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Generative AI-Driven Optimization of Intelligent Supply Chain Decision-Making: Mechanisms and Applications

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Abstract

Modern supply chains face mounting complexity due to volatility in demand, frequent disruptions, and fragmented data systems. Conventional decision-making approaches, which are often rule based, siloed, and reactive, lack the adaptability required in today's dynamic environment. Generative artificial intelligence (GenAI) offers a transformative solution by integrating heterogeneous data, generating realistic counterfactual scenarios, and enabling continuous, context-aware optimization. This paper outlines how GenAI enhances supply chain intelligence through four key mechanisms: probabilistic forecasting under uncertainty, proactive risk simulation, adaptive resource allocation using reinforcement learning, and automated generation of strategic plans from both structured and unstructured data. Real-world applications span procurement (e.g., resilient supplier selection), warehouse management (demand-responsive inventory planning), logistics (dynamic routing), and after-sales service (predictive maintenance). Looking forward, the convergence of GenAI with digital twins and multi-enterprise collaboration platforms will enable more autonomous, transparent, and resilient operations. However, effective deployment requires human-AI governance that ensures explainability, ethical alignment, and strategic oversight. By shifting supply chains from reactive problem-solving to anticipatory intelligence, GenAI paves the way for next-generation operational excellence.

Keywords

Generative AI; Supply Chain Optimization; Intelligent Decision-Making; Digital Transformation; Scenario Simulation

1. Introduction

Global supply chains have transformed into highly interconnected and dynamic networks, underpinned by intricate coordination across suppliers, manufacturers, logistics providers, distributors, and end consumers. The rise of digital commerce, the growing heterogeneity of consumer preferences, and the rapid pace of technological advancement have collectively intensified the operational complexity of these systems. In this context, firms must interpret vast, heterogeneous data streams and execute timely decisions amid persistent uncertainty and volatility. Such heterogeneity often spans multiple modalities and data granularities, making multimodal representation learning and fusion increasingly relevant for operational analytics (Jabeen et al., 2023).Recent empirical research confirms that AI-enabled analytics significantly enhances supply chain agility, resilience, and integration performance (Benzidia et al., 2021; Dubey et al., 2022; Shavaki & Ghahnavieh, 2023). Conventional decision-support systems, however, remain constrained by siloed data architectures and rule-based optimization paradigms. Although functional under stable conditions, such approaches exhibit limited adaptability and insufficient foresight when confronted with demand volatility,

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sudden disruptions, or systemic shocks. The escalating frequency of global supply chain crises, ranging from geopolitical tensions to pandemics, has further underscored the inadequacy of static models and manual planning processes. Consequently, organizations are increasingly turning to advanced computational technologies capable of synthesizing multi-source data, modeling complex contingencies, and producing responsive, forward-looking strategies. Recent work has also demonstrated the feasibility of hybrid AI-driven scheduling and logistics optimization within intelligent supply chain systems, indicating a shift from static planning toward adaptive optimization (Cheng et al., 2025). Moreover, cross-organizational data integration increasingly faces privacy and governance constraints, motivating decentralized learning paradigms that can leverage multimodal data without centralized sharing (Huang et al., 2024). Generative artificial intelligence (AI), particularly large foundation models endowed with sophisticated reasoning and content-generation capacities, presents a compelling avenue for addressing these limitations. Advances in large-scale multimodal model pretraining and efficiency optimization further strengthen the technical foundation for deploying such models in data-intensive decision environments (Ji et al., 2025). Emerging studies have begun to explore the implications of generative AI tools, such as large language models, in supply chain analytics and decision support contexts (Frederico, 2023). Moving beyond traditional predictive analytics, which often extrapolate linearly from historical patterns, generative AI enables the exploration of diverse counterfactual scenarios, the formulation of context-aware optimization policies, and continuous adaptation to shifting operational realities. This study investigates how generative AI can be systematically integrated into supply chain decision-making through structured optimization frameworks and real-world implementation contexts, thereby advancing the field toward more resilient, agile, and intelligent operations.

2. Challenges in Traditional Supply Chain Decision-Making

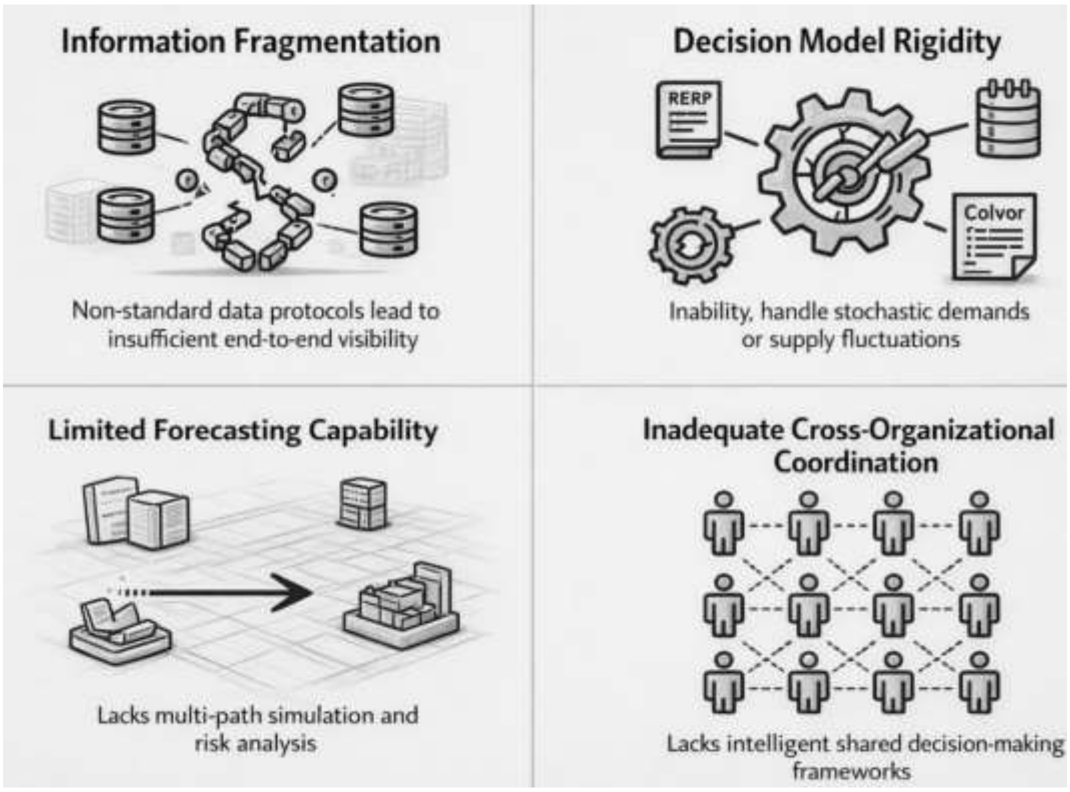

Figure 1: *Structural Limitations of Traditional Supply Chain Decision-Making Systems*

As illustrated in the Figure 1, traditional supply chain decision-making systems are hampered by structural limitations that impede both operational efficiency and adaptive capacity. A

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primary obstacle is information fragmentation: Participants across the supply chain, including suppliers, manufacturers, and logistics providers, typically rely on disparate enterprise resource planning (ERP) systems, procurement platforms, and logistics databases. The absence of standardized data protocols and integrated digital infrastructures fosters data silos, which undermine end-to-end visibility and hinder real-time coordination. Consequently, critical signals, such as demand fluctuations, inventory positions, and shipment statuses, often remain unsynchronized across network nodes, resulting in distorted forecasts and suboptimal operational decisions. In real-world digital industry settings, missing and even completely unobservable data streams can further degrade situational awareness, motivating generative imputation and cross-modal completion strategies (Kang et al., 2024). A second key constraint stems from the inherent rigidity of conventional decision models. Many organizations still depend on rule-based logic or deterministic optimization approaches calibrated for stable, predictable conditions. While these models offer baseline reliability, they lack the flexibility to manage stochastic demand, supply-side volatility, or competing optimization objectives (e.g., cost minimization versus service-level maximization). Moreover, heavy reliance on manual adjustments in planning workflows further extends decision latency and diminishes agility in responding to dynamic market shifts. Third, predictive capabilities remain narrowly scoped. Traditional forecasting tools typically generate single-point estimates without exploring a range of plausible futures. This limited scenario coverage constrains enterprises' ability to conduct robust risk assessments or evaluate alternative contingency plans. For instance, in the event of a potential supplier default or transportation disruption, legacy systems rarely support multi-path simulations or probabilistic impact analyses, which renders decision-making largely reactive rather than anticipatory. Traditional AI-based resilience models demonstrate that dynamic analytics capabilities are critical to coping with supply chain disruptions (Dey et al., 2024; Gupta et al., 2024). Finally, cross-organizational coordination remains underdeveloped. Supply chains inherently comprise multiple entities with divergent goals, incentives, and performance indicators. In the absence of intelligent, shared decision frameworks, misaligned priorities and communication lags erode systemic efficiency. Most conventional platforms optimize decisions at the local level without accounting for network-wide objectives, leading to fragmented improvements that fall short of holistic supply chain performance. Systematic reviews further suggest that AI integration across supply chain functions remains uneven and fragmented, limiting network-wide optimization (Bhattacharya et al., 2024). Collectively, these structural deficiencies underscore the urgent need for next-generation intelligent technologies that are capable of dynamic learning, context-aware reasoning, and generative, forward-looking optimization, in order to enable truly adaptive and resilient supply chain decision-making.

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3. Generative AI-Driven Optimization Mechanisms

***Figure 2**: Generative AI-Driven Optimization Mechanisms in Intelligent Supply Chains*

As depicted in the Figure 2, generative artificial intelligence (GenAI) represents a paradigm shift in supply chain decision-making, moving beyond conventional predictive analytics toward a new form of generative intelligence. Its transformative potential manifests through several interrelated mechanisms that collectively enhance operational agility and strategic foresight. First, GenAI significantly augments predictive capabilities by integrating heterogeneous data sources, including transactional records, logistics metrics, market signals, and external environmental indicators, within probabilistic modeling frameworks. Multimodal or multisensory fusion literature has long established that combining complementary modalities improves robustness and decision quality in complex environments (Khaleghi et al., 2013; Lahat et al., 2015; Jiao et al., 2024).This enables more accurate demand forecasting and inventory planning under uncertainty. Unlike static statistical models, generative architectures continuously refine their internal representations in response to incoming data, facilitating real-time adaptation. Formally, this process can be framed as an optimization problem aimed at minimizing total operational costs while satisfying predefined service-level constraints amid stochastic demand. Digital twin-enabled machine learning models have shown strong potential in supporting inventory and cash flow optimization under uncertainty (Badakhshan & Ball, 2023). Second, GenAI enables intelligent scenario generation and simulation. Leveraging counterfactual reasoning and probabilistic inference, it can synthesize a wide range of plausible operational scenarios, such as demand surges, supplier disruptions, or transportation bottlenecks. This capability supports robust "what-if" analyses, allowing organizations to evaluate alternative strategies before deployment. By generating realistic yet hypothetical futures, GenAI strengthens the resilience and adaptability of strategic planning. Third, adaptive resource allocation becomes feasible through the integration of reinforcement learning and dynamic optimization within generative frameworks. Prior studies in smart manufacturing have shown that multi-agent architectures coupled with reinforcement learning can enable distributed intelligence and adaptive decision-making under uncertainty, providing methodological grounding for GenAI-enabled resource allocation in supply networks (Kim et al., 2020).Decisions concerning production scheduling, warehouse inventory distribution, and vehicle routing can be continuously adjusted based on real-time feedback from the operating environment. Rather than relying on fixed parameters, GenAI dynamically tunes decision variables to balance competing objectives: cost efficiency, service performance, and risk exposure. Fourth, GenAI facilitates automated strategy formulation. Large foundation models equipped with natural language reasoning can interpret both structured and unstructured data to produce

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actionable outputs, such as procurement plans, logistics policies, supplier evaluation reports, and contingency protocols. This automation reduces manual analytical effort while promoting greater coherence across strategic initiatives. Moreover, built-in explainability features in advanced generative models enhance the transparency and auditability of decisions. The importance of explainability and trustworthy AI governance has been widely emphasized in recent XAI literature (Ali et al., 2023). Finally, GenAI enhances risk detection and early-warning systems. By combining anomaly detection algorithms with knowledge graph–based reasoning, it uncovers latent interdependencies among supply chain nodes and anticipates emerging disruptions. Data-driven risk management frameworks based on data mining have previously been proposed to support timely SCRM decision-making under information overload, which motivates the use of generative risk simulation and early-warning intelligence (Kara et al., 2020).Predictive stress-testing simulations further enable proactive alerts and prescriptive recommendations, thereby bolstering overall supply chain resilience.

Together, these mechanisms redefine supply chain management, shifting it from a reactive, problem-solving orientation to a proactive, adaptive, and intelligence-generating system.

4. Application Scenarios

Figure 3. *Application Scenarios of Generative AI in Supply Chain Operations*

As presented in the Figure 3， the practical deployment of generative artificial intelligence (GenAI) extends across multiple domains of supply chain management, delivering value through intelligent automation and adaptive decision support. In procurement, GenAI leverages historical supplier performance data, pricing trajectories, and contractual terms to formulate optimized sourcing recommendations. Through scenario-based simulation, organizations can assess alternative supplier portfolios under diverse risk profiles, such as geopolitical instability, financial volatility, or operational disruptions, thereby strengthening procurement resilience and strategic flexibility. Within warehouse operations, GenAI enables demand-responsive inventory forecasting and automates replenishment planning. By modeling stochastic stock-flow dynamics, the system refines warehouse layout design and optimizes order-picking sequences. These enhancements reduce handling costs, improve space utilization, and mitigate the risk of stockouts without excessive safety stock. In logistics and distribution, generative routing algorithms dynamically recalibrate transportation plans in response to real-time variables, including traffic congestion, adverse weather, and shifting delivery priorities. This continuous re-optimization reconciles competing objectives of cost

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efficiency and service reliability, leading to more agile and responsive distribution networks. Case-based research highlights how AI-driven routing and analytics improve operational responsiveness and performance (Cannas et al., 2024). Finally, in after-sales service management, GenAI analyzes product telemetry and customer feedback to anticipate maintenance requirements and generate personalized service interventions. Such proactive support not only elevates customer satisfaction but also minimizes unplanned service failures and associated warranty costs. AI-powered predictive maintenance models have been linked to improved supply chain resilience and reduced system vulnerability (Gupta et al., 2024).

Collectively, these applications illustrate how generative AI transforms discrete supply chain functions into an integrated, anticipatory, and self-optimizing ecosystem.

5. Future Development Trends

The integration of generative artificial intelligence (GenAI) into supply chain operations is catalyzing the emergence of autonomous operational ecosystems. Within predefined governance protocols. AI agents can execute decisions independently, orchestrating procurement schedules, managing inventory levels, and coordinating logistics dispatches with minimal human intervention. Multi-agent reinforcement learning provides a formal foundation for coordinating multiple decision entities, and recent reviews summarize algorithmic advances relevant to decentralized operational control (Liang et al., 2025). This shift toward autonomy markedly enhances system responsiveness, operational continuity, and scalability. Decentralized autonomous paradigms have been proposed to strengthen resilience under disruptions, offering conceptual parallels to GenAI-enabled autonomous decision ecosystems in supply networks (Leng et al., 2023). The synergy between GenAI and digital twin technologies further amplifies this transformation. Digital twin research further indicates that multi-agent approaches can automate anomaly detection and bottleneck identification in complex operational systems, aligning with GenAI-enabled proactive monitoring and prescriptive decision support (Latsou et al., 2023). Digital twins provide high-fidelity virtual replicas of physical supply chain processes, enabling real-time monitoring and scenario testing. When coupled with GenAI, these simulated environments become dynamic testbeds for optimizing decision policies, allowing strategies to be iteratively refined and validated before deployment in the physical world. This convergence significantly improves both simulation fidelity and operational transparency. Recent digital twin research demonstrates the feasibility of integrating AI-driven optimization into real-time supply chain simulation environments (Badakhshan & Ball, 2023). Looking ahead, cross-enterprise generative collaboration platforms are poised to become foundational infrastructure for supply chain networks. Federated learning surveys emphasize that data silos and privacy constraints increasingly limit centralized analytics, motivating decentralized model training as a practical pathway toward cross-organization intelligence (Leng et al., 2025).These shared, AI-driven environments facilitate seamless data interoperability and synchronized decision-making across organizational boundaries. Related research suggests that blockchain-enabled smart contracts can serve as a decentralized coordination layer for digital-twin-based systems, supporting consensus and resilience in multi-stakeholder operational networks (Leng et al., 2023).By aligning incentives and actions at the ecosystem level, such platforms enhance collective efficiency, risk mitigation, and adaptive capacity. Nevertheless, human-AI collaborative governance remains indispensable. The responsible deployment of autonomous systems demands robust mechanisms for explainability, ethical alignment, and accountability. Human oversight must be strategically embedded, not as a bottleneck but as a complementary layer that ensures strategic coherence, regulatory compliance, and societal trust. Sustainable adoption thus hinges on balancing algorithmic autonomy with principled human stewardship.

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6. Conclusion

Generative artificial intelligence (GenAI) constitutes a transformative driver in the evolution of intelligent supply chain decision-making. By advancing predictive intelligence, enabling adaptive optimization, facilitating high-fidelity scenario simulation, and automating strategic planning, GenAI substantially elevates operational efficiency, cost effectiveness, and systemic resilience to disruption. This paradigm shift moves supply chain management beyond rigid, rule-based architectures toward dynamic, learning-enabled frameworks capable of real-time adaptation and anticipatory response. As digital transformation intensifies across industries, organizations that successfully embed GenAI into their supply chain operations stand to secure significant competitive advantages, particularly in agility, operational flexibility, and strategic foresight. Future research should prioritize empirical validation through field studies, the development of hybrid optimization models that integrate generative and classical approaches, and in-depth analyses of real-world implementation challenges. Such efforts will be critical to maturing GenAI-driven frameworks into robust, scalable, and ethically grounded solutions for next-generation supply chains.

References

[1] Jabeen, S., Li, X., et al. (2023). A review on methods and applications in multimodal deep learning. *ACM Transactions on Multimedia Computing, Communications, and Applications, 19*(2).

[2] Benzidia, S., Makaoui, N., & Bentahar, O. (2021). The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technological Forecasting and Social Change, 165*, 120557.

[3] Dubey, R., Bryde, D. J., et al. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. *International Journal of Production Economics, 250*, 108613.

[4] Shavaki, F. H., & Ghahnavieh, A. E. (2023). Applications of deep learning into supply chain management: A systematic literature review and a framework for future research. *Artificial Intelligence Review, 56*(5), 4447–4489.

[5] Cheng, H. M., Huang, S. K., & Lin, C. W. (2025). Hybrid manufacturing logistics optimization scheduling algorithm based on intelligent supply chain management and artificial intelligence. *International Journal of Advanced Manufacturing Technology*. Advance online publication.

[6] Huang, W., Wang, D. X., et al. (2024). Multimodal federated learning: Concept, methods, applications and future directions. *Information Fusion, 112*.

[7] Ji, L. X., Xiao, S. J., et al. (2025). Multimodal large model pretraining, adaptation and efficiency optimization. *Neurocomputing, 619*, 129138. https://doi.org/10.1016/j.neucom.2024.129138

[8] Frederico, G. F. (2023). ChatGPT in supply chains: Initial evidence of applications and potential research agenda. *Logistics, 7*(2), 23.

[9] Kang, M. Y., Zhu, R., et al. (2024). CM-GAN: A cross-modal generative adversarial network for imputing completely missing data in digital industry. *IEEE Transactions on Neural Networks and Learning Systems, 35*(3), 2917–2926.

[10] Dey, P. K., Chowdhury, S., et al. (2024). Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small- and medium-sized enterprises. *International Journal of Production Research, 62*(15), 5417–5456.

[11] Gupta, S., Modgil, S., et al. (2024). Artificial intelligence and information system resilience to cope with supply chain disruption. *IEEE Transactions on Engineering Management, 71*, 10496–10506.

[12] Bhattacharya, S., Govindan, K., Sharma, P., et al. (2024). Applications of artificial intelligence in closed-loop supply chains: Systematic literature review and future research agenda. *Transportation Research Part E: Logistics and Transportation Review, 184*, 103364.

ISSN: 3079-6342

[13] Khaleghi, B., Khamis, A., et al. (2013). Multisensor data fusion: A review of the state-of-the-art. *Information Fusion, 14*(1), 28–44.

[14] Lahat, D., Adali, T., & Jutten, C. (2015). Multimodal data fusion: An overview of methods, challenges, and prospects. *Proceedings of the IEEE, 103*(9), 1449–1477.

[15] Jiao, T. Z., Guo, C. P., et al. (2024). A comprehensive survey on deep learning multi-modal fusion: Methods, technologies and applications. *CMC—Computers, Materials & Continua, 80*(1), 1–35.

[16] Badakhshan, E., & Ball, P. (2023). Applying digital twins for inventory and cash management in supply chains under physical and financial disruptions. *International Journal of Production Research, 61*(15), 5094–5116.

[17] Kim, Y. G., Lee, S., et al. (2020). Multi-agent system and reinforcement learning approach for distributed intelligence in a flexible smart manufacturing system. *Journal of Manufacturing Systems, 57*, 440–450.

[18] Ali, S., Abuhmed, T., et al. (2023). Explainable Artificial Intelligence (XAI): What we know and what is left to attain trustworthy artificial intelligence. *Information Fusion, 99*, 101805.

[19] Kara, M. E., Firat, S. Ü. O., & Ghadge, A. (2020). A data mining-based framework for supply chain risk management. *Computers & Industrial Engineering, 139*, 106166.

[20] Cannas, V. G., Ciano, M. P., et al. (2024). Artificial intelligence in supply chain and operations management: A multiple case study research. *International Journal of Production Research, 62*(9), 3333–3360.

[21] Liang, J., Miao, H., Li, K., Tan, J., Wang, X., Luo, R., & Jiang, Y. (2025). A review of multi-agent reinforcement learning algorithms. *Electronics, 14*(4), 820. https://doi.org/10.3390/electronics14040820

[22] Leng, J. W., Zhong, Y. W., et al. (2023). Towards resilience in Industry 5.0: A decentralized autonomous manufacturing paradigm. *Journal of Manufacturing Systems, 71*, 95–114.

[23] Latsou, C., Farsi, M., & Erkoyuncu, J. A. (2023). Digital twin-enabled automated anomaly detection and bottleneck identification in complex manufacturing systems using a multi-agent approach. *Journal of Manufacturing Systems, 67*, 242–264.

[24] Leng, J., Li, R., et al. (2025). Federated learning-empowered smart manufacturing and product lifecycle management: A review. *Advanced Engineering Informatics, 65*, 103179. https://doi.org/10.1016/j.aei.2025.103179

[25] Leng, J. W., Zhu, X. F., et al. (2023). ManuChain II: Blockchained smart contract system as the digital twin of decentralized autonomous manufacturing toward resilience in Industry 5.0. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 53*(8), 4715–4728.

[26] Leng, J. W., Su, X. Y., et al. (2025). Diffusion model-driven smart design and manufacturing: Prospects and challenges. *Journal of Manufacturing Systems, 82*, 561–577.

[27] Leng, J. W., Zheng, K. Y., et al. (2026). AIGC-empowered smart manufacturing: Prospects and challenges. *Robotics and Computer-Integrated Manufacturing, 97*, 103076. https://doi.org/10.1016/j.rcim.2025.103076