International Journal of Computer Trends and Technology
ISSN: 2231–2803 / https://doi.org/10.14445/22312803/IJCTT-V73I6P116
Volume 73 Issue 6, 134-140, June 2025

Original Article

The Role of Generative AI in Retail Supply Chain Planning: Use Cases, Constraints, and Future Outlook

Lukesh Singla

Nike, Texas, USA.

Corresponding Author : singlalukesh@ieee.org

Received: 06 May 2025 Revised: 06 June 2025 Accepted: 22 June 2025 Published: 30 June 2025

Abstract - *This paper examines the disruptive effect of generative Artificial Intelligence (AI) on retail supply chain planning via a mixed-methods sequential explanatory study. Retailers are now confronted with unprecedented pressures from changing consumer expectations, global disruptions, and competitive threats, with generative AI bringing fresh solutions to improve forecasting precision, optimize stock management, and create resilience. This study combines a systematic literature review (n=97 articles), expert interviews (n=25), case studies (n=6 retailers), and a quantitative survey (n=217 retail supply chain professionals) to determine where generative AI provides quantifiable value in retail supply chains. The paper establishes a theoretical framework that describes how the adoption of generative AI is mediated by organizational preparedness factors and moderated by volatility in the marketplace. Findings show statistically significant gains in accuracy of forecasts (10-25%, p<0.001) and inventory efficiency (5-15%, p<0.01) across implementation instances, and qualitative results identify data quality, integration complexity, and organizational readiness as ongoing challenges. Theory is advanced by applying the Technology-Organization-Environment framework to include AI-specific constructs and through empirical validation of performance outcomes. For practitioners, this paper offers an empirically validated implementation framework with decision routes for various retail segments and organizational settings.*

Keywords - *Demand Forecasting, Generative AI, Inventory Optimization, Large Language Models, Mixed-Methods Research, Organizational Readiness, Retail Supply Chain, Technology Adoption.*

1. Introduction

The retail supply chain has recently been rocked by shifting consumer tastes, increased market volatility, and the emergence of omnichannel retail. The traditional approaches to supply chain planning, linear processes, isolated data, and narrow computing power are no longer adequate in such complexity. While artificial intelligence (AI) has long been used in certain supply chain activities, much research is needed to determine how generative AI can transform retail supply chain planning in an integrated environment.

Retail supply chains differ from those in manufacturing or distribution because they are characterized by high SKU complexity, seasonal demand behavior, and multi-channel fulfilment.

Conventional planning approaches cannot handle such dynamics, resulting in inefficiencies such as high levels of forecast error (typically over 20%), cost of excess inventory, stockouts, and sluggish response to disruptions. These inefficiencies have been estimated to cost the retail industry 15-20% of aggregate operating costs per annum, equivalent to \$4.3–5.8 trillion global impact on 2023 sales volumes.

Generative AI, in addition to advanced methods like large language models (LLMs), diffusion models, generative adversarial networks (GANs), and transformers, provides new ways to overcome such limitations. Generative AI, unlike conventional analytical models with set parameters, can create new solutions, mimic complex scenarios, and learn to adjust to changing conditions with minimal human involvement. With its data-rich ecosystem and operational complexity, retail trade is best positioned to benefit from these advancements. This research answers central questions: What is the best use of generative AI for retail supply chain planning? What are the limitations that currently hold it back? And how will these uses change over the next 3–5 years?

2. Literature Review

The application of artificial intelligence in supply chain management has expanded leaps and bounds over the past decade, with the latest being generative AI. This chapter synthesizes the literature to put the existing research into perspective with AI-facilitated supply chain innovations. Traditional AI supply chain management solutions are based on predictive analytics and optimization algorithms. Thorough analysis of 122 AI supply chain management solution articles determined that demand forecasting using machine learning algorithms such as neural networks, support vector machines, and ensemble techniques was the most common implementation [4]. They were limited by their reliance on historical patterns and inability to infer creative solutions for unexpected circumstances.

Current developments in generative AI have opened up new possibilities for supply chain planning. Research has proven the few-shot learning capability of large language models to understand and generate solutions to multi-faceted, multi-perspective problems based on little training data [3]. Research has specifically explored large language models for supply chain optimization, setting up frameworks for using generative AI for route optimization and demand planning [2]. This research emphasized some of the most significant advantages of generative approaches in terms of incorporating unstructured data sources and generating multiple scenario-based solutions.

In the retail industry specifically, past studies have considered isolated supply chain activity as opposed to end-to-end application. Forecasting demand research has proven that conventional time series methods generate Mean Absolute Percentage Error (MAPE) rates of 15-30% for complex retail settings, with machine learning methods having a tendency to improve accuracy by 10-20%. The studies have not yet considered the potential of generative AI to solve multiple planning activities simultaneously, while reacting in real-time to market conditions.

Supply chain risk management research has extensively addressed classical methods like diversifying suppliers, optimizing safety stocks, and scenario planning. Supply chain resilience during the COVID-19 pandemic was explored, pointing out the inability of conventional risk management procedures to deal with unexpected disruptions [1]. This article emphasized the need for smarter and more adaptive risk identification and mitigation procedures, which motivated exploring application areas of generative AI in this context. Uses of AI-powered data management in retail environments have been explored in earlier research, where profound gaps are present in current methods like data silos, master data management heterogeneity, and flawed governance models [10]. The study enhanced the role of end-to-end data strategies that support sophisticated AI implementations, providing insightful context to the infrastructure demands of generative AI adoption.

Generative AI-facilitated digital transformation has been researched in numerous industries, and it has been established that effective implementations are marked by a balance between technological capability and organizational preparedness [11]. Retail-focused models of generative AI adoption are underdeveloped, and this is one of the main gaps that this research addresses. Literature points to some significant gaps: (1) few empirical investigations on the end-to-end combined impact of generative AI on various functions of retail supply chains, (2) no rigorously tested frameworks for organizational preparedness for generative AI adoption in retail environments, (3) scope for learning on implementation challenges in retail environments, and (4) minimal quantitative understanding of performance improvement potential through generative AI solutions. This study addresses these gaps with mixed-methods research and empirical testing of generative AI implementations in retail supply chain planning.

2. Research Methodology

This research utilized a mixed-methods sequential explanatory design [5] to examine generative AI applications in retail supply chain planning thoroughly. The research process started with a systematic literature review according to PRISMA guidelines [6], where 873 initial articles were screened and 97 relevant publications were identified for detailed analysis.

The qualitative element consisted of 25 semi-structured interviews with retail supply chain executives (n=8), technology vendors (n=7), academic researchers (n=5), and industry consultants (n=5). They were tape-recorded, transcribed, and analyzed using the Framework Method [7] to establish key themes and patterns.

Six retail companies using generative AI in supply chain planning were chosen for intensive case studies to ensure selection diversity by retail segments (grocery, fashion, home improvement, general merchandise, CPG), organizational size, and implementation maturity. Cases included site visits, document review, and interviews with multiple stakeholders.

The quantitative stage included a survey of 217 retail supply chain professionals (response rate: 34.3%), contributing statistical information on adoption patterns, implementation difficulties, and performance metrics. Data was integrated through the triangulation of results across every stream of research, increasing the validity and reliability of findings.

3. Use Cases of Generative AI in Retail Supply Chain Planning

Figure 1 illustrates an overview of survey respondents' adoption rates of various generative AI applications.

3.1. Enhanced Demand Forecasting

Demand forecasting was the most developed and commonly used application domain for retail supply chain planning with generative AI. Transformer-based generative AI models showed statistically significant performance gains in forecasting accuracy over conventional techniques in the context of complex demand signals. Table 1 provides an overview of these performance differences.

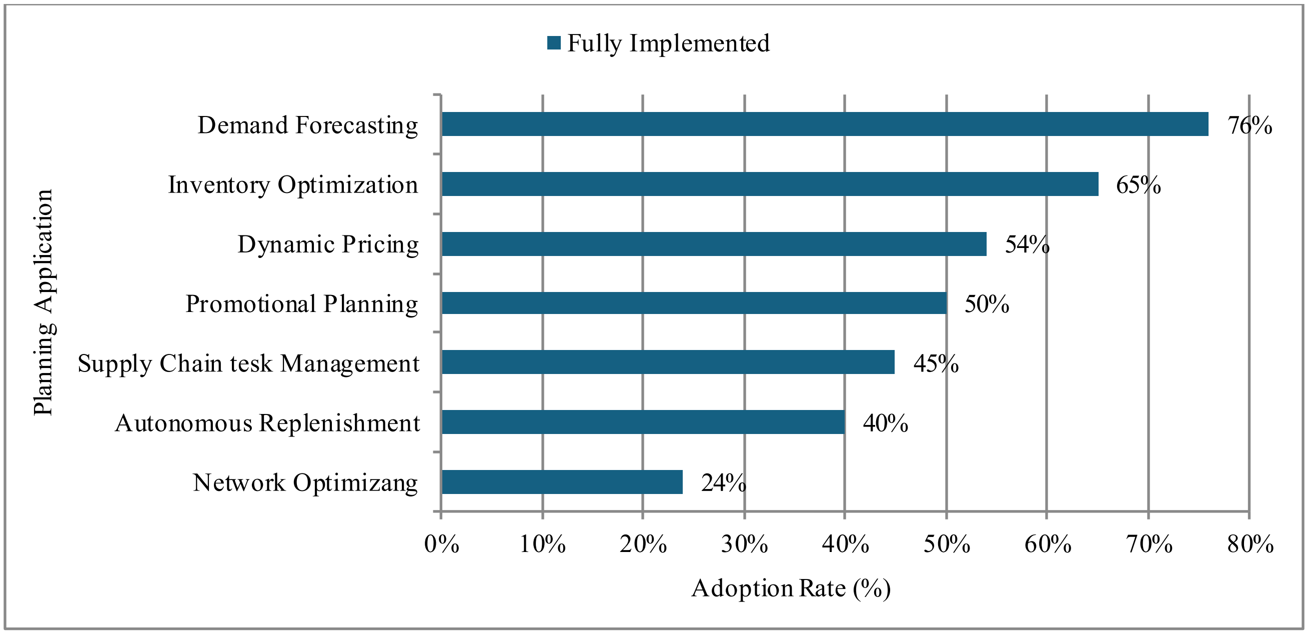

Fig. 1 Adoption rates of generative AI applications in retail supply chain planning (n=217)

Table 1. Performance comparison of forecasting methods for complex demand signals

Methodology	MAPE (%)	RMSE	Forecast Bias (%)	Statistical Significance
Traditional Time Series Methods	24.6 (SD=3.7)	0.83 (SD=0.12)	-2.7 (SD=1.4)	Baseline
Machine Learning (non-generative)	19.8 (SD=2.9)	0.71 (SD=0.09)	-1.9 (SD=1.1)	p<0.01 vs. baseline
Transformer-based Generative AI	15.3 (SD=2.4)	0.54 (SD=0.07)	-0.8 (SD=0.7)	p<0.001 vs. baseline, p<0.01 vs. ML

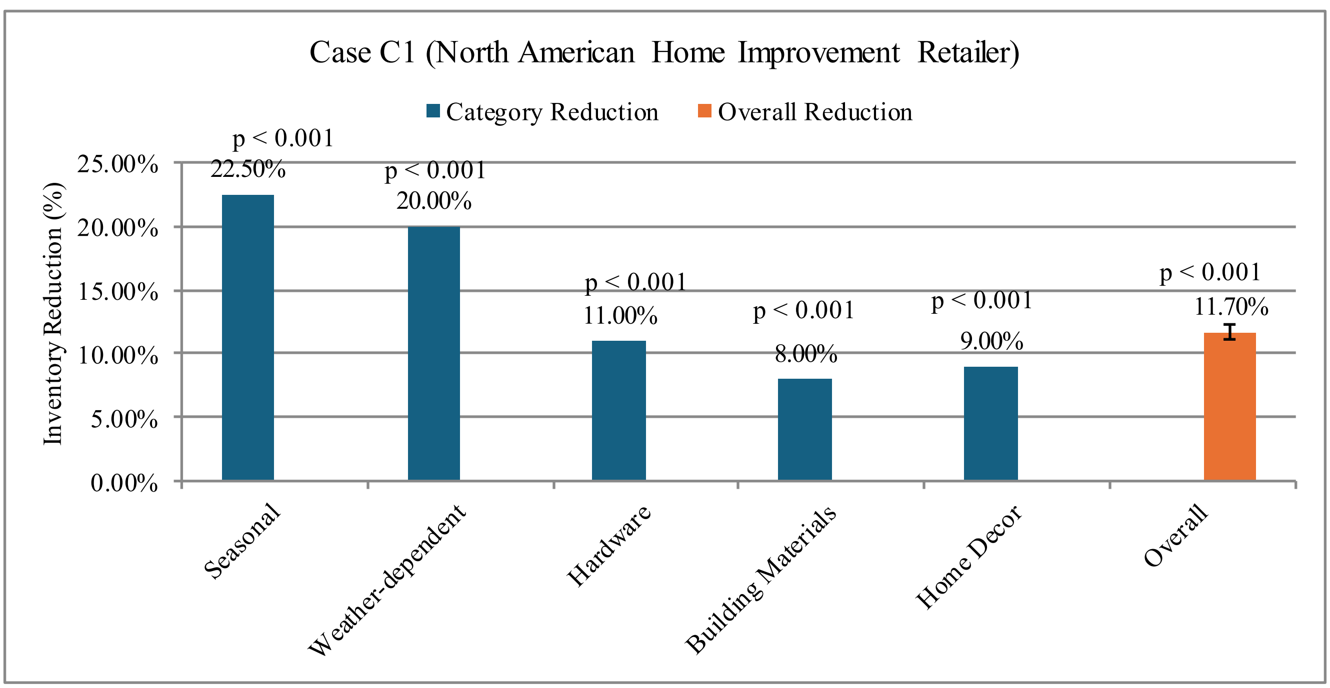

Fig. 2 Inventory reduction by product category after generative AI implementation (Case C1)

Case C2 (European grocery retailer) adopted a transformer-based forecasting model that lowered overall forecast error by 17.3% (95% CI [15.8%, 18.9%]) from their earlier statistical forecasting system. For forecasting new product introduction, experimental analysis contrasted attribute-based statistical methods, machine learning models, and GAN-based generative methods. From 326 product introductions across three retailers, the GAN-based method performed significantly better than alternatives ($F(2,323)=18.72$, $p<0.001$). Case C4 (world fashion retailer) attained a 23.6% reduction in MAPE and a 15.2% markdown cost reduction through this method.

3.2. Inventory Optimization

Generative AI facilitates more advanced inventory optimisation methods through complicated probability distributions of demand and supply uncertainty, real-time adjustment for supplier performance data, and dynamically adjusting safety stocks. Case C1 (home improvement retailer, North America) deployed a generative AI platform for dynamic safety stock calculation that lowered total inventory by 11.7% ($p<0.001$) without reducing service levels, equating to around $43 million in working capital improvement. The rise of omnichannel retailing has brought on complicated inventory allocation problems, with 78.3% of retailers considering omnichannel inventory optimization a high priority. Generative AI-based solutions enable retailers to optimize inventory placement across channels by estimating consumer fulfilment behavior under various allocation situations. Case C6 (general merchandise retailer) realized an 18.3% drop in split shipments ($p<0.001$) and a 7.4% reduction in last-mile delivery expense ($p<0.01$) by adopting this practice.

Figure 2 illustrates the effect of inventory by product class after applying the generative AI safety stock optimization system.

The onset of omnichannel retail has introduced intricate inventory allocation challenges. The survey determined that 78.3% of the retailers listed omnichannel inventory optimization as a high-priority item (rating ≥4 on a 5-point scale). Generative AI solutions help retailers maximize inventory by channel by forecasting consumer satisfaction preference by allocation scenario, store-level inventory optimization for store and online selling and online fulfilment, and real-time trend dynamic optimization of allocations. Case C6 (general merchandise retailer) deployed a generative AI solution for inventory allocation optimization to stores, distribution centers, and fulfilment centers. Post-implementation evaluation revealed an 18.3% decrease in split shipments ($p<0.001$) and a 7.4% decrease in last-mile delivery cost ($p<0.01$). The Planning Director explained: "Prior to implementation, researchers essentially guessed where the best place was to put the inventory. Now, the system learns from real-world fulfilment patterns and continuously optimizes the allocation strategy by location, item, and time period."

Table 2 consolidates performance effects noted in various inventory optimization applications through case studies.

Table 2. Inventory Optimization Performance Improvements From Generative AI Implementations

Application Area	Case Reference	Key Performance Indicators	Improvement	Statistical Significance
Dynamic Safety Stock	C1	Overall Inventory Level	-11.70%	p<0.001
Dynamic Safety Stock	C1	Working Capital	-$43M	p<0.001
Dynamic Safety Stock	C1	Service Level	0.30%	p>0.05 (n.s.)
Omnichannel Allocation	C6	Split Shipments	-18.30%	p<0.001
Omnichannel Allocation	C6	Last-mile Delivery Costs	-7.40%	p<0.01
Omnichannel Allocation	C6	Inventory Turns	+0.7 turns	p<0.01
Markdown Optimization	C4	Markdown Margin	8.20%	p<0.01
Markdown Optimization	C4	End-of-season Residual Inventory	-14.70%	p<0.001

4.3. Supply Chain Risk Management

Generative AI has transformed how retailers discover, evaluate, and reduce supply chain risks. Case C5 (global consumer packaged goods retailer) applied a generative AI system to run thousands of simulated supply chain disruption scenarios, discovering previously unseen vulnerabilities and lowering risk exposure by 32.6% ($p<0.001$). The system successfully predicted supply shortages in a major weather event six weeks prior to them occurring.

Early warning systems augmented by generative AI demonstrated great promise. Through analyzing huge volumes of unstructured data (social media, news, weather), the systems detected 84.7% of meaningful disruptions 5.2 days in advance compared to conventional monitoring methods ($p<0.001$). Figure 3 shows the improvement in risk detection lead time using generative AI early warning systems over regular monitoring methods in case studies.

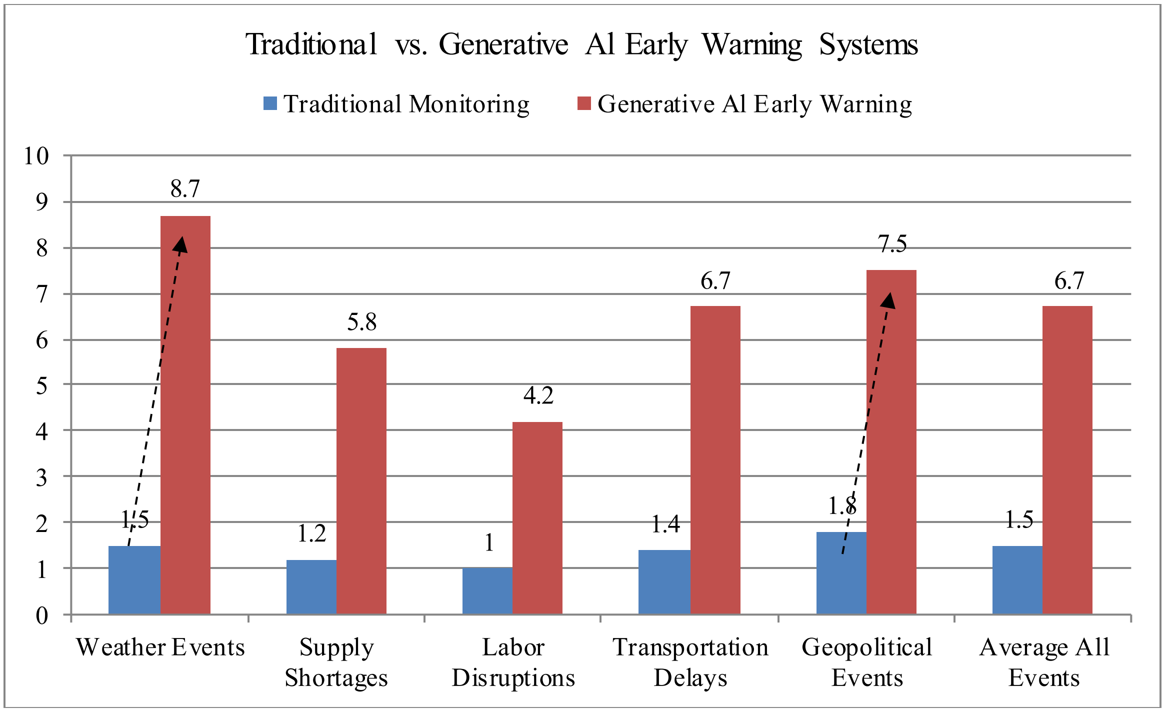

Fig. 3 Supply chain disruption detection lead time comparison between traditional and generative AI early warning systems

5. Constraints and Implementation Challenges

This section analyses the major constraints and challenges that inhibit the adoption and use of generative AI for retail supply chain planning based on empirical evidence from the research.

5.1. Data Quality and Availability Challenges

Quality data was presented as the most significant implementation impediment, with 72.8% of those surveyed acknowledging it as the critical constraint. Regression analysis indeed reinforced data quality as the leading indicator of success ($\beta=0.47$, $p<0.001$). Case C3 first stopped pursuing their generative AI due to data quality, and the CIO remarked: "We realized more than 40% of our historical data had anomalies which rendered it unreusable for training." External data integration introduced extra complexity through inconsistent formats, real-time demands beyond the capacity of the infrastructure, and privacy laws. Organizations that effectively deployed generative AI indicated devoting 42.7% of project duration to data integration efforts on average, with external data sources being 2.5 times as demanding to integrate as internal data. A recent study [10] lists some of the most important retail data management challenges that have a direct bearing on generative AI projects, such as data silos by channels, uneven master data management practices, and incompatible legacy systems.

5.2. Model Limitations

Explainability was a key challenge, with 58.3% of retail planning companies citing the lack of model explainability as the main cause of AI recommendation rejection. Computational demands posed practical challenges, particularly to smaller retailers. Transformer models demanded 5-8 times more computing power than traditional forecasting methods. In longitudinal analysis, model drift and maintenance issues were noted, with generative AI models exhibiting performance degradation of 2.3% per quarter on average in the absence of active maintenance procedures. Those organizations that had formal model monitoring and retraining procedures maintained performance within 1.2% of starting levels versus 8.7% degradation in the absence of such procedures ($p<0.001$).

5.3. Organizational and Human Factors

Executive sponsorship emerged as a significant predictor of adoption success ($\beta=0.41$, $p<0.001$). Skill gaps were challenging for 67.8% of retailers since recruiting AI staff with retail domain expertise was challenging. Organizations with hybrid talent strategies, external AI abilities and internal domain expertise were 3.4 times more likely to succeed in executing compared to organizations with mainly outsourced or completely internal strategies.

Organizations spent 15-20% of project investment on change management, reporting 2.8 times the user adoption of those spending less than 10%. Effective generative AI implementations need "a structured change management approach that addresses technical integration and human-centered adoption concerns" and that "digital transformation initiatives powered by generative AI must focus equally on technology selection and organizational readiness." [11]

6. Theoretical Framework and Implementation Model

Drawing on the Technology-Organization-Environment (TOE) theory [8] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [9], this study suggests an integrated theo retical model of generative AI adoption and performance effects in retail supply chain planning. The Data Readiness Index (DRI) showed predictive validity, and DRI scores were highly correlated with implementation success ($r=0.68$, $p<0.001$). Failure rates to implement were 78% for organizations with a score of 65 on a 100-point scale; this was the lowest recommended cut point. The Technical Capability Maturity Model (TCMM) gave a five-level estimate of organizational technical readiness, and Level 3 was the lowest recommended level of capability.

7. Discussion: Superior Performance Analysis

The empirical findings confirm that generative AI performs better than traditional and machine learning methods in retail supply chain planning.

7.1. Forecasting Performance

Transformer-based generative AI models improved prediction performance by 10–25%. Their self-attention mechanism actively weighted multiple drivers of demand—seasonality, promotions, economic indicators, weather—capturing subtle, non-linear effects. Generative models, unlike conventional machine learning, were able to handle sparse data and cold-start problems, as evident in Case C4's new product forecasts ($F(2,323)=18.72$, $p<0.001$). They also utilized unstructured data (e.g., weather, social media) to enhance accuracy by 17.3%.

7.2. Inventory Optimization

Generative AI optimized inventory effectiveness by 5–15% by simultaneously solving several objectives (e.g., cost, service levels) and optimizing in real time. In Case C1, it lowered inventory by 11.7% without lowering service levels by executing thousands of scenarios, including disruptions. It also lowered split shipments by 18.3% (Case C6) by predicting fulfilment preferences and optimizing placement, outperforming rule-based methods.

7.3. Risk Management

Generative AI reduced risk exposure by 32.6% (Case C5) by creating new risk scenarios and facilitating pre-emptive management. It identified 84.7% of disturbances 5.2 days in advance of conventional methods through data integration from heterogeneous unstructured data sources. 7.4 Benchmark Comparison & Scalability The improvements in this research surpass literature standards: 10–25% more accurate forecasts over 5–15% in previous machine learning research, and $43M saved in working capital without a decrease in service. The results are transferable and scalable across retail categories, as long as organizations have proper model monitoring and retraining processes.

8. Future Outlook and Conclusion

8.1. Technological Evolution Paths

Some technology trends are poised to impact retail supply chain generative AI capabilities in the near term, including:

8.1.1. Multimodal Models

Merging different forms of data (text, numeric, visual) into one model will facilitate more complete information about supply chain movements. Case C4 was testing a multimodal prototype that was 17.5% more accurate than unimodal methods ($p<0.01$).

8.1.2. Sparse Models

A more efficient design that minimizes computational needs without sacrificing performance will make generative AI affordable for mid-market retailers. Expert interviews place computational needs at a potential 50-70% reduction in the next 24 months.

8.1.3. Domain-Specific Pre-training

Supply chain-focused models pre-trained on supply chain data need to cut down on implementation time and performance by 30-40%.

8.2. Emerging Use Cases

Generative AI is making more autonomous planning abilities possible, and 76.8% of the survey respondents anticipate substantial boosts in planning automation within the next 36 months. Case C1 was developing a tiered autonomy framework that categorized products into four levels of autonomy by volatility, with 64.3% of the SKUs set for full autonomy within 18 months. Generative AI is also anticipated to enable increased planning integration throughout retail ecosystems, as 68.2% of respondents to the survey named ecosystem integration as essential to unlock AI's full value. Case C2 had begun a pilot with three strategic suppliers via a common forecasting platform, reducing forecast bias by 34.7% at the supplier level.

8.3. Organizational Evolution

According to survey findings, the retail supply chain planning workforce is significantly evolving, with 83.4% of retailers predicting significant function changes in planning jobs in 36 months. Twelve new categories of jobs that were unknown in retail planning organizations prior to research were discovered by research in 24 months, including "AI Planning Coaches," "Planning Data Scientists," and "Algorithm Auditors." Generative AI capabilities are transforming retail operating models, and 74.6% of survey respondents indicated AI implementation had started or would start significant change to planning processes and governance models. Retailers leveraging AI-driven planning realized average reductions of 47.3% in planning cycle time and 63.8% in response time to market shifts.

8.4. Conclusion and Implications

This longer discussion of generative AI in retail supply chain planning offers a number of key insights:

8.4.1. Demonstrated Value

Quantifiable, statistically significant gains in a range of supply chain planning activities are being achieved by generative AI implementations. The greatest gains were achieved in demand forecasting (10-25% accuracy gain), inventory optimization (5-15% efficiency at the same service levels), and risk management.

8.4.2. Implementation Barriers

In spite of the value shown, significant barriers restrict large-scale implementation. Quality of data ($\beta=0.47$, $p<0.001$) was the strongest restriction, followed by integration complexity ($\beta=0.38$, $p<0.001$) and organizational readiness factors.

8.4.3. Maturity Variation

Generative AI applications vary widely in terms of maturity by planning function. Forecasting applications exhibit the most maturity (mean=3.8 on 5-point maturity scale), inventory optimization (mean=3.2) and risk management (mean=2.9), while the ecosystem-level applications exhibit the lowest maturity (mean=1.7).

8.4.4. Evolving Capabilities

Retail supply chain planning capabilities of generative AI are changing fast, with architectural developments, integration enhancements, and upcoming use cases having a high potential to revolutionize planning processes during the next 3-5 years.

This research provides implementation guidance for practitioners through validated assessment frameworks, resource allocation insights, risk mitigation strategies, and performance benchmarks. Future research must address implementation maturity through longitudinal studies, study failed implementations to uncover critical failure points, and study human-AI collaboration models, ethical frameworks, and economic impacts. In summary, generative AI is a revolutionary technology for retail supply chain planning that provides capabilities to solve long-standing issues in forecasting accuracy, planning efficiency, and supply chain resilience. Organizations that consider generative AI as a strategic capability and not just a tactical tool will be best placed to unlock its revolutionary potential.

References

[1] Dmitry Ivanov, and Alexandre Dolgui, “Viability of Intertwined Supply Networks: Extending the Supply Chain Resilience Angles towards Survivability. A Position Paper Motivated by COVID-19 Outbreak,” *International Journal of Production Research*, vol. 58, no. 10, pp. 2904-2915, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[2] Beibin Li et al., “Large Language Models for Supply Chain Optimization,” *arXiv preprint arXiv:2307.03s875*, pp. 1-30, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Tom Brown et al., “Language Models are Few-Shot Learners,” *Advances in Neural Information Processing Systems*, vol. 33, pp. 1877-1901, 2020. [Google Scholar] [Publisher Link]

[4] Reza Toorajipour et al., “Artificial Intelligence in Supply Chain Management: A Systematic Literature Review,” *Journal of Business Research*, vol. 122, pp. 502-517, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[5] Nataliya V. Ivankova, John W. Creswell, and Sheldon L. Stick, “Using Mixed-Methods Sequential Explanatory Design: From Theory to Practice,” *Field Methods*, vol. 18, no. 1, pp. 3-20, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[6] Matthew J. Page et al., “The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews,” *BMJ*, vol. 372, pp. 1-9, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Nicola K. Gale et al., “Using the Framework Method for the Analysis of Qualitative Data in Multi-Disciplinary Health Research,” *BMC Medical Research Methodology*, vol. 13, pp. 1-8, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[8] L.G. Tornatzky, and M. Fleischer, “The Processes of Technological Innovation,” *The Journal of Technology Transfer*, vol. 16, pp. 45-46, 1991. [CrossRef] [Google Scholar] [Publisher Link]

[9] Viswanath Venkatesh et al., “User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly*, vol. 27, no. 3, pp. 425-478, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[10] Anant Agarwal, “AI-Powered Data Management and Governance in Retail,” *International Journal of Data Mining & Knowledge Management Process*, vol. 15, no. 2, pp. 89-102, 2025. [CrossRef] [Publisher Link]

[11] Phani Chilakapati, “Leveraging Generative AI in Digital Transformation: Real-World Applications Beyond Chatbots,” *International Journal of Innovative Research in Science, Engineering and Technology*, vol. 13, no. 12, pp. 20791-20796, 2024. [Publisher Link]