit common strengths, but also systemic limitations when assessed against PI principles. A common limitation across all clusters is the predominance of firm-centric, siloed architectures. The majority of AI implementations are optimized for single organizations or closed networks, relying on proprietary data, internal control systems, and localized optimization objectives  (Ambrosino & Xie, 2024; Mamede et al., 2023).

Interoperability also remains a major unresolved challenge. Although many AI models demonstrate strong performance within bounded domains, their designs often lack standardized interfaces or open communication protocols necessary for seamless integration. For instance, container terminal optimization systems (Jahangard et al., 2025; Zhang, 2023) and last-mile urban logistics models (Nejadshamsi et al., 2025) typically operate as isolated solutions, optimized for specific environments but disconnected from broader logistics ecosystems. This structural limitation severely restricts the scalability, flexibility, and cross-actor collaboration required for PI-enabled networks (Singh Chadha and Venkatadri, 2024).

Another systemic gap concerns the modularity of decision-making. Although emerging works on dynamic facility placement (Pei & Yu, 2023) and modular stacking optimization (Zhang, 2023) suggest a move toward modular thinking, most AI systems still assume fixed optimization boundaries and stable network topologies, rather than embracing reconfigurability at the decision-making level. This undermines the core principle of dynamic modularity critical to PI architecture.

Finally, governance, transparency, and explainability issues in AI models remain underdeveloped across SCM applications. While predictive maintenance and risk forecasting frameworks (Wang et al., 2022; Atak and Arslanoğlu, 2022) demonstrate high technical potential, few incorporate explainable AI methods or ethical data-sharing mechanisms, which are essential for building trust among multiple logistics actors in an open, decentralized PI network.

Future research should prioritize the development of modular, interoperable AI systems that can be embedded within distributed infrastructures and π-hubs, supporting seamless communication, reusability, and system-wide orchestration across diverse operational environments. Sustainability-focused AI design also remains an underexplored frontier. Although select studies have incorporated environmental criteria, such as emission reduction and circular maintenance planning, these considerations are rarely embedded into the core of AI optimization strategies. There is a timely opportunity to advance models that optimize not only for cost or time, but also the inclusion of social and environmental. This would directly reinforce the long-term vision of the PI as a sustainable, resource-aware logistics system.

## 5 Conclusions

This study has explored the current landscape of AI applications in SCM and examined how these developments align with the foundational principles of the PI. Through a structured scoping literature review, 48 empirical studies were identified, categorized into five thematic clusters: demand forecasting, transportation optimization, terminal operations, risk management, and urban logistics. Each cluster reflects distinct areas where AI is actively enhancing operational efficiency, decision-making, and system responsiveness across the supply chain.

The findings demonstrate that AI is being widely implemented to support key SCM functions such as forecasting, routing, stacking, and disruption detection. These applications increasingly rely on advanced machine learning, deep learning, and hybrid architectures to achieve higher accuracy and adaptability in dynamic logistics environments. Notably, several contributions showcase sophisticated models with measurable impacts on real-world logistics performance. While many of these models are not explicitly designed for PI contexts, they embody principles such as modularity, interoperability, and decentralization, indicating a latent compatibility between current AI capabilities and the PI paradigm.

However, the review also reveals important challenges and gaps that must be addressed to fully realize the potential of AI in PI-enabled supply chains. The majority of existing AI applications are highly localized, often relying on data from specific terminals, regions, or organizations. There is limited evidence of scalable, interoperable AI solutions that can operate across heterogeneous logistics networks or coordinate autonomously across multiple nodes. Additionally, explainability, sustainability, and governance remain underexplored dimensions in the integration of AI with logistics infrastructure.

In light of these findings, future research should focus on developing AI architectures that are not only accurate but also modular, transferable, and compatible with decentralized logistics environments.

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