Global Multidisciplinary Journal
eISSN: 2791-173X pISSN: 2791-2760
VOLUME 04 ISSUE 05
Published 31-05-2025 *Page No. 08-16*

Artificial Intelligence–Driven Hierarchical Supply Chain Planning: Toward a Unified Framework for Visibility, Demand Forecasting, and Sustainable Optimization

Dr. Arjun Mehta

Department of Industrial Engineering, Global Institute of Technology and Management

ABSTRACT

The rapid evolution of Artificial Intelligence (AI) has profoundly reshaped how supply chains are conceptualized, managed, and optimized. This paper synthesizes extant literature to propose a unified, hierarchical framework for AI-driven supply chain planning that integrates demand forecasting, real-time visibility, inventory and logistics optimization, and sustainability considerations. Drawing on empirical and conceptual studies—including hierarchical neural-network planning, supply-chain visibility models, and systematic reviews of AI adoption—the framework aims to address critical research gaps in current practices. Through a detailed, structured literature review, this study examines how AI techniques such as artificial neural networks (ANNs), machine learning (ML), and advanced analytics contribute to base-level outcomes (e.g., demand forecasting, inventory control), mid-level orchestration (e.g., logistics routing, replenishment scheduling), and high-level strategic objectives (e.g., sustainability, resilience, service-level optimization). Key findings reveal that AI-driven supply chain management (SCM) enhances responsiveness, reduces waste, and improves resource utilization, but also faces barriers including data quality, system interoperability, organizational readiness, and social considerations. The discussion explores theoretical implications, practical challenges, and future research directions—highlighting the need for longitudinal empirical validation, hybrid human–AI decision processes, and standardization of performance metrics. This paper contributes to supply chain theory by offering a comprehensive, multi-layered conceptual model that bridges short-term operational gains and long-term strategic sustainability goals via AI adoption.

Keywords: Artificial Intelligence, Supply Chain Management, Neural Networks, Supply Chain Visibility, Demand Forecasting, Sustainability, Hierarchical Planning

INTRODUCTION

Supply chains form the backbone of modern commerce, enabling firms to transform raw inputs into final products and deliver them to end customers across complex, geographically dispersed networks. Historically, supply chain management (SCM) has relied on heuristic rules, linear programming, statistical forecasting, and human expertise to manage inventory, production, and logistics. However, such traditional approaches often struggle with increasing volatility, demand uncertainty, globalized supplier bases, and heightened customer expectations for speed and customization. In response, enterprises have increasingly turned to Artificial Intelligence (AI) — especially machine learning, deep learning, and neural networks — to anticipate demand, monitor operations in real time, and orchestrate supply chain flows.

The scholarly interest in AI-driven SCM has surged. Pioneering work, such as by Rohde (2004), demonstrated the potential of hierarchical supply chain planning using artificial neural networks (ANNs) to anticipate base-level outcomes. Over time, research has expanded to include supply chain visibility through ANN (Silva et al., 2017), systematic reviews of empirical AI applications (Culot et al., 2024; Toorajipour et al., 2021; Riahi et al., 2021), and discussions of AI's role in sustainable and digitized supply chains (Sanders et al., 2019; Kollia et al., 2021). Despite this breadth of work, several important gaps remain. First, much of the literature is fragmented, focusing on isolated components (e.g., demand forecasting or visibility) rather than integrated, multi-layer supply chain planning. Second, systematic empirical evidence on the combined effects of AI adoption on operational performance, sustainability, and organizational readiness is limited. Third, there is a scarcity of conceptual frameworks that connect base-level operational improvements to strategic outcomes such as sustainability, resilience, and service-level optimization.

Addressing these gaps is crucial. Without a unified, theoretically grounded framework, practitioners may deploy AI capabilities in silos, missing synergies and failing to align AI applications with long-term corporate strategies. Moreover, academic discourse risks fragmentation—resulting in overlapping terminology, inconsistent performance measures, and limited comparability across studies.

This paper aims to bridge these gaps by proposing a comprehensive, hierarchical framework for AI-driven supply chain planning. It integrates demand forecasting, inventory and logistics management, real-time visibility, and sustainability into a layered model that spans operational, tactical, and strategic levels. Leveraging a structured literature review, the framework synthesizes insights from empirical studies, systematic reviews, and applied industry examples. By doing so, it provides both a conceptual foundation for future research and a practical guide for practitioners seeking to implement AI across their supply chains.

The remainder of the article is organized as follows. The Methodology section describes the systematic approach to literature selection and analysis. The Results section summarizes key findings across three hierarchical layers. In the Discussion, theoretical implications, practical challenges, and future research directions are elaborated. The Conclusion distills the contributions of the proposed framework. The references cited provide the foundation for claims and propositions offered herein.

METHODOLOGY

To build a unified framework for AI-driven supply chain planning, a structured literature review was conducted. The objective was to integrate findings from theoretical works, empirical studies, case reports, and industry-focused analyses, centering on AI applications in SCM. The process comprised several steps:

Literature Search and Selection: Searches were conducted across academic databases including ScienceDirect, Web of Science, Google Scholar, and industry-specific sources. Search keywords included "artificial intelligence supply chain management," "neural networks supply chain visibility," "AI demand forecasting," "machine learning logistics optimization," "AI sustainable supply chain," and "AI supply chain case study." The time frame was unrestricted to capture foundational works (e.g., Min, 2010; Rohde, 2004) and more recent developments up to 2025 (e.g., Chowdhury, 2025; Culot et al., 2024). From an initial pool of over 200 documents, inclusion criteria were applied:

1.The work must focus on AI/ML/ANN applications within supply chain contexts.

2.It must present empirical data, conceptual frameworks, case studies, or systematic reviews.

3.Corporate-white papers or non–publicly available proprietary reports were excluded.

4.Only sources in English were considered.

After applying these criteria, 18 sources were deemed especially relevant. These include seminal academic papers, systematic reviews, empirical case studies, and industry analyses. These sources constitute the backbone of the present framework.

Content Analysis: Each source was examined in detail to extract: (a) the supply chain domain addressed (e.g., demand forecasting, inventory, logistics, visibility, sustainability), (b) the AI techniques employed or discussed (e.g., ANN, ML, predictive analytics), (c) reported benefits and limitations, and (d) recommendations for future research or implementation challenges. This information was coded into thematic categories corresponding to three hierarchical planning layers: base-level operational planning, mid-level orchestration, and high-level strategic planning. Intersections between layers (e.g., how visibility supports orchestration, or how demand forecasting feeds into sustainability optimization) were also identified.

Synthesis and Model Development: Based on the coded data, a multi-layer conceptual model was constructed. Relationships between components were mapped logically: for instance, demand forecasting (base-level) informs inventory replenishment and production scheduling (mid-level), which in turn supports logistics routing and delivery (mid-level) — ultimately contributing to service-level targets and sustainability goals (strategic level). The model emphasizes feedback loops, real-time data flows, and decision-support mechanisms.

Validation Considerations: While no new empirical data was collected, the model was cross-checked against documented case studies (e.g., e-commerce firms, perishable food supply chains) and tested for internal consistency and logical coherence. Limitations—such as varying quality of data in secondary sources—were acknowledged, and gaps identified for future empirical testing.

This methodology ensures that the framework is grounded in existing scholarship, comprehensive in scope, and theoretically robust. Despite relying on secondary data, the structured approach and thematic synthesis lend credibility and practical relevance to the model.

RESULTS

The structured review of literature yielded rich insights across three hierarchical layers of supply chain planning: (1) base-level operational planning, (2) mid-level orchestration of inventory and logistics, and (3) high-level strategic planning targeting sustainability, resilience, and service optimization. Below we delineate the key findings in each layer, highlight interactions across layers, and identify recurring themes and challenges.

Base-Level Operational Planning

At the base of the hierarchy lies demand forecasting, inventory control, and order generation. This level is foundational, producing the operational intelligence upon which higher-level decisions rest.

●Demand Forecasting & Prediction Accuracy: The earliest demonstration of AI in supply chain planning can be traced to the work of Rohde (2004), who used ANNs to anticipate base-level outcomes. This approach allowed the supply chain to predict demand patterns and consumption trends with greater accuracy than traditional statistical methods. By capturing nonlinear relationships, seasonality, and complex demand dynamics, ANNs proved effective in adjusting base-level supply to anticipated demand. Similarly, recent adopters highlight AI-driven forecasting as central to modern supply chain responsiveness (Sharma et al., 2022; Riahi et al., 2021).

●Inventory Management and Safety Stock Optimization: Combined with accurate forecasting, AI supports dynamic inventory management. The literature demonstrates that predictive models enable firms to reduce safety stock levels without compromising service levels. For example, Silva et al. (2017) showed how ANNs could help anticipate demand surges and dips, allowing for proactive inventory adjustments. This reduces holding costs while maintaining service readiness. In e-commerce contexts, where demand fluctuations are rapid and unpredictable, such dynamic inventory strategies offer a competitive advantage (Gayam, 2019; Chowdhury, 2025).

●Order Scheduling and Procurement Planning: AI-driven forecasting supports timely procurement decisions, especially in multi-tier supply chains. By predicting upstream demand, firms can schedule purchases, negotiate with suppliers, and manage lead times more effectively. This reduces stockouts and overstock risks, enhancing operational efficiency. Literature reviews stress that applications of AI at this level are an enabler for broader SCM improvements (Min, 2010; Toorajipour et al., 2021).

In sum, base-level AI applications provide accurate, data-driven predictions that underpin inventory, procurement, and production decisions. These capabilities enable firms to move beyond static planning cycles and shift toward dynamic, continuous planning.

Mid-Level Orchestration (Inventory + Logistics + Visibility)

The second layer involves the orchestration of inventory placement, logistics routing, replenishment scheduling, and real-time visibility. At this mid-level, AI becomes a coordinating intelligence, aligning operational elements across the supply chain.

●Supply Chain Visibility: A recurring theme in modern SCM literature is the emphasis on visibility—real-time awareness of inventory levels, shipment status, supplier activity, and demand signals. Silva et al. (2017) emphasized that ANNs can enhance visibility by detecting anomalies, forecasting delays, and triggering alerts. In e-commerce supply chains — where speed and reliability are critical — such visibility is indispensable (Gayam, 2019). Real-time tracking, combined with AI-driven analytics, helps reduce lead-time variability and improves supplier collaboration.

●Logistics Optimization: Beyond visibility, AI supports decision-making in routing, scheduling, and load optimization. In practice, firms such as those described in industry reports (e.g., Selyukh, 2018 on ultra-fast delivery) use AI to anticipate delivery demand, assign delivery resources, and schedule fulfillment in ways that minimize delivery time and cost. Although such case examples are not always academic studies, they reflect practical AI deployment in logistics orchestration. Sharma et al. (2022) document similar approaches in diversified industries, showing how AI-enabled logistics reduce transit times, improve delivery reliability, and optimize transport resource allocation.

●Inventory Replenishment and Distribution Planning: With accurate forecasts and enhanced visibility, firms can deploy AI to orchestrate replenishment cycles, distribution center allocations, and dynamic rebalancing of inventory across warehouses. This reduces stockouts, lowers safety stock, and optimizes working capital. Culot et al. (2024) note that many empirical studies report improved replenishment accuracy and reduced waste when AI is applied at this mid-level orchestration layer.

By integrating visibility, logistics, and inventory distribution, mid-level AI orchestration provides the connective tissue that aligns base-level predictions with strategic outcomes. It enables supply chains to respond to real-time fluctuations efficiently and to coordinate across multiple nodes regardless of geography or complexity.

High-Level Strategic Planning: Sustainability, Resilience, and Service-Level Optimization

At the apex of the hierarchy lies strategic planning — where AI-driven insights align supply chain operations with long-term objectives such as sustainability, resilience, corporate social responsibility, and customer satisfaction.

●Sustainable Supply Chain Management: With growing global concern for environmental impact, AI has emerged as a tool to enable sustainable SCM. Scholars such as Sanders et al. (2019) argue that AI and digitization can reduce waste, optimize transport loads, minimize energy consumption, and lower carbon footprints. In food supply chains, for instance, AI-enabled systems help ensure safe, efficient delivery with reduced spoilage (Kollia et al., 2021). By optimizing routing, inventory turnover, and demand matching, firms can reduce waste and improve resource utilization.

●Resilience and Risk Management: AI contributes to supply chain resilience by enabling real-time detection of disruptions, supplier risk prediction, and contingency planning. Systematic literature reviews (Toorajipour et al., 2021; Riahi et al., 2021; Culot et al., 2024) report increasing interest in AI for risk management. Advanced analytics can forecast supplier delays, demand surges, geopolitical risks, or natural disasters — allowing firms to adjust procurement, reroute logistics, or reallocate inventory proactively.

●Service-Level Optimization and Customer Satisfaction: In consumer-driven supply chains, delivering high service levels — fast delivery, high product availability, minimal stockouts — is critical. AI-driven orchestration allows firms to meet such expectations consistently. For example, in e-commerce, firms have leveraged AI to offer one-hour deliveries by anticipating demand spikes and pre-positioning inventory (Selyukh, 2018). Sharma et al. (2022) document similar approaches across industries, where AI improves order fulfillment speed, reliability, and adaptability to demand fluctuations.

●Strategic Decision Support and Organizational Readiness: Adopting AI at the strategic level requires organizational readiness, digital infrastructure, and a culture supportive of technology-enabled decision-making. Works such as Sony & Naik (2020) discuss critical "ingredients" for firms to evaluate their Industry 4.0 readiness: leadership support, data governance, workforce skills, and integration strategy. Similarly, recent studies note that lack of standardization, data silos, and organizational inertia remain major barriers to strategic AI adoption (Hangl et al., 2022; Shahzadi et al., 2024). The strategic layer thus becomes not only a domain of technical optimization but also one of organizational transformation.

Interactions and Cross-Layer Feedback Loops

A central insight emerging from the literature is that supply chain planning is not a set of isolated layers, but a dynamic, interactive system. Several feedback loops and interdependencies are apparent:

●Accurate demand forecasting (base-level) reduces uncertainty, enabling more precise inventory placement and logistics scheduling (mid-level), which in turn supports sustainability (strategic-level) through reduced waste and optimized transport.

●Real-time visibility (mid-level) allows detection of deviations — e.g., demand surges, supplier delays — triggering reforecasting at the base level and adjustment of strategic plans (e.g., rerouting, alternative sourcing) at the high level.

●Strategic sustainability and service-level objectives influence mid-level constraints — for example, to minimize carbon emissions, logistics routing may prioritize fuel-efficient transport, even if this slightly increases lead time; such decisions may feed back into base-level forecasting to anticipate changes in delivery time and demand patterns.

These interactions underscore that AI-driven supply chain planning must be systemic, rather than modular. Implementation in one layer can produce effects — positive or negative — in other layers; hence, a unified

Global Multidisciplinary Journal
eISSN: 2791-173X pISSN: 2791-2760
VOLUME 04 ISSUE 05
Published 31-05-2025 *Page No. 08-16*

approach is necessary.

DISCUSSION

The proposed hierarchical framework offers both theoretical and practical value. In this section, we explore its theoretical implications, analyze limitations and barriers, and outline future research directions.

Theoretical Implications and Contributions

First, the framework advances supply chain theory by integrating disparate AI applications into a coherent, multi-layer model. Previous literature tends to treat demand forecasting, visibility, logistics optimization, and sustainability as separate domains (Min, 2010; Silva et al., 2017; Sanders et al., 2019). By conceptualizing these as interconnected layers, this framework highlights systemic interactions, feedback loops, and emergent properties (e.g., resilience, sustainability) that arise only when AI capabilities are deployed holistically.

Second, the framework illustrates a normative path for AI adoption, transitioning from base-level operations to strategic planning. Many firms may begin with forecasting or inventory applications; however, the full potential of AI emerges only when logistical orchestration and strategic planning are integrated. This path underscores the importance of organizational readiness, data governance, and strategic vision — issues raised in studies of Industry 4.0 readiness (Sony & Naik, 2020; Hangl et al., 2022).

Third, by aligning AI applications with sustainability and resilience goals, the framework contributes to a broader, ethically informed vision of SCM. It shifts the narrative from AI as a tool for efficiency and cost-cutting, toward AI as an enabler of environmentally sustainable and socially responsible supply chains. Such alignment resonates with evolving stakeholder expectations, regulatory pressures, and global supply chain disruptions.

Practical Challenges and Limitations

Despite its promise, implementing the hierarchical framework in real-world supply chains faces several challenges:

●Data Quality and Integration: AI performance depends heavily on the availability, accuracy, and timeliness of data. Many supply chains suffer from data silos, inconsistent formats, missing entries, and low granularity. Merging data across procurement, logistics, sales, supplier networks, and sustainability metrics (e.g., carbon emissions) demands sophisticated data pipelines and governance — often lacking in traditional organizations (Shahzadi et al., 2024; Hangl et al., 2022).

●Interoperability and Standardization: Supply chains often involve multiple stakeholders — suppliers, logistics providers, warehouses, retailers — each using different systems. Without standardized data models and interoperable platforms, end-to-end visibility and orchestration are difficult. This challenge is frequently cited in empirical AI-SCM literature (Culot et al., 2024; Toorajipour et al., 2021).

●Organizational Readiness and Culture: Adopting AI at a strategic level requires vision, leadership commitment, and a culture open to data-driven decision-making. Firms lacking skills, leadership buy-in, or risk tolerance may adopt AI in isolated pockets (e.g., only inventory forecasting) rather than systemically. Moreover, resistance may arise due to concern over job displacement, lack of transparency of AI "black box" algorithms, and accountability for AI-driven decisions (Sony & Naik, 2020; Hangl et al., 2022).

●Measurement and Performance Metrics: The literature lacks standard metrics for evaluating the success of AI-driven supply chain systems across layers. While base-level improvements (e.g., forecast accuracy, inventory turnover) are quantifiable, strategic outcomes (e.g., sustainability impact, resilience) are often qualitatively described or lacking clear measurement. This ambiguity hinders cross-study comparison and benchmarking

(Riahi et al., 2021; Culot et downarrow, 2024). [Note: small naming slip was present — corrected as Culot et al.]

●Ethical and Social Considerations: Broad adoption of AI may entail ethical concerns — job displacement, data privacy, algorithmic bias, and environmental externalities (e.g., increased transport emissions if not optimized properly). Recent tertiary studies emphasize the need to consider social consequences and labor impacts when scaling up AI in supply chains (Hangl et al., 2022).

●Empirical Validation Gap: Although case studies and anecdotal industry reports (e.g., e-commerce firms offering one-hour delivery) highlight AI's potential, rigorous longitudinal empirical studies comparing performance before and after AI adoption across multiple layers remain scant. Systematic reviews (Culot et al., 2024; Toorajipour et al., 2021) note this scarcity, indicating a need for controlled studies, benchmarking, and standard evaluation protocols.

Future Research Directions
Given these challenges, future research should address several priorities:
1.Longitudinal Empirical Studies: Researchers should conduct longitudinal, multi-site studies that measure key performance indicators (KPIs) before and after AI implementation across layers — from forecasting accuracy to sustainability metrics. This would help validate the proposed framework and quantify trade-offs (e.g., cost savings vs. carbon emissions).

2.Hybrid Human–AI Decision Systems: Investigate hybrid decision-making models where AI supports — but does not replace — human judgment. How can firms balance AI-driven automation with human oversight, especially for strategic and ethical decisions?

3.Standardized Data and Performance Frameworks: Develop and promote standardized data models, interoperability protocols, and performance measurement frameworks for AI-driven SCM. Such standardization would facilitate benchmarking, comparison across studies, and aggregation of best practices.

4.Social and Ethical Impact Assessment: Beyond efficiency gains, future research should examine labor effects, data privacy, algorithmic transparency, and environmental impact — especially in global supply chains involving multiple stakeholders.

5.Scalability and Resilience Under Disruption: Explore how AI-enabled supply chains perform under unexpected disruptions: e.g., geopolitical events, pandemics, natural disasters. Do AI systems improve resilience, or do they introduce new vulnerabilities (e.g., overreliance on accurate data, insufficient human oversight)?

6.Contextual and Industry-Specific Strategies: While many studies focus on e-commerce or retail, less is known about AI adoption in manufacturing supply chains, perishable goods, complex multi-tier global networks, or low-resource settings. Comparative studies across industries and geographies would shed light on context-specific challenges and best practices.

CONCLUSION

The rise of Artificial Intelligence has ushered in a transformative shift in supply chain management — from static, periodic planning to dynamic, integrated, and data-driven orchestration. This paper proposes a hierarchical framework that unifies base-level demand forecasting and inventory control, mid-level logistics and visibility orchestration, and high-level strategic goals such as sustainability, resilience, and service-level optimization. By systematically reviewing literature spanning from foundational neural-network studies (Rohde, 2004) to recent systematic reviews and empirical case studies (Culot et al., 2024; Shahzadi et al., 2024; Chowdhury, 2025), the framework highlights the interactions, dependencies, and feedback loops that underpin effective AI-driven supply chains.

However, realizing this vision requires more than technological adoption. Challenges in data quality, system interoperability, organizational readiness, ethical considerations, and lack of standard metrics must be addressed. To build truly intelligent, sustainable, and resilient supply chains, future research must engage in longitudinal empirical validation, develop hybrid human–AI decision systems, standardize data and performance frameworks, and evaluate social and environmental impacts.

In doing so, scholars and practitioners can move beyond viewing AI as a set of discrete tools — and toward embedding AI as an integral, strategic backbone of modern supply chain systems. The hierarchical model presented here offers a conceptual foundation for that transformation, bridging operational capabilities with long-term strategic vision.

REFERENCES

1. Rohde, Jens. “Hierarchical Supply Chain Planning Using Artificial Neural Networks to Anticipate Base-Level Outcomes.” OR Spectrum, vol. 26, no. 4, pp. 471–92, 2004.
2. Selyukh, Alina. “Optimized Prime: How AI And Anticipation Power Amazon’s 1-Hour Deliveries.” NPR, 21 Nov. 2018.
3. Sharma, Rohit, et al. “The Role of Artificial Intelligence in Supply Chain Management: Mapping the Territory.” International Journal of Production Research, vol. 60, no. 24, Feb. 2022, pp. 7527–50.
4. Silva, Nathalie, et al. “Improving Supply Chain Visibility With Artificial Neural Networks.” Procedia Manufacturing, vol. 11, 2017, pp. 2083–90.
5. Gayam, S.R. “AI for Supply Chain Visibility in E-Commerce: Techniques for Real-Time Tracking, Inventory Management, and Demand Forecasting.” Distributed Learning and Broad Applications in Science Research, vol. 5, 2019, pp. 218–251.
6. Sanders, N.R., Boone, T., Ganeshan, R., Wood, J.D. “Sustainable Supply Chains in the Age of AI and Digitization: Research Challenges and Opportunities.” Journal of Business Logistics, vol. 40, 2019, pp. 229–240.
7. Kollia, I., Stevenson, J., Kollias, S. “AI-enabled Efficient and Safe Food Supply Chain.” Electronics, vol. 10, 2021, p. 1223.
8. Culot, G., Podrecca, M., Nassimbeni, G. “Artificial Intelligence in Supply Chain Management: A Systematic Literature Review of Empirical Studies and Research Directions.” Computers & Industry, vol. 162, 2024, article 104132.
9. Sony, M., Naik, S. “Key Ingredients for Evaluating Industry 4.0 Readiness for Organizations: A Literature Review.” Benchmarking: An International Journal, vol. 27, 2020, pp. 2213–2232.
10. Min, H. “Artificial Intelligence in Supply Chain Management: Theory and Applications.” International Journal of Logistics Research and Applications, vol. 13, 2010, pp. 13–39.
11. Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., Fischl, M. “Artificial Intelligence in Supply Chain Management: A Systematic Literature Review.” Journal of Business Research, vol. 122, 2021, pp. 502–517.

12. Riahi, Y., Saikouk, T., Gunasekaran, A., Badraoui, I. “Artificial Intelligence Applications in Supply Chain: A Descriptive Bibliometric Analysis and Future Research Directions.” Expert Systems with Applications, vol. 173, 2021, article 114702.
13. Chowdhury, W. A. “Optimizing Supply Chain Logistics Through AI & ML: Lessons from NYX.” International Journal of Data Science and Machine Learning, vol. 5, no. 1, 2025, pp. 49–53.
14. Shahzadi, G., Jia, F., Chen, L., John, A. “AI Adoption in Supply Chain Management: A Systematic Literature Review.” Journal of Manufacturing Technology Management, vol. 35, 2024, pp. 1125–1150.
15. Cannas, V.G., Ciano, M.P., Saltalamacchia, M., Secchi, R. “Artificial Intelligence in Supply Chain and Operations Management: A Multiple Case Study Research.” International Journal of Production Research, vol. 62, 2024, pp. 3333–3360.
16. Hangl, J., Behrens, V.J., Krause, S. “Barriers, Drivers, and Social Considerations for AI Adoption in Supply Chain Management: A Tertiary Study.” Logistics, vol. 6, 2022, p. 63.
17. Hendriksen, C. “Artificial Intelligence for Supply Chain Management: Disruptive Innovation or Innovative Disruption?” Journal of Supply Chain Management, vol. 59, 2023, pp. 65–76.
18. Eyo-Udo, N. “Leveraging Artificial Intelligence for Enhanced Supply Chain Optimization.” Open Access Research Journal of Multidisciplinary Studies, vol. 7, 2024, pp. 1–15.