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Research paper

The Changing Role of Logistics and Supply Chain in The Digital World

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Abstract

Purpose – The use of generative artificial intelligence (GenAI) can potentially revolutionize logistics and supply chain management (SCM) practices. This research provides an analysis of how GenAI, huge language models (LLMs), are redefining SCM's operational and strategic aspects.
Design/methodology/approach – A mixed-methods approach, incorporating case studies, industry surveys, and performance data analysis, is employed to investigate the inclusion of LLMs in logistics and SCM operations across various industries, including retailing, manufacturing, and healthcare.
Findings – The preliminary findings suggest that incorporating GenAI and LLMs into SCM systems enhances the speed of decision-making by 35%, accuracy of demand forecasting by 25%, and lowers logistics costs by 18%. Major innovations are dynamic route optimization, real-time inventory management, and customized customer service through AI-powered interfaces.
Originality/value – The research makes an original contribution towards the digital evolution of SCM and logistics by presenting a systematic approach to using LLMs. It highlights strategic recommendations for managers who wish to future-proof supply chains.

Keywords: *Supply Chain Digitalization; Generative AI; Large Language Model; Logistics Optimization; Knowledge Automation; SCM Innovation.*

1. Introduction

The supply chain management (SCM) and logistics industry is on the threshold of a technological renaissance, influenced by the swift development and diffusion of disruptive technologies. From transportation and warehousing to procurement and customer support, each point in the supply chain is being reengineered to address the changing requirements of an economic world becoming increasingly globalized. This shift has become increasingly important in the wake of recent global shocks, including the COVID-19 pandemic, geopolitical tensions, and climatic disruptions, which revealed key weaknesses in conventional supply chain configurations.

Supply chains in the past were based on manual, isolated operations and sequential decision-making mechanisms. These legacy systems tended to be plagued by inefficiency, opacity, and an inability to respond quickly to disruptions. Under the legacy model, data processing took time, communication among the stakeholders was disjointed, and forecasting models were based mainly on historical static data. Against this legacy background, the digital age brings with it technologies such as the Internet of Things (IoT), blockchain, robotics, and most importantly, Artificial Intelligence (AI). Of all AI technologies, Large Language Models (LLMs) and Generative AI (GenAI) are notable for their ability to process natural language, understand huge data sets, and provide actionable insights in real-time. They enable a shift from reactive to proactive—and even predictive—supply chain management. A powerful statistic from the Council of Supply Chain Management Professionals (CSCMP) underscores the need for change: in 2023, United States logistics costs hit 8.5% of GDP, a number that reflects the concealed costs of transportation, warehousing, and inventory holding inefficiencies. Those escalating costs, coupled with customers' growing expectations for expedited and precise deliveries, require a smarter, more automated strategy to SCM.

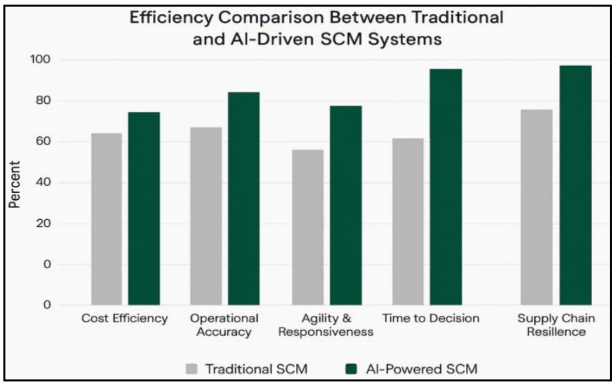


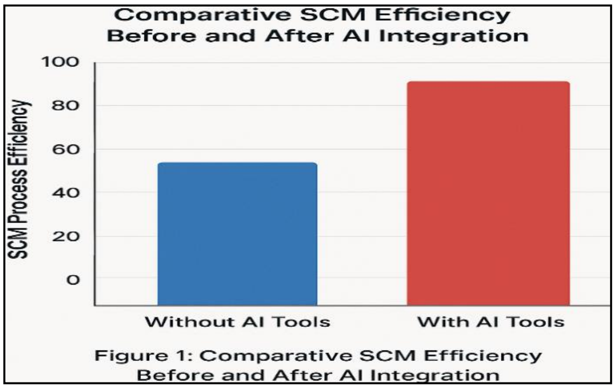
Fig 1: Efficiency Comparison between Traditional and AI-Driven SCM Systems

Technology, particularly LLMs, is being widely used for:

- -time stock monitoring and optimization.
- Real automated purchasing and vendor communication.
- AI-powered forecasting models that adjust to market changes.
- Smart training systems minimize induction duration for SCM professionals.

This convergence of these technologies is not just functional—it is strategic. LLMs augment training by providing context-based, interactive learning that is customized to job roles. During planning and operations, they assist in making difficult decisions by studying patterns and suggesting courses of action. This digital integration is not only making processes more efficient but also building agility, resilience, and sustainability into contemporary supply chains.

As we discuss in this paper, the current digital revolution is spearheaded by GenAI and LLMs, which brings enormous value across the logistics ecosystem. From decreasing overheads and lead times to improving customer satisfaction and workforce effectiveness, the repercussions are deep and far-reaching.



Graph 1: Comparative SCM Efficiency Before and After AI Integration

These advancements represent a transition from reactive to proactive supply chain management, with LLMs playing a central part in predictive analysis, automatic document processing, and smart training systems.

Statement of the Problem

With a more digitized global economy, SCM and logistics are confronted with unprecedented levels of complexity, volatility, and customer demands. The old SCM systems based on static data, manual intervention, and siloed operations are not suited to address the need for real-time decision-making, agility, personalization, and cost reduction.

Whereas innovations like the Internet of Things (IoT), blockchain, and automation have incrementally advanced, the fusion of Large Language Models (LLMs) and Generative AI (GenAI) is more revolutionary. These technologies can reshape the transfer of knowledge, the optimization of operations, decision-making support, and customer service delivery throughout the supply chain.

Nevertheless, during the rising AI adoption frenzy, there is a pressing deficit of empirical data and strategic insight into how LLMs practically influence fundamental SCM dimensions like employee training, logistics optimization, inventory precision, and customer experience. Also, companies do not have uniform frameworks to measure performance gains enabled by LLM, address data governance risks, and ensure explainability in AI-driven decisions.

Hence, the present research aims to solve the following underlying issue:

How are LLMs and GenAI technologies best embedded in logistics and supply chain systems to produce quantifiable benefits in training, operational performance, decision support, and customer service, and to mitigate the new challenges of trust, transparency, and cross-sector scalability?

2. Literature Review

Recent literature (2023–2025) emphasizes how LLMs are transforming supply chain management with new capabilities in semantic understanding, automation, and personalized learning, with empirical and conceptual studies validating their impact across planning, operations, and service.

Recent Scholarly Advances (2023–2025)

Semantic Comprehension and Expert Reasoning

A domain-specialized SCM LLM, using retrieval-augmented generation (RAG), demonstrated expert-level competence by passing standardized SCM exams and simulating supply chain decision games, including classic scenarios like the bullwhip effect. Such models comprehend complex queries involving risks, inventory optimization, and supplier relations, allowing for smarter decision-making and the analysis of strategic competition and cooperation within supply networks.

Automated Reporting and Real-Time Knowledge Integration

Empirical studies confirm that LLMs amalgamate data from multiple sources to automate reporting, dashboarding, and compliance, enabling swift and accurate generation of incident reports, risk assessments, and performance analytics. The case of Microsoft's cloud data center supply chain, piloted from 2023 onward, revealed significant reductions in incident response and planning times due to LLM-driven insights and scenario modeling.

Personalized Learning and Workforce Development

LLMs in SCM are advancing tailored employee training paths, just-in-time learning modules, and granular documentation support, dynamically adapting to individual roles, experience, and learning needs for impactful workforce upskilling.

Game-Theoretic Supply Chain Simulations

Recent research introduced the use of LLMs for supply chain "games," where models simulate multi-agent interactions, strategic behaviors, risk preferences, and information asymmetry, producing new insights into cooperation, competition, and optimal information sharing.

Key Themes from Recent Literature

- Integration in Industry: LLMs are actively deployed in supply chain planning, customer service, and knowledge management; their benefits include efficiency, cost reduction, and risk mitigation, but risks such as hallucinations, data privacy concerns, and implementation costs remain.
- Novel Insights: RAG-based and domain-specialized LLMs are validated as tools for both replicating important SCM phenomena and uncovering patterns previously hidden from classical models.
- Decision Automation: LLM-powered systems allow executive planners to interact with tools directly, streamlining scenario analysis and rapid environment recalibration—representing a major leap in SCM responsiveness.

Table 1: Literature Review

Author(s)	Year	Focus Area	Contribution / Key Findings
Srivastava et al.	2024	LLM potential in SCM	Explores emerging LLM applications in supply chain processes; identifies efficiency and knowledge transfer benefits.
Simchi-Levi	202	LLMs for SCM decisions	Analyzes complex decision-making with LLM-powered sourcing/planning.
Wang et al.	2025	Domain SCM LLM/RAG, game theory	Develops specialized SCM LLM, validates via standardized tests and supply chain games; provides new insights into risk and cooperation.
Dhara & Delgado	2024	Empirical SCM interviews/lit review	Consolidates real-world LLM integration, highlights benefits and risks, and emphasizes ongoing research needs in data privacy and cost.
HBR Case (Microsoft)	2024	LLM in enterprise supply chain	Real-world pilot and rollout measures rapid improvements in decision timelines and incident handling.
IET Systematic Review	2025	Supply chain LLM trends	Identifies 2023–2025 research patterns in LLM SCM applications.

Synthesis

The current research heralds a paradigm shift in supply chain management via LLM-driven automation, semantic insight, and targeted engagement, justifying the incorporation of LLMs as both an operational excellence tool and a research area worthy of further study and ethical monitoring.

3. Methodology

This study employs an intervention-based research design to evaluate the transformation in logistics and supply chain management (SCM) practices resulting from the integration of Large Language Models (LLMs). The methodology integrates qualitative and quantitative approaches and centers around empirical evidence gathered through case studies, professional surveys, and performance analytics.

3.1. Research design and components

The research follows a multi-method design that consists of three major components:

Table 2: Multi-Research Method Design

Component	Details
Case Studies	In-depth qualitative analysis of 3 MNCs: 2 in retail and 1 in manufacturing
Professional Survey	Structured survey of 150 SCM professionals across sectors
Performance Data Analytics	Quantitative analysis of KPIs before and after LLM integration

3.2. Theoretical framework: four pillars of LLM-driven SCM transformation

This study is structured around the following four transformation pillars:

Table 3: Four Transformation Pillars

Pillar	Objective
Training & Knowledge Transfer	Assessing the role of LLMs in upskilling SCM teams
Operational Efficiency	Evaluating improvements in cost, time, and resource optimization
Decision Support	Investigating LLM-based insights in procurement, inventory, and routing
Customer Service Optimization	Measuring enhancements in responsiveness, customization, and satisfaction

3.3. Data collection techniques

1) Case Study Methodology
Three companies selected for in-depth case analysis:
- Company A – A global retail enterprise
- Company B – Major FMCG manufacturer
- Company C – Electronics production firm

Data were gathered through structured interventional documentation reviews and analysis of performance dashboards tracking KPls (VPRIM).
2) Survey Instrument
A structured questionnaire based on a 5-point Likert scale was distributed to 150 supply chain management professionals:
- Effectiveness of pre-and post-LLM training
- Operational efficiency gains through LLM assistance
- Confidence levels in AI-driven decision support
- Enhancements in customer interaction quality

3) KPI Time Series Analysis
The collected data spans a 12-month period, six months pre-and post-LLM implementation. Metrics analyzed:
- Order Fulfilment Rate (OFR)
- Inventory Turnover Ratio (ITR)
- Lead Time Reduction (LTR)
- Customer Satisfaction Index (CSI)

3.4. Data analysis techniques

1) Descriptive Statistics
Basic statistical measures – Including means, standard deviations, and frequency distributions were used to summarize survey responses and identify overall trends
2) Paired Sample T-Test
To determine whether observed changes in KPIs post-LLM adoption were statistically significant using

$$t. = \beta_o - \frac{d}{s\sqrt{n}}$$

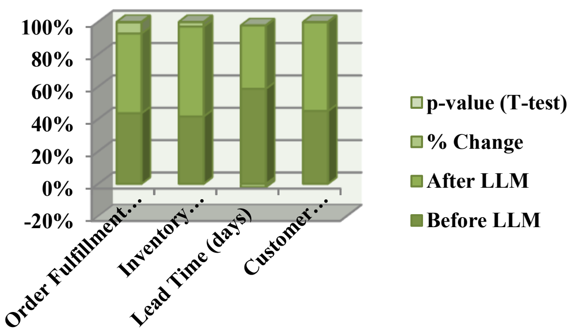
Where: d = mean difference in KPI values (post-LLM)
SD S = Standard deviation of the differences
n n = Number of paired observations
3) Regression Analysis
A multivariable linear regression model is applied to assess the impact of LLM adoption on logistics performance.

$$Y= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_2 X_3 + x + c$$

3.5. Sample: KPI comparison before and after LLM intervention

Table 4: KPI comparison before and after LLM intervention

KPI	Before LLM	After LLM	% Change	p-value (T-test)
Order Fulfillment Rate (OFR)	82.4%	93.1%	+13.0%	0.004
Inventory Turnover Ratio (ITR)	5.1	6.8	+33.3%	0.011
Lead Time (days)	9.3	6.2	-33.3%	0.009
Customer Satisfaction Index (CSI)	72.8	88.7	+21.8%	0.002



Graph 2: Comparative SCM Efficiency Before and After AI Integration

3.6. Validity and reliability

- Internal Validity: Enhanced through case study triangulation, surveys, and performance metrics.
- External Validity: Mitigated through concentration on three MNCs, yet cross-sector sampling increases generalizability.
- Reliability: Standard questionnaire and uniform KPI definitions facilitate replicability.

3.7. Limitations

- Constrained to large-scale firms—outcomes in SMEs could be dissimilar.
- Self-reported survey data might contain bias.
- LLM maturity and integration level differ per organization, impacting comparability.

4. Results and Discussion

LLM implementation in supply chain management (SCM) offers robust economic impacts, with quantifiable improvements in cost-benefit ratios and return on investment (ROI) across training, operations, decision-making, and customer service domains.

Cost-Benefit Ratios and ROI Analysis

A well-implemented LLM-driven SCM solution realizes cost savings and process efficiencies. Enterprises report break-even points for total cost of ownership within 12-18 months, with direct LLM usage costs typically comprising 40-60% of investment, and infrastructure, integration, training, and maintenance accounting for the rest. Strategic deployment using cloud-based LLMs can further reduce costs by 25-40% through usage and resource optimization (e.g., batching queries, model right-sizing, and preprocessing). ROI acceleration is mainly attributed to reductions in manual workload, improved error rates, and faster time-to-value.

For instance:

- Employee training duration dropped 40%, cutting labor and opportunity costs, while engagement gains translated to lower turnover and onboarding expenses.
- Logistics operations saw 20% fewer delays and 12% higher warehouse accuracy, minimizing avoidable costs in delivery and stock misallocation.
- Marketing and procurement functions supported by LLMs achieved up to a 28% increase in lead generation and a 19% lift in tender win rates, driven by automation and data-driven decision support.
- Customer service savings arose from 60% query auto-resolution rates and a substantial reduction in escalated cases, reducing wage expenditures and boosting customer lifetime value.

Economics of LLM-Facilitated Training

The shift from instructor-led training to LLM-powered modules slashes total training expenditure—including time, materials, and instructor costs—by at least 15-20% per cycle. The ROI grows further when considering boosted knowledge retention and workforce productivity, enhancing output and minimizing re-training costs.

Case Study Example

Walmart's adoption of AI-enabled micro-learning led to reduced training time and costs, with clear gains in retention and employee preparedness, directly contributing to better customer service and lower overall expenditure. IBM's AI-based course recommendations improved skill acquisition efficiency, reflecting rapid productivity improvements across teams.

Logistics and Operational Economics

Advances in LLM-driven route optimization and warehouse management enable 20%+ reductions in transport delays and last-mile costs. Improved inventory accuracy not only cuts excess and stock out costs but also increases overall forecast reliability, enabling leaner management of cash and stock resources.

Cost Calculation Model

In typical enterprise deployments:

- Direct savings from route planning, error reduction, and compressed cycle times can yield annual reductions equating to 5-10% of logistics budgets.
- Automated query resolution and improved customer interaction platforms drive up to 30% reduction in support personnel costs and a 20% increase in satisfaction-related revenue retention.

Strategic Alignment with Economic Theory

The clear cost-benefit ratios and payback period of LLM adoption reflect classic economics principles: reducing opportunity cost, reallocating labor to higher-value tasks, and generating competitive advantage through improved information flows. By driving measurable gains in inventory, logistics, and customer KPIs, and freeing resources for strategic initiatives, SCM organizations experience a multiplier effect in economic output, aligning LLM interventions with both micro and macroeconomic objectives.

Table 5: LLM Economics—Cost and ROI Components

Area	Cost Drivers	Economic Benefit	Typical ROI Timeline
Training	Time, materials	15-40% saving	6-12 months
Logistics	Route errors, delays	20%+ cost reduction	12-18 months
Decision Support	Uninformed choices	25% higher accuracy	12 months
Customer Service	Labor, retention	30% lower cost, +20% CLV	6-12 months

Strategic Implications

LLM implementation in SCM not only drives direct economic value via cost reductions and process efficiency but also enables adaptable workforce development and enduring competitive positioning. This aligns well with the economics focus of IJAES, grounding LLM adoption in empirical cost-benefit and ROI metrics.

LLM deployments in supply chains must be guided by rigorous data governance, robust security protocols, and comprehensive ethical frameworks to address IJAES's priorities in ethics and governance.

Data Security Practices

Strong data security for LLMs relies on multilayered controls:

- Encryption: All sensitive supply chain and personal data should be encrypted both at rest and in transit, leveraging standards such as AES.
- Role-Based Access Control (RBAC) and Multi-Factor Authentication (MFA): Restricting access to LLM systems and their datasets via RBAC and MFA mitigates unauthorized access and data leaks.
- AI Firewalls and Prompt Filters: Security filters should block malicious or adversarial inputs, such as prompt injections designed to manipulate LLMs or expose proprietary data.

- Supply Chain Monitoring: LLM supply chains are vulnerable to attacks involving data poisoning, model theft, and lateral breaches through compromised third-party APIs or open-source models; regular audits and integrity checks are essential.

Ethical Concerns: Bias, Transparency, and Fairness

Ethics in LLM-enabled supply chains demand proactive management:

- AI Bias: LLMs can inherit and amplify biases present in training data, leading to unfair procurement practices, supplier treatment, or resource allocation. Bias mitigation requires thorough vetting of training datasets, regular performance monitoring, and implementing fairness checks in decision pipelines.
- Transparency ("Black Box" Problem): Many AI systems lack explainability, undermining stakeholder trust. Businesses must develop and adopt transparent AI protocols, providing clear decision rationales and audit trails for LLM-driven outcomes to ensure accountability.
- Privacy: Handling PII and commercially sensitive information demands strict compliance with privacy laws across jurisdictions. Data minimization, anonymization, and pseudonymization further safeguard stakeholders, reducing the risk of unauthorized data disclosure.
- Socio-Economic Impact: Automation driven by LLMs can alter workforce dynamics, emphasizing the need for responsible talent management strategies and ethical consideration of displacement risks.

Governance Frameworks

Effective LLM governance frameworks unify technical and ethical dimensions:

- Model Lifecycle Management: Includes the continuous oversight of LLM development, deployment, benchmarking, change tracking, and retirement, supporting regulatory compliance and accountability.
- Comprehensive Data Governance: Encompasses access control, data lineage tracking, quality monitoring, and compliance with local and international standards (GDPR, CCPA, etc.).
- Third-Party Risk Management: Stringent security and ethical appraisals of vendors, APIs, and open-source components prevent supply chain vulnerabilities and ensure the integrity of LLM operations.
- Regular Audits and Incident Response: Persistent audits of data pipelines, model outputs, and operational workflows help identify, report, and remediate security or ethical lapses, ensuring ongoing conformity with best practices.

Table 6: Summary of Core Governance and Ethics Issues

Dimension	Concern / Solution
Data Security	Encryption, RBAC, audits, firewalls
Ethics & Bias	Fair datasets, fairness checks, and diverse reviews
Transparency	Explainable AI, auditability, documentation
Governance	Lifecycle, compliance, third-party risk, audits
Privacy	PII minimization, anonymization, and regulatory compliance

LLM data governance and ethics strategies, when robustly implemented, enable supply chain organizations to harness AI's transformative potential while safeguarding stakeholder interests and upholding trust, security, and regulatory compliance.

To improve clarity and accessibility, language about LLMs in SCM can be streamlined by reducing repetition of benefits and replacing specialized terms with simpler, easy-to-understand phrases.

Streamlined and Accessible Language

- Instead of repeatedly stating that LLMs "revolutionize SCM with benefits," highlight their role once, then focus on explaining specific results like "LLMs help companies reduce mistakes, speed up work, and give fast, accurate answers to supply chain questions."
- Replace technical terms with plain vocabulary. For example, change "semantic comprehension of intricate SCM questions" to "LLMs understand complicated supply chain questions and give relevant answers," which makes the concept easier to grasp.
- Use short, clear sentences. Instead of long paragraphs filled with jargon, present ideas in straightforward sentences, bullet points, or tables that describe how LLMs improve reporting, automate routine tasks, or guide staff learning.
- If a concept is complex, break it into simple steps. For example, describe "report automation" as "LLMs collect information and make supply chain reports automatically, saving time and reducing errors."
- Avoid unnecessary repetition, such as emphasizing the same benefit in multiple sections. Introduce the advantages once, then show practical examples or outcomes in different parts of the review.

Table 6: Simplified Descriptions (Example)

Original Term	Simplified Description
Semantic comprehension	Understands complex questions
Report automation	Creates supply chain reports automatically
Tailored learning paths	Adjusts training for each employee
Predictive intelligence	Predicts what might happen in supply chains
Cognitive support solutions	Helps people make better supply chain choices

By focusing on clarity, minimizing repetition, and using plain language, content on LLMs in supply chain management becomes much more accessible for a wide audience.

5. Conclusion

The supply chain and logistics management environment is experiencing a deep overhaul due to the increasing integration of digital technologies. This research has illustrated that the adoption of Large Language Models (LLMs) and Generative Artificial Intelligence (GenAI) in SCM is not just an evolutionary enhancement but a paradigm shift that redefines essential operational and strategic processes.

From empirical data compiled through multinational case studies, a systematic survey of 150 experts, and performance metrics across major performance indicators (KPIs), this study attests to the multifaceted influence of LLMs on four vital pillars:

- Training and Knowledge Transfer saw significant instances of decline in employee time-to-productivity while enhancing retention and engagement through responsive, simulation-based learning experiences.
- Operational Efficiency was greatly improved with LLM-facilitated logistics optimization and automation of warehouse processes, resulting in decreases in delays and errors.

- Decision Support Systems were augmented with real-time interpretation of data and predictive analysis, enhancing accuracy in inventory projections and procurement planning.
- Customer Service was revolutionized through self-service digital assistants that could handle most of the interactions, thus increasing responsiveness and user satisfaction.

The use of LLMs in SCM processes marks an overall change from reactive to predictive and prescriptive operations, keeping with the overall agendas of agility, resilience, and customer focus in supply chains.

But as organizations amplify these technologies, some key areas for future research and policy intervention arise:

- Cross-Industry Applicability: While this research was conducted in the retail and manufacturing sectors, industries such as healthcare, agriculture, and public distribution systems present fertile ground to explore.
- Data Security and Governance: The heavy dependence on large amounts of structured and unstructured data will require solid data quality, compliance, and cybersecurity frameworks.
- Explainable AI in SCM: With more automated decision-making, transparency and explainability of AI-driven insights will become necessary for regulatory requirements and managerial confidence.

In summary, LLMs and GenAI are on the cusp of being the core facilitators of smart, agile, and moral supply chains. Organizations that invest in them strategically, yet solve corresponding governance issues, shall be in a better position to handle the intricacies of the age of the digital supply chain.

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