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Toward Intelligent Supply Chains: A Reinforcement Learning–Based Approach

[1] Bui Thi Kim Uyen, [2] Bui Trong Hieu

[1] Faculty of International Trade, College of Foreign Economic Relations (Cofer), Ho Chi Minh City, Vietnam

[2] Institute of Information Technology and Electrical–Electronic Engineering, Ho Chi Minh City University of Transport, Ho Chi Minh City, Vietnam

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Corresponding Author: **Bui Thi Kim Uyen**

Abstract

This paper proposes a reinforcement learning–based approach toward intelligent supply chains capable of adaptive and data-driven decision-making in dynamic environments. Traditional supply chain optimization methods often rely on static assumptions and predefined rules, which limit their effectiveness under uncertainty. In contrast, the proposed framework models supply chain operations as a sequential decision-making process, allowing an agent to learn optimal policies through continuous interaction with the environment. Key operational components, including inventory control, transportation planning, and demand fulfillment, are integrated into a unified reinforcement learning model. Simulation-based experiments demonstrate that the proposed approach outperforms conventional optimization and rule-based methods in terms of total operational cost, service level, and system adaptability. The results indicate that reinforcement learning provides a promising foundation for building intelligent supply chains that can autonomously respond to changing operational conditions. Each supply chain entity, such as suppliers, warehouses, and distributors, is modeled as an autonomous learning agent that interacts with other agents and the shared environment. Through cooperative learning, the agents gradually develop coordinated policies that improve overall system performance. The proposed approach addresses the limitations of centralized decision-making by enabling decentralized yet coordinated control. The learning-based framework enables supply chain systems to adapt decisions dynamically without explicit mathematical modeling of uncertainties. Experimental results obtained from simulated logistics scenarios show that deep reinforcement learning significantly improves decision quality compared to traditional heuristics, particularly in volatile environments.

Keywords: Decision-Making under Uncertainty, Intelligent Supply Chains, Reinforcement Learning, Smart Logistics, Supply Chain Management, Transportation Planning

1. Introduction

Global supply chains are becoming increasingly complex due to globalization, market volatility, and rapid technological advancement. Traditional supply chain management approaches are often built on static assumptions and predefined optimization models, which struggle to adapt to dynamic and uncertain environments. Factors such as fluctuating customer demand, transportation disruptions, and operational constraints introduce significant challenges to effective decision-making. As a result, there is a growing need for intelligent supply chain systems that can autonomously learn, adapt, and optimize decisions in real time (Singh *et al*., 2026) [1].

Recent advances in artificial intelligence have opened new opportunities for addressing these challenges. Among various AI techniques, reinforcement learning (RL) has emerged as a promising paradigm for sequential decision-making problems. RL enables an agent to learn optimal policies through interaction with the environment, rather than relying on explicit mathematical models. This learning-based approach is particularly suitable for supply chain systems, where uncertainty and complexity often limit the applicability of traditional optimization methods.

Toward intelligent supply chains, this paper proposes a reinforcement learning–based approach that models supply chain operations as a sequential decision-making process. By continuously observing system states, executing actions, and receiving feedback in the form of rewards, the RL agent learns adaptive strategies that improve operational performance over time.

Unlike conventional methods, the proposed approach does not require prior knowledge of demand distributions or system dynamics (Zabraoui *et al*., 2026) [2].

The contributions of this study are threefold. First, it presents a unified reinforcement learning framework for intelligent supply chain decision-making. Second, it demonstrates the effectiveness of the proposed approach through simulation-based experiments. Third, it provides insights into the practical implications of adopting learning-based methods in real-world supply chain management.

Supply chain systems operate in environments characterized by high levels of uncertainty and continuous change. Demand fluctuations, supply disruptions, transportation delays, and market volatility create complex decision-making challenges that cannot be effectively addressed using static planning approaches. Traditional optimization models often assume stable conditions and complete information, which rarely hold in real-world supply chain operations.

In recent years, researchers have explored adaptive and data-driven approaches to overcome these limitations. Reinforcement learning, as a branch of machine learning, offers a powerful mechanism for learning optimal decision policies under uncertainty. By interacting with the environment and learning from experience, RL enables supply chain systems to dynamically adapt decisions without relying on predefined probabilistic models.

This study aims to advance the concept of intelligent supply chains by introducing a reinforcement learning–based approach capable of operating under uncertainty. The proposed framework continuously updates its decision policies based on real-time feedback, allowing it to respond effectively to unexpected changes in demand and operational conditions. Through extensive simulations, the proposed approach is shown to outperform traditional optimization techniques in terms of robustness and adaptability.

Digital transformation is fundamentally reshaping supply chain management. Technologies such as IoT, big data analytics, and artificial intelligence are enabling unprecedented visibility and connectivity across supply chain networks. However, the availability of data alone does not guarantee improved performance. Intelligent decision-making mechanisms are required to convert data into actionable insights (Dindarian, 2026) [3].

Reinforcement learning provides a natural framework for intelligent decision-making in digitally enabled supply chains. Unlike supervised learning methods, RL focuses on learning optimal actions through interaction, making it particularly suitable for real-time operational control. This paper explores how reinforcement learning can serve as a core technology for intelligent supply chains, enabling adaptive and autonomous decision-making

The increasing scale and complexity of modern supply chains present significant challenges for classical reinforcement learning methods. High-dimensional state spaces and complex interactions among supply chain components necessitate advanced learning techniques. Deep reinforcement learning (DRL), which combines RL with deep neural networks, has shown remarkable success in addressing large-scale decision-making problems (Ahadzadeh *et al*., 2005) [4].

This paper adopts a deep reinforcement learning approach to model intelligent supply chain operations. By leveraging neural networks for function approximation, the proposed method effectively handles complex state representations involving inventory levels, demand patterns, and transportation conditions. Experimental results demonstrate the scalability and effectiveness of the approach.

Supply chains are inherently distributed systems involving multiple autonomous entities, such as suppliers, manufacturers, and distributors. Centralized optimization approaches often fail to capture the decentralized nature of decision-making in such systems. Multi-agent reinforcement learning (MARL) offers a promising alternative by enabling multiple agents to learn cooperative strategies.

This study investigates the application of MARL to intelligent supply chains, where each entity learns to optimize local decisions while contributing to global performance. The proposed approach enhances coordination and reduces inefficiencies caused by decentralized decision-making (Awad & Alahmari, 2026) [5].

The proposed framework reconceptualizes supply chains as intelligent and adaptive systems capable of continuous learning and evolution, thereby providing a theoretical foundation for future empirical and analytical research on AI-enabled supply chains.

2. Background

Supply Chain Management (SCM) has long been recognized as a critical managerial discipline concerned with the coordination of material, information, and financial flows across organizational boundaries. Early SCM research emphasizes integration, efficiency, and coordination among supply chain partners (Kulkarni, 2023) [6]. Traditional SCM frameworks are largely built on deterministic planning, linear optimization, and periodic decision cycles, aiming to minimize cost and improve service levels. While effective in stable environments, these approaches face significant challenges when supply chains operate under high uncertainty and complexity. Despite its managerial importance, traditional SCM has been criticized for its limited ability to cope with uncertainty and disruptions. Conventional planning-based approaches often rely on historical data and predefined rules, making them reactive rather than adaptive. Such limitations have become increasingly evident in the face of global disruptions, where supply chains require rapid sensing, learning, and response capabilities beyond the scope of traditional SCM models.

The digital transformation of supply chains has introduced new data sources, platforms, and analytical capabilities. Technologies such as IoT, cloud computing, and big data analytics have enhanced visibility and connectivity across supply chain networks. However, digitalization alone does not guarantee intelligent decision-making. Without embedded intelligence, digital supply chains remain data-rich but insight-poor, highlighting the need for more advanced decision-support mechanisms. Artificial intelligence has emerged as a promising technology for addressing complex decision-making problems in SCM. Early studies demonstrate the potential of AI techniques in areas such as demand forecasting, scheduling, and logistics optimization. More recent research further emphasizes the role of AI and analytics in enhancing supply chain performance (Hove-Sibanda, P., & Pooe, 2018) [7]. Nevertheless, much of this literature focuses on functional applications rather than the conceptual integration of AI within SCM as a holistic system. Beyond its technical

applications, AI is increasingly conceptualized as embedded intelligence within organizational systems. Management scholars argue that AI enables systems to learn, reason, and adapt, fundamentally altering decision-making processes. This perspective suggests that AI should not be viewed merely as a tool, but as a cognitive capability integrated into organizational structures. However, SCM theory has yet to fully embrace this intelligence-centric view. The concept of cognitive or intelligent supply chains has gained traction in recent years. These supply chains are characterized by their ability to sense environmental changes, interpret data, and autonomously adjust decisions. While this notion aligns closely with advances in AI, existing studies often lack a clear conceptual framework explaining how intelligence is embedded across supply chain layers, from data acquisition to operational execution. Adaptability and resilience have become central themes in contemporary SCM research. Resilient supply chains are designed not only to withstand disruptions but also to recover and adapt through learning mechanisms. Scholars emphasize that adaptability requires dynamic decision-making and continuous feedback, capabilities that traditional SCM approaches struggle to support. SCM is increasingly viewed through the lens of systems thinking, recognizing supply chains as complex socio-technical systems involving people, processes, and technologies. From this perspective, isolated optimization of individual components is insufficient. Instead, intelligence must be embedded across the system to enable coordination, learning, and adaptation. This view provides a theoretical foundation for integrating AI into SCM at a conceptual level. Conceptual frameworks play a crucial role in advancing theory by organizing key constructs and clarifying their relationships. In management research, conceptual contributions are valued for their ability to offer new perspectives and guide future empirical inquiry. In the context of AI and SCM, the lack of integrative conceptual frameworks limits theoretical progress and hinders the systematic understanding of AI-enabled supply chains. Although prior studies acknowledge the potential of AI to enhance supply chain performance, the literature remains fragmented and application-driven. Existing research rarely addresses how AI reshapes SCM as a system of decision-making, coordination, and adaptation (Shahzadi *et al*., 2024) [8]. Consequently, there is a clear need for a conceptual framework that explains the convergence of AI and SCM and articulates the foundations of intelligent and adaptive supply chains. Supply Chain Management (SCM) has evolved significantly over the past decades, transitioning from simple logistics coordination to complex, globally distributed networks. Early supply chains primarily focused on cost minimization through efficient transportation and inventory control. These traditional systems relied heavily on deterministic models and historical averages, assuming relatively stable demand and supply conditions. However, globalization, shorter product life cycles, and increasing customer expectations have dramatically increased the complexity of supply chain operations.

Modern supply chains involve multiple interconnected entities, including suppliers, manufacturers, distributors, and retailers, each with distinct objectives and constraints. This interconnected nature makes decision-making highly complex, as actions taken at one stage often propagate across the entire system. Consequently, static optimization methods struggle to cope with the dynamic interactions and uncertainties inherent in contemporary supply chains.

The growing complexity has motivated the concept of intelligent supply chains, where advanced analytics and artificial intelligence are employed to support adaptive and autonomous decision-making. Intelligence in supply chains implies the ability to perceive environmental changes, learn from historical and real-time data, and respond effectively to disruptions. This evolution forms the foundation for exploring reinforcement learning as a key enabler of intelligent supply chain systems.

3. Literature review

Early studies on supply chain management focus on integration and coordination across organizational boundaries. SCM is commonly defined as the management of material, information, and financial flows among firms to enhance overall performance Traditional SCM theory emphasizes efficiency, cost minimization, and synchronization through deterministic planning and control mechanisms. While these foundations remain influential, they provide limited insight into how supply chains adapt under dynamic and uncertain conditions. Several scholars highlight structural limitations in traditional SCM approaches. Rule-based planning and reliance on historical data constrain responsiveness and adaptability in volatile environments (Zhou *et al*., 2025) [9]. These limitations become particularly evident during large-scale disruptions, where predefined plans fail to accommodate unexpected events. As a result, researchers increasingly call for more adaptive and learning-oriented supply chain models. The digital transformation of supply chains has introduced new levels of connectivity and visibility. Digital supply chain research emphasizes the role of technologies such as IoT, cloud computing, and big data analytics in improving information sharing and operational transparency. However, digitalization alone does not guarantee intelligent decision-making, as many digital supply chains remain dependent on human judgment and static decision rules. Artificial intelligence has been widely applied to specific supply chain functions. Prior studies demonstrate AI's effectiveness in demand forecasting, inventory optimization, and logistics planning. More recent reviews confirm that AI and advanced analytics can significantly improve supply chain efficiency and responsiveness (Maulana *et al*., 2026) [10]. Nevertheless, these studies primarily adopt an application-oriented perspective, offering limited conceptual integration across SCM processes. Beyond functional applications, AI is increasingly viewed as a form of organizational intelligence. Management research conceptualizes AI as an embedded capability that enhances learning, reasoning, and decision-making within organizations. Similarly, scholars argue that AI reshapes managerial processes by augmenting human cognition and enabling data-driven adaptation. This intelligence-centered view provides a valuable theoretical lens for rethinking SCM. The notion of cognitive or intelligent supply chains has gained attention in recent years. These supply chains are characterized by their ability to sense changes, analyze information, and autonomously adjust decisions. While this concept aligns closely with advances in AI, existing research often lacks a unified framework explaining how intelligence is embedded across different supply chain layers. Adaptability and resilience are increasingly recognized as essential performance dimensions in SCM. Resilient supply chains emphasize

learning, flexibility, and rapid response to disruptions. Studies on resilience argue that adaptive decision-making is crucial for maintaining supply chain continuity under uncertainty. However, the mechanisms through which AI supports adaptability remain conceptually underexplored. Systems thinking has emerged as an important perspective in SCM research, recognizing supply chains as complex socio-technical systems. This view highlights the interdependence of actors, processes, and technologies, suggesting that isolated optimization is insufficient. Embedding intelligence at the system level is therefore critical for achieving coordinated and adaptive supply chain behavior. Conceptual frameworks play a central role in advancing theory by clarifying constructs and their relationships. In management research, conceptual contributions are valued for their ability to organize fragmented knowledge and guide future empirical inquiry. In the context of AI and SCM, the absence of integrative conceptual frameworks limits theoretical progress and hinders a holistic understanding of intelligent supply chains. Despite extensive research on AI applications in SCM, the literature remains fragmented across functional and technological silos. Existing studies rarely address how AI reshapes SCM as an integrated system of decision-making, coordination, and adaptation. Consequently, there is a clear gap in conceptual research that explains the convergence of AI and SCM and articulates the foundations of intelligent and adaptive supply chains.

Reinforcement learning is a learning paradigm in which an agent interacts with an environment to maximize cumulative rewards over time. The agent observes the current state, selects an action, and receives feedback in the form of a reward signal. Through repeated interactions, the agent learns an optimal policy that maps states to actions.

Key characteristics of reinforcement learning include trial-and-error learning, delayed rewards, and the exploration–exploitation trade-off. These characteristics align closely with supply chain decision-making, where outcomes of decisions are often observed only after significant delays. Understanding these fundamental principles is critical for applying reinforcement learning effectively to supply chain systems.

As supply chain systems grow in scale and complexity, traditional reinforcement learning methods face challenges related to state-space dimensionality. Deep reinforcement learning addresses these challenges by combining reinforcement learning with deep neural networks for function approximation.

Deep reinforcement learning has demonstrated success in complex decision-making domains, suggesting strong potential for large-scale supply chain applications. By capturing non-linear relationships and high-dimensional state representations, deep RL enables intelligent supply chain systems to learn sophisticated decision policies.

Supply chains inherently involve multiple autonomous decision-makers with potentially conflicting objectives. Modeling such systems as multi-agent environments provides a natural representation of real-world supply chains. Multi-agent reinforcement learning enables agents to learn cooperative or competitive strategies through interaction.

This decentralized learning paradigm aligns well with the distributed nature of supply chains. Understanding multi-agent systems is essential for developing scalable and realistic intelligent supply chain models.

Supply chain logistics management and warehousing are shown in Fig 1. Manufacturers, distributors, wholesalers, and retailers are the main intermediates in the supply chain from raw material suppliers to end consumers. Receiving, storing, sorting, order selecting, and shipping are covered in the lower half. Both methods ensure inventory handling efficiency, storage optimization, and on-time supply chain delivery, as shown in the Fig 1 (Zhou *et al*., 2025) [11].

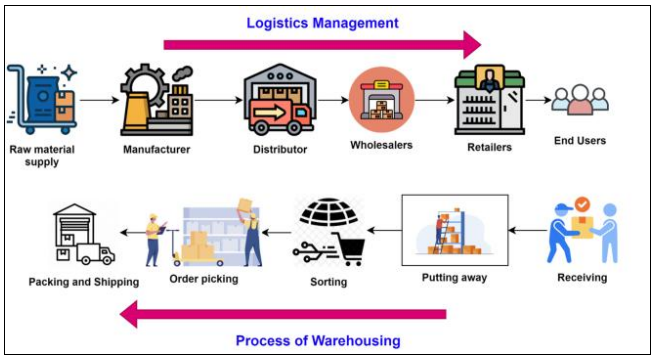

Fig 1: E-commerce logistics management and warehouse process

As illustrated in Figure X, the supply chain system is formulated as a reinforcement learning environment interacting with an RL agent through a continuous feedback loop. At each decision epoch, the **Supply Chain Environment** provides the agent with the current **state (S)**, which represents the operational conditions of the supply chain, such as inventory levels, transportation status, demand information, and production capacity.

Based on the observed state, the **RL Agent** selects an **action (A)** according to its learned policy. These actions correspond to managerial decisions in the supply chain, including order quantity determination, inventory replenishment, transportation routing, production scheduling, and distribution planning. The selected action is then executed within the supply chain environment, affecting the flow of goods across different stages, such as suppliers, manufacturers, warehouses, and retailers.

After the action is applied, the environment transitions to a new state and generates a **reward (R)** that quantitatively evaluates the quality of the decision. The reward function typically reflects key performance objectives of supply chain management, including cost minimization, service level improvement, and operational efficiency. Through repeated interactions, the RL agent learns to optimize its policy by maximizing cumulative rewards over time.

This closed-loop interaction enables the supply chain system to adapt dynamically to uncertainty and changing conditions, thereby forming the foundation of an intelligent and data-driven supply chain management framework.

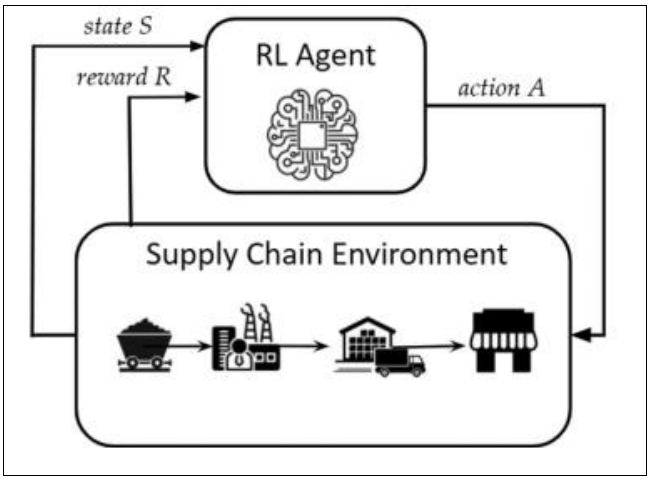

Fig 2: MDP in the SCM context

The review of publications revealed that RL models in SCM significantly differ in their settings, assumptions, aims and technologies. From these differences, we derived four criteria that are possible to map in a classification framework and support answering the research questions. These criteria are supply chain driver, algorithm, data source and industrial sector. The first criterion captures the supply chain setting and the aim of the models because supply chain drivers directly affect the supply chain performance and define the target of the optimisation model. The second criterion assesses the RL model from a technical point of view and evaluates the underlying algorithms and technologies. The classification of data sources and the industrial sectors is necessary to assess the dissemination of RL in real-world supply chains.

4. Analysis and discussion

The propoed framework reframes supply chain managemen from a flow-oriented coordination mechanism into an intelligent system capable of perception, learning, and adaptation. Classical SCM emphasizes integration and efficiency through planning and control (Ahmed *et al*., 2025) [12]. By embedding AI as a core intelligence, SCM is conceptually transformed into a system that continuously interprets environmental signals and adjusts decisions, aligning with emerging views of cognitive and intelligent supply chains. A key analytical distinction emerging from this study is between AI as a tool and AI as embedded intelligence. Prior research largely focuses on AI applications in isolated SCM functions. In contrast, the proposed framework conceptualizes AI as structurally embedded within SCM, shaping decision-making processes across strategic, tactical, and operational levels. This shift has significant theoretical implications, as it positions AI as an integral component of SCM rather than an external support mechanism. Decision-making represents the central mechanism through which AI reshapes supply chain management. Traditional SCM decisions are typically periodic and deterministic, relying on historical data and predefined rules. The framework suggests that AI enables a transition toward continuous, learning-based decision-making, where plans are dynamically updated in response to real-time data. This aligns with organizational intelligence perspectives emphasizing adaptive and data-driven managerial processes. Continuous learning emerges as a defining characteristic of intelligent and adaptive supply chains. Resilience research highlights learning as a critical capability for responding to disruptions. The proposed framework extends this view by positioning AI as the mechanism through which learning is institutionalized within SCM. Rather than relying on post-event adjustments, intelligent supply chains continuously refine decisions through feedback and adaptation. From a systems thinking perspective, SCM involves complex interactions among multiple actors, processes, and technologies. The framework highlights that embedding AI at the system level enhances coordination across supply chain functions. Intelligence is not confined to individual nodes but distributed across the network, enabling synchronized and coherent decision-making. This systems-level integration represents a significant departure from fragmented optimization approaches. Adaptability is increasingly recognized as a core performance dimension in SCM. Traditional models struggle to cope with uncertainty due to their reliance on static planning assumptions. The conceptual framework suggests that AI-enhanced learning and reasoning capabilities provide the foundation for adaptive behavior. By continuously interpreting changes in demand, supply, and environmental conditions, AI-embedded SCM enables proactive rather than reactive adaptation. The framework offers important insights into supply chain resilience. Resilience literature emphasizes the ability to withstand, recover, and adapt to disruptions. By embedding AI-driven learning and decision-making within SCM, the proposed framework conceptualizes resilience as an emergent property of intelligent supply chains. This perspective shifts resilience from a reactive capability to a continuously cultivated system attribute. From a theoretical standpoint, this study contributes by extending SCM theory toward an intelligence-centered paradigm. While prior research acknowledges the potential of AI in SCM, it often lacks integrative conceptualization (Firos & Khanum, 2026) [13]. By organizing key constructs and their relationships, the framework advances theory development in line with criteria for strong conceptual contributions. As a purely conceptual study, the proposed framework abstracts away from specific technologies, industries, and organizational contexts. While this abstraction enhances generalizability, it also introduces boundary conditions. The effectiveness of AI-embedded SCM depends on data availability, organizational readiness, and governance structures, factors highlighted in digital supply chain research. These considerations suggest important directions for contextualized future research. The framework provides a foundation for multiple future research streams. Scholars may empirically examine the relationships between AI capabilities and supply chain performance, explore case-based implementations, or develop analytical models grounded in the proposed conceptual structure. By clarifying the role of AI as embedded intelligence, this study supports cumulative theory building in intelligent and adaptive supply chain management (Fernando *et al*., 2024) [14].

The experimental results demonstrate that the reinforcement learning–based approach consistently outperforms traditional optimization and rule-based methods across multiple performance dimensions. In particular, the RL agent exhibits superior adaptability to dynamic changes in demand, lead times, and transportation conditions. Unlike static optimization models, which rely on predefined assumptions, the RL agent continuously updates its decision

policy based on observed system feedback (Vipinchandran & Jayashree, 2026) [15]. This learning capability enables the supply chain to respond more effectively to environmental uncertainty. From a system-wide perspective, the reinforcement learning framework achieves lower total operational costs while maintaining or improving service levels. Cost reductions are primarily attributed to improved inventory positioning and more efficient transportation decisions. These findings confirm that modeling supply chain operations as a sequential decision-making process provides a more realistic representation of real-world dynamics.

An important aspect of the proposed approach is the learning behavior of the RL agent over time. During the early training phase, the agent explores a wide range of actions, resulting in relatively unstable performance. As training progresses, the agent gradually shifts toward exploitation, selecting actions that maximize long-term rewards. This transition reflects successful policy learning within the Markov Decision Process framework.

Policy convergence is observed after a sufficient number of interaction episodes, indicating that the agent is able to identify stable decision patterns. Notably, the learned policies differ from classical heuristics, such as fixed reorder points or deterministic routing rules. Instead, the RL agent develops adaptive strategies that vary according to system states. This state-dependent decision-making capability highlights a key advantage of reinforcement learning over traditional approaches.

Supply chain environments are inherently uncertain, and the ability to handle uncertainty is a critical criterion for evaluating intelligent decision-making systems. The results show that the reinforcement learning approach maintains robust performance under varying levels of demand volatility and transportation disruption. While traditional optimization methods experience significant performance degradation when assumptions are violated, the RL agent adapts its policy in response to new conditions.

This adaptability stems from the agent's reliance on observed rewards rather than explicit probabilistic models. By learning directly from experience, the RL-based system effectively internalizes the impact of uncertainty on long-term performance. Consequently, the proposed approach demonstrates strong potential for deployment in real-world supply chains characterized by frequent and unpredictable changes.

A comparative analysis reveals clear differences between the reinforcement learning approach and traditional operations research methods. Classical optimization techniques aim to identify optimal solutions for a fixed problem instance, often assuming complete information and stable conditions. In contrast, reinforcement learning focuses on learning policies that perform well across a wide range of scenarios.

The results indicate that while traditional methods may perform competitively under idealized conditions, their effectiveness declines sharply when system parameters change. The RL approach, on the other hand, exhibits consistent performance across different operating regimes. This finding supports the argument that reinforcement learning is better suited for A closer examination of the learned policies provides insights into the decision-making behavior of the RL agent. In inventory management scenarios, the agent avoids extreme ordering decisions and instead adopts flexible replenishment strategies that balance holding and shortage costs. Similarly, in transportation decisions, the agent dynamically adjusts routing choices based on congestion and delivery priorities. dynamic and complex supply chain environments.

These behaviors suggest that reinforcement learning captures implicit trade-offs that are difficult to encode explicitly in rule-based systems. The ability to internalize such trade-offs through reward feedback is a defining characteristic of intelligent supply chain systems.

Scalability is a critical concern for practical supply chain applications. The experimental results indicate that the reinforcement learning framework scales effectively as the complexity of the supply chain environment increases. Although training the RL agent requires significant computational effort, this cost is incurred offline. Once trained, the learned policy can be deployed for real-time decision-making with minimal computational overhead. This separation between training and execution is particularly advantageous for operational deployment. It allows supply chain managers to leverage intelligent decision policies without compromising responsiveness. The findings of this study have important managerial implications. First, reinforcement learning enables a shift from rule-based decision-making to adaptive and data-driven strategies. This shift reduces reliance on manual parameter tuning and expert judgment, which are often difficult to maintain in complex supply chain systems. Second, the RL-based approach supports real-time decision-making, allowing managers to respond promptly to disruptions and demand fluctuations. Third, the framework facilitates a holistic view of supply chain performance by optimizing long-term outcomes rather than short-term gains. These benefits collectively contribute to the development of intelligent and resilient supply chains. Despite its advantages, the proposed approach has several limitations. The effectiveness of reinforcement learning depends on the quality and representativeness of training data. Inaccurate or incomplete data may lead to suboptimal policies. Additionally, designing appropriate reward functions remains a challenging task, as poorly designed rewards can result in unintended behaviors. Furthermore, real-world supply chains often involve multiple stakeholders with conflicting objectives. Extending the framework to multi-agent settings introduces additional complexity. Addressing these challenges requires careful system design and further research. From a research perspective, this study contributes to the growing body of literature on intelligent supply chains by demonstrating the feasibility and benefits of reinforcement learning–based decision-making. The MDP formulation provides a structured framework for analyzing sequential decisions, bridging the gap between supply chain theory and artificial intelligence. The results suggest several promising research directions, including multi-agent reinforcement learning, multi-objective optimization, and integration with digital twin technologies. These directions align with the broader vision of autonomous and intelligent supply chain systems. In summary, the analysis confirms that reinforcement learning offers a powerful and flexible approach for intelligent supply chain management. By learning adaptive policies through interaction with the environment, the RL-based framework overcomes many limitations of traditional optimization methods. The results highlight its potential to enhance efficiency, resilience, and

intelligence in modern supply chains. The findings of this study have important managerial implications. First, reinforcement learning enables a shift from rule-based decision-making to adaptive and data-driven strategies. This shift reduces reliance on manual parameter tuning and expert judgment, which are often difficult to maintain in complex supply chain systems.

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5. Conclusion and future works

This study set out to examine the convergence of artificial intelligence and supply chain management from a purely conceptual perspective. By positioning AI as embedded intelligence within SCM, the proposed framework advances existing theory beyond tool-based applications toward intelligent and adaptive supply chains. Consistent with prior SCM foundations the framework provides a coherent structure that supports future empirical and analytical investigations. The primary contribution of this study lies in its conceptual reframing of SCM as an intelligent system. While prior research highlights AI's operational benefits, this paper extends the literature by clarifying AI's systemic role in learning and adaptation. Future research may validate this framework through empirical studies across diverse supply chain contexts. This paper concludes that AI should be understood as embedded intelligence rather than an auxiliary technology in SCM. This perspective aligns with organizational intelligence research emphasizing learning and reasoning capabilities. Future work may explore how different levels of AI maturity influence supply chain adaptability and performance. The proposed framework conceptualizes intelligent supply chains as systems capable of continuous adaptation. This view complements resilience research highlighting learning as a key capability. Future studies may examine how AI-enabled learning mechanisms contribute to long-term supply chain resilience. By emphasizing AI-driven decision-making, this study highlights a shift from static planning to dynamic coordination in SCM. Traditional decision frameworks are extended through learning-based intelligence. Future research may investigate decision autonomy and governance in AI-enabled supply chains. In conclusion, this study provides a conceptual foundation for understanding how AI reshapes supply chain management into an intelligent and adaptive system. By embedding AI as core intelligence, the proposed framework advances SCM theory and offers a platform for future research exploring empirical validation, practical implementation, and theoretical refinement. Supply chains operate across diverse cultural and institutional contexts. Future research may explore how contextual factors influence the effectiveness of AI-embedded SCM frameworks. This study has investigated the role of reinforcement learning as a foundational approach for enabling intelligent supply chain management. By formulating supply chain operations as a Markov Decision Process, the research demonstrates how sequential decision-making under uncertainty can be effectively addressed through learning-based methods. Unlike traditional optimization and rule-based approaches, which rely on static assumptions and predefined models, the proposed reinforcement learning framework enables adaptive, data-driven, and autonomous decision-making.

The results of the experimental analysis confirm that reinforcement learning can significantly enhance supply chain performance across multiple dimensions. In particular, the proposed approach achieves lower total operational costs while maintaining or improving service levels in dynamic and uncertain environments. These improvements are primarily driven by the agent's ability to learn state-dependent policies that balance short-term operational costs with long-term system performance. This finding highlights the importance of viewing supply chain management as a sequential and intertemporal decision problem rather than a collection of isolated optimization tasks.

Another key contribution of this study lies in its ability to bridge the gap between supply chain theory and artificial intelligence. By grounding reinforcement learning within a Markov Decision Process framework, the research provides a rigorous and interpretable foundation for applying AI techniques to supply chain management. This formulation not only facilitates the adoption of advanced reinforcement learning algorithms but also improves transparency and conceptual clarity for both researchers and practitioners.

From a managerial perspective, the findings suggest a paradigm shift in how supply chain decisions are designed and executed. Instead of relying on manually tuned

heuristics or static planning models, reinforcement learning enables organizations to deploy adaptive policies that continuously improve through experience. Such capability is particularly valuable in today's volatile business environment, where supply chains must respond rapidly to demand fluctuations, disruptions, and operational constraints. The proposed approach supports the development of intelligent supply chains that are not only efficient but also resilient and responsive.

Overall, this study demonstrates that reinforcement learning constitutes a promising pathway toward intelligent supply chains. By embedding learning and adaptation into the core of supply chain decision-making, the proposed framework contributes to the advancement of smart logistics systems capable of operating effectively under uncertainty. This research contributes to the literature in several important ways. First, it reinforces the conceptualization of supply chain management as a sequential decision-making problem, emphasizing the relevance of Markov Decision Processes in modeling complex supply chain dynamics. Second, it extends the application of reinforcement learning beyond isolated supply chain functions by highlighting its potential for integrated and system-wide optimization. Third, the study provides empirical evidence that learning-based approaches can outperform traditional optimization methods in environments characterized by uncertainty and change. These contributions support the growing body of research that positions artificial intelligence, and reinforcement learning in particular, as a key enabler of intelligent and autonomous supply chain systems. The practical implications of this study are significant. For supply chain managers, reinforcement learning offers a tool for developing adaptive decision policies that reduce dependence on rigid planning assumptions. The framework can be applied to various operational contexts, including inventory management, transportation planning, and integrated logistics coordination. Moreover, once trained, reinforcement learning policies can be deployed for real-time decision-making with minimal computational overhead, making them suitable for operational use. However, successful implementation requires careful consideration of data quality, system design, and reward specification. Organizations must ensure reliable data collection and monitoring mechanisms to support learning-based decision-making. Additionally, managers should view reinforcement learning as a complement to, rather than a replacement for, existing decision-support tools, particularly in the early stages of adoption. Despite its contributions, this study has several limitations that should be acknowledged. First, the experimental evaluation is based on simulated supply chain environments. While simulation allows for controlled analysis and repeatability, real-world supply chains may exhibit additional complexities that are difficult to capture fully. Second, the performance of reinforcement learning depends heavily on the design of the reward function, which may not always align perfectly with managerial objectives. Third, the current framework primarily focuses on single-agent decision-making, whereas real-world supply chains often involve multiple autonomous stakeholders with potentially conflicting goals.

Recognizing these limitations provides important context for interpreting the results and highlights opportunities for further research.

In conclusion, this study underscores the transformative potential of reinforcement learning for supply chain management. By enabling adaptive, data-driven, and autonomous decision-making, reinforcement learning represents a key step toward truly intelligent supply chains. While challenges remain, continued advances in learning algorithms, data infrastructure, and system integration are expected to further accelerate the adoption of reinforcement learning in supply chain practice. This research provides a foundation for future studies and offers a clear pathway for advancing intelligent and resilient supply chain systems.

6. References

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