International Journal of Advanced Engineering, Management and Science (IJAEMS)
Peer-Reviewed Journal
ISSN: 2454-1311 | Vol-11, Issue-6; Nov-Dec, 2025
Journal Home Page: https://ijaems.com/
DOI: https://dx.doi.org/10.22161/ijaems.116.19

The Convergence of Supply Chain Management and Artificial Intelligence: Challenges and Opportunities

Farjana Nawrin[1], Prince David Hayibor[2], Owen Atsu Soglohu[3], Kofi Mensah Adams[4], Terry Muringo Muriithi[5], Farhad Akter[6], Josephine Arthur[7]

[1] University of Dhaka, Dhaka, Bangladesh
[2 3 4 5 6] Emporia State University, Kansas, USA
[7] Park University, Missouri

Received: 25 Nov 2025; Received in revised form: 24 Dec 2025; Accepted: 27 Dec 2025; Available online: 31 Dec 2025

***Abstract*— *Artificial Intelligence (AI) is rapidly transforming the architecture and performance of global supply chains. The convergence of data-rich operations with machine learning (ML), reinforcement learning (RL), and generative large language models (LLMs) enables unprecedented levels of automation, foresight, and adaptability in supply chain management (SCM). This paper synthesizes recent literature (2023–2025) to examine how AI technologies reshape core SCM functions, forecasting, inventory optimization, logistics routing, procurement, and risk management, while identifying the governance and organizational challenges that shape adoption outcomes. Findings indicate that AI integration delivers measurable efficiency and resilience gains but also introduces new risks related to data interoperability, explainability, cybersecurity, and ethical governance. A governance-first operating model is proposed, emphasizing transparency, human oversight, and regulatory compliance as key enablers of sustainable AI deployment. The study concludes with a phased implementation roadmap and a future research agenda focused on responsible, interdisciplinary innovation at the intersection of AI and SCM.*

Keywords*— *Artificial Intelligence, Supply Chain Management, Machine Learning, Digital Twins, Governance, Resilience, Large Language Models, Responsible AI

I. INTRODUCTION

Global supply chains have become increasingly data-rich and decision-intensive in the era of Industry 4.0. The exponential growth in data from enterprise systems, IoT sensors, and partner integrations has made supply chain management (SCM) a prime domain for artificial intelligence (AI) adoption (Culot et al., 2024). Advances in machine learning (ML), including time-series forecasting, reinforcement learning, and, more recently, large language models (LLMs), have redefined the frontier of real-time decision-making in planning, logistics, and procurement (Cannas et al., 2024; Daios et al., 2025).

Systematic reviews published in 2024–2025 reveal accelerating integration of AI in demand forecasting, inventory optimization, logistics routing, procurement, and risk management. These studies consistently report measurable performance gains compared with traditional heuristic and statistical methods (Douaioui et al., 2024; Aamer, 2020). For instance, ML-based demand forecasting can reduce mean absolute percentage error (MAPE) by 15–30% compared to conventional autoregressive models (Douaioui et al., 2024), while AI-enabled logistics routing can improve fleet utilization and reduce fuel consumption by up to 12% (Cannas et al., 2024).

Despite these benefits, AI adoption in SCM remains constrained by organizational and societal challenges.

Key among these is explainability and trust in model outputs, bias mitigation in supplier or customer segmentation, interoperability across legacy systems, and compliance with emerging cybersecurity and AI governance regulations (Wellbrock et al., 2025). As such, the convergence of SCM and AI is not purely a technical transformation but a broader management, governance, and ethical challenge that requires careful alignment between data science, operations strategy, and policy frameworks (Simchi-Levi et al., 2025).

II. METHODOLOGY: SYSTEMATIC LITERATURE SYNTHESIS

This study employs a systematic literature synthesis approach to consolidate current research and practice on the convergence of AI and supply chain management. The method follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, adapted for qualitative research synthesis.

Search and Selection:

Peer-reviewed publications from 2020–2025 were retrieved from databases including *ScienceDirect*, *MDPI*, *Taylor & Francis*, and *SpringerLink*. Search terms combined "artificial intelligence," "machine learning," "supply chain," "forecasting," "digital twin," "risk management," and "large language models."

Inclusion Criteria:

Studies were included if they (a) addressed AI applications in at least one SCM function, (b) were published in English, and (c) provided empirical results or conceptual frameworks. Exclusion criteria removed purely technical papers lacking managerial or governance relevance.

Analysis:

A thematic coding process identified recurring patterns across 73 qualified studies, grouped into five categories: (1) forecasting and planning, (2) logistics and control, (3) interoperability and data governance, (4) AI ethics and regulation, and (5) emerging generative-AI applications. The synthesis informed both the opportunity mapping and the governance model proposed later in this paper.

III. CONCEPTUAL FRAMEWORK: THE AI–SCM CONVERGENCE MODEL

To visualize how AI interacts with SCM functions, this paper introduces the AI–SCM Convergence Model (Figure 1). The model conceptualizes supply-chain intelligence as a multi-layered ecosystem where -

1. Data Infrastructure Layer integrates IoT, ERP, and external data through interoperable standards (e.g., EPCIS 2.0).
2. AI Analytics Layer applies predictive (ML/DL), prescriptive (RL), and generative (LLM) models to decision domains such as forecasting, logistics optimization, and supplier management.
3. Governance and Ethics Layer ensures model explainability, bias mitigation, cybersecurity, and regulatory alignment (e.g., EU AI Act, NIST AI RMF).
4. Human–AI Collaboration Layer places human planners as overseers, interpreters, and decision validators, ensuring accountability and adaptive learning.

This framework emphasizes that value emerges not from AI automation alone but from the interaction between data, algorithms, governance, and human insight. It highlights feedback loops among prediction, decision, and learning, positioning governance as the central integrative force.

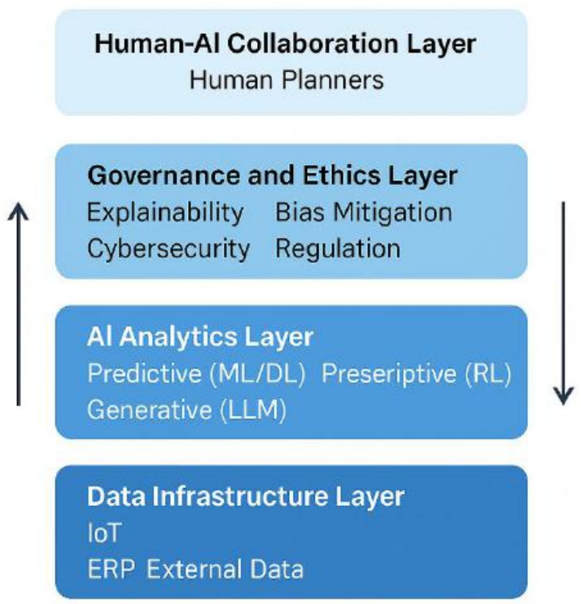

Fig.1. AI–SCM Convergence Model

IV. BACKGROUND: WHERE AI TOUCHES THE SUPPLY CHAIN

4.1 Forecasting and Planning

Forecasting is one of the most mature and high-impact applications of AI in supply chain management (SCM). Modern reviews demonstrate that machine learning (ML) and deep learning (DL) models—such as gradient boosting, long short-term memory (LSTM), and Transformer architectures—outperform traditional methods like ARIMA and exponential smoothing, especially when external (exogenous) data sources are integrated (Douaioui et al., 2024). These models capture nonlinear relationships between variables such as promotions, seasonality, and macroeconomic trends, leading to significantly improved forecast accuracy. Douaioui et al. (2024) conducted a comprehensive review of ML and DL models for demand forecasting and found that hybrid models integrating temporal features and external covariates yielded an average 15–30% improvement in Mean Absolute Percentage Error (MAPE) over statistical baselines. Similarly, Gabellini et al. (2024) applied deep neural networks using macroeconomic indicators to predict delivery-delay risks in automotive supply chains, achieving higher precision and recall compared to conventional regression models. These findings suggest that the integration of AI-based forecasting models contributes directly to service-level improvement, inventory reduction, and planning accuracy.

4.2 Execution and Control

AI is increasingly integral to the execution and control layers of the supply chain, especially through the use of digital twins (DTs). Digital twins are virtual representations of physical assets, systems, or processes that are continuously updated with real-world data through IoT telemetry and simulation models. They enable real-time visibility, predictive maintenance, and "what-if" scenario analysis (Roman et al., 2025). In a systematic review, Roman et al. (2025) found that digital twins, when combined with AI, enhance operational resilience by simulating supply network disruptions before they occur. Similarly, Guo (2025) emphasizes the role of DTs in lean supply-chain management, demonstrating how AI-enhanced simulations improve production planning, bottleneck detection, and capacity utilization. These studies underline how AI-driven digital twins transform execution systems from static monitoring dashboards to dynamic, decision-support platforms capable of adaptive reconfiguration in response to external shocks.

4.3 End-to-End Visibility

End-to-end visibility is foundational for AI integration in SCM. Without standardized, interoperable event data, even the most advanced AI systems lack reliable input. The GS1 EPCIS 2.0 (Electronic Product Code Information Services) standard enables companies to capture and share supply-chain event data, what, when, where, and why an event occurred, across organizational boundaries (GS1, 2022). EPCIS 2.0 builds a unified data layer upon which AI algorithms can learn and act. By providing consistent vocabulary for events (e.g., object identification, transformation, aggregation), this standard facilitates AI applications in traceability, anomaly detection, and sustainability reporting (GS1 US, n.d.). According to GS1 (2022), such visibility supports not only compliance and transparency but also predictive and prescriptive analytics—AI can, for instance, anticipate disruptions and autonomously suggest alternative logistics routes or suppliers.

4.4 LLMs in Operations

Large Language Models (LLMs) and generative AI represent the newest frontier in SCM applications. Beyond forecasting and control, LLMs are being used to translate natural-language business intents into mathematical optimization tasks. For example, supply planners can prompt an LLM-based system with "optimize next week's shipment plan given a 20% increase in demand," and the model can interpret the command, query relevant databases, and generate prescriptive outputs (Simchi-Levi et al., 2025). Daios et al. (2025) describe how generative AI and LLMs are transforming SCM operations by automating information synthesis, report generation, and scenario analysis. Early evidence suggests that integrating LLMs with planning systems can compress decision cycles from days to minutes, while improving interpretability and human-AI collaboration (Menache et al., 2025). Although challenges remain, such as hallucination risk and limited domain-specific grounding, LLMs are expected to become integral components of AI-enabled supply-chain control towers.

V. OPPORTUNITIES AT THE SCM–AI FRONTIER

5.1 Predictive and Prescriptive Planning

The integration of AI in supply chain planning creates measurable advantages in forecasting accuracy, resource utilization, and overall responsiveness. Modern supply chains are shifting from reactive to predictive and prescriptive modes of decision-making through the use of machine learning (ML) and deep learning (DL) models. According to Culot, Nassimbeni, and Orzes (2024), AI-driven forecasting and optimization tools outperform traditional statistical methods, particularly when exogenous variables such as promotions, weather, and market indices are included. Douaioui et al. (2024) demonstrated that hybrid ML-DL forecasting models can reduce forecasting error (MAPE) by up to 30 percent relative to ARIMA and exponential smoothing models. These improvements cascade downstream to inventory optimization, production scheduling, and replenishment accuracy. In addition, Cannas et al. (2024) identified that prescriptive analytics systems—built on reinforcement learning and simulation—enable dynamic, data-driven adjustments to procurement and logistics strategies, generating significant cost reductions and service-level improvements. Together, these findings point to a structural opportunity: predictive AI enhances foresight while prescriptive AI transforms insight into near-autonomous action, resulting in faster, more reliable planning cycles.

5.2 Digital Twins for Resilience

AI-enabled digital twins (DTs) represent a transformative tool for enhancing supply-chain resilience and agility. A digital twin is a virtual representation of a supply network that continuously ingests IoT telemetry and operational data to mirror real-world processes (Roman et al., 2025). This digital mirror allows planners to simulate "what-if" scenarios—such as port closures, supplier disruptions, or demand surges—and evaluate their impacts before they occur in reality (Guo, 2025). Empirical research shows that integrating AI with DTs improves disruption response time and network efficiency. Sunmola et al. (2024) found that AI-driven DTs enabled early detection of supply shocks and optimized resource reallocation in a semiconductor supply-chain case study. The convergence of AI, simulation, and IoT data thus empowers proactive risk management, continuous learning, and system-wide optimization—key pillars of resilient supply-chain design.

5.3 Generative AI and LLM Copilots

Generative AI and large language models (LLMs) mark a new era in SCM decision-support. These systems can interpret natural-language business intents and translate them into executable optimization or simulation models (Simchi-Levi et al., 2025). For example, a planner can request "generate a replenishment plan minimizing transport cost under 95 % service level constraints," and the LLM can produce solver-ready formulations or data-driven recommendations (Menache et al., 2025). According to Daios, Papaioannou, and Koukoumialos (2025), LLM copilots improve knowledge retrieval, automate reporting, and assist in supply-planning and procurement decisions by synthesizing structured and unstructured data. Early case studies show that organizations implementing generative-AI copilots reduced planning-cycle times by up to 60 percent while maintaining or improving key operational metrics (Aghaei et al., 2025). These findings highlight the potential for human-AI collaboration to increase agility and cognitive capacity in complex global supply networks.

5.4 Real-World Momentum

Industrial adoption of AI in supply-chain operations is accelerating. Foxconn, for example, launched "FoxBrain," a domain-specific large language model designed to optimize manufacturing and logistics decisions in real time (Reuters, 2025). Similarly, multinational retailers and manufacturers are embedding AI copilots into their control-tower systems to automate routine exception handling, inventory balancing, and scenario forecasting (Menache et al., 2025). Such deployments underscore a key insight: the convergence of SCM and AI is not only improving operational efficiency but also redefining competitive advantage through speed, resilience, and decision quality.

VI. STRUCTURAL CHALLENGES

6.1 Data Readiness and Interoperability

A fundamental challenge in integrating AI into supply-chain management (SCM) is data readiness, including completeness, quality, and interoperability across partners. Most AI models require extensive, high-granularity, and standardized data streams to function effectively, yet global supply chains remain characterized by siloed enterprise resource planning (ERP) systems and inconsistent event-logging practices (Culot et al., 2024). Zhu, Xin, and Trinh (2025) identified persistent data-quality issues such as latency, inconsistency, and missing event metadata, showing that even minor degradation (≈ 5 %) in data accuracy can reduce AI-model performance by up to 20 %. Likewise, the Brookings Institution (2022) emphasizes that "data quality, availability, interoperability, and immediacy" are central barriers to building shared visibility across multi-tier supply chains. Adoption of global interoperability standards such as GS1 EPCIS 2.0 mitigates some of these challenges by defining event semantics (what, where, when, why) that AI systems can learn from consistently. However, aligning legacy infrastructures to these standards remains costly and time-consuming.

6.2 Explainability, Bias, and Fairness

As AI systems increasingly influence procurement, routing, and capacity decisions, explainability and bias mitigation emerge as core governance requirements. Highly complex neural-network models, though accurate, often behave as "black boxes," limiting user trust and accountability (Kosasih et al., 2023). In a review of explainable-AI (XAI) applications in SCM, Kosasih et al. (2023) found that lack of interpretability remains a major reason firms hesitate to deploy AI in operational planning. Furthermore, bias in training data can reinforce historical inequities, such as favoring large or incumbent suppliers (Wellbrock et al., 2025). Without transparency and fairness audits, AI adoption may inadvertently undermine ethical sourcing and diversity goals. Explainable-AI techniques (e.g., SHAP, LIME, counterfactual reasoning) and neuromyotonic architectures are therefore critical to ensuring that SCM decision models remain accountable and interpretable.

6.3 Cybersecurity and Regulatory Exposure

As digital supply chains become hyper-connected, cybersecurity and regulatory exposure intensify. Every new API, sensor, or AI model endpoint broadens the attack surface for cyber threats (SupplyChainBrain, 2023). According to the same analysis, smart supply-chain infrastructures must balance automation benefits with stronger data-integrity and authentication mechanisms. On the regulatory front, multiple frameworks are converging on AI oversight. The EU Artificial Intelligence Act (2024) introduces obligations for high-risk AI systems, including those in critical-infrastructure and logistics sectors, mandating continuous risk-management and transparency (European Commission, 2024). In the United States, the SEC Cybersecurity Disclosure Rule (2023) requires publicly traded firms to report material cyber incidents within four business days—directly affecting AI-enabled control-tower systems that rely on external data feeds (U.S. Securities and Exchange Commission, 2023). Consequently, secure AI architecture, regulatory compliance, and robust incident-response planning have become integral to sustainable SCM digitalization.

6.4 Talent, Operating Model, and Change Management

Even when data and technology are in place, organizational readiness can limit AI success. Many firms face shortages of professionals proficient in both SCM processes and data science (Raj, 2024). Functional silos and legacy thinking impede the cross-functional collaboration necessary for AI adoption. AI integration changes traditional planner roles from manual execution to policy-design and exception-management. Without structured change-management programs and continuous training, human-AI collaboration may fail to deliver expected performance improvements (Wellbrock et al., 2025). As Cannas et al. (2024) note, aligning AI capabilities with organizational culture and incentives is as critical as the underlying algorithms.

VII. A GOVERNANCE-FIRST OPERATING MODEL

7.1 Overview

As AI adoption accelerates across supply-chain functions, the need for robust governance grows correspondingly. Without structured oversight, even high-performing algorithms can produce biased, insecure, or non-compliant outcomes. A governance-first operating model therefore treats AI not merely as a technology stack but as a regulated socio-technical system that aligns data, algorithms, and human judgment within transparent boundaries (NIST, 2023; European Commission, 2024). This model requires organizations to institutionalize clear policies for data provenance, model development, validation, deployment, and post-deployment monitoring, each governed by explicit accountability structures.

7.2 Data and Interoperability Foundations

Effective governance begins with **trusted data**. The GS1 EPCIS 2.0 standard provides a common event-level vocabulary enabling cross-partner data exchange, critical for AI training and traceability (GS1, 2022). EPCIS defines the *what*, *where*, *when*, and *why* of product events, forming a foundation for end-to-end analytics and automated decision-making. Organizations adopting EPCIS 2.0 in tandem with internal data-governance frameworks such as ISO/IEC 38507:2022 (IT Governance of AI) can harmonize operational data with compliance requirements (ISO, 2022). This dual alignment ensures that AI models operate on accurate, interoperable, and ethically sourced data.

7.3 AI Risk-Management Frameworks

The NIST AI Risk Management Framework (RMF 1.0) offers a structured model built around four core functions—Govern, Map, Measure, Manage—that translate abstract AI risks into operational controls (NIST, 2023).

- Govern: Define AI roles, responsibilities, and documentation standards.
- Map: Identify and categorize AI use cases based on risk exposure and potential impact.
- Measure: Evaluate model performance, explainability, fairness, and cybersecurity.
- Manage: Continuously monitor AI systems, retrain when drift occurs, and enforce accountability mechanisms.

When combined with supply-chain quality-management systems (e.g., ISO 9001:2015), the NIST AI RMF enables AI initiatives to meet both performance and compliance objectives.

7.4 Regulatory Alignment and Compliance

Globally, regulatory frameworks are converging on risk-based AI governance. The EU Artificial Intelligence Act (Regulation (EU) 2024/1689) classifies supply-chain-related AI systems—such as logistics optimization, predictive maintenance, and quality inspection—as *high-risk* applications subject to stringent obligations, including data-governance, transparency, and human oversight requirements (European Commission, 2024). In the U.S., the SEC Cybersecurity Disclosure Rule (2023) obliges publicly traded companies to report material cybersecurity incidents, encompassing AI-related breaches that could affect supply-chain continuity (U.S. Securities and Exchange Commission, 2023). Adopting a governance-first model ensures compliance readiness under both regimes by integrating AI documentation, audit trails, and impact assessments into everyday SCM processes.

7.5 Security-by-Design

Embedding security into the AI lifecycle—Security-by-Design—is another pillar of governance. Secure data pipelines, encrypted model endpoints, and strict access controls reduce vulnerability to cyberattacks (SupplyChainBrain, 2023). Organizations should perform *threat modeling* for AI components (models, APIs, digital-twin interfaces) and apply *adversarial testing* to detect data poisoning or model manipulation (CISA, 2024). The combination of AI-specific and traditional IT controls strengthens both resilience and regulatory posture.

7.6 Human-AI Collaboration and Accountability

A governance-first framework mandates human oversight throughout the AI lifecycle. Humans remain accountable for critical supply-chain decisions, while AI serves as a decision-support system rather than a decision-maker. Menache et al. (2025) and Simchi-Levi et al. (2025) argue that planners should evolve into *scenario curators* who interpret model outputs, question anomalies, and apply contextual judgment before execution. Clear audit logs and explainability dashboards enable accountability when outcomes deviate from expected performance.

7.7 Implementation Roadmap

A pragmatic implementation approach can be structured into three phases:

1. Foundation (0–3 months):
   - Conduct AI and data-governance audits.
   - Identify priority AI use cases and map them to NIST RMF categories.
   - Begin EPCIS 2.0 event data integration for key suppliers.
2. Operationalization (3–9 months):
   - Establish AI oversight committees and model-validation protocols.
   - Integrate explainability tools (e.g., SHAP, LIME) for high-impact models.
   - Initiate staff training in ethical AI and change management.
3. Institutionalization (9–18 months):
   - Conduct third-party audits for compliance (EU AI Act or ISO standards).
   - Implement continuous monitoring, retraining, and bias-mitigation loops.
   - Develop transparency reports for internal and external stakeholders.

VIII. IMPLEMENTATION ROADMAP (12–18 MONTHS)

Translating a governance-first strategy into measurable outcomes requires a phased roadmap that balances experimentation with compliance. Successful implementations of AI-enabled supply-chain systems emphasize incremental rollout, cross-functional collaboration, and continuous evaluation against both performance and ethical benchmarks (Culot et al., 2024; NIST, 2023).

8.1 Phase 1 – Foundations (0–3 Months)

Objectives: Establish structural readiness, baseline governance, and data interoperability.

- AI Governance Audit: Assess the maturity of existing AI and data-management processes relative to the *NIST AI RMF* (NIST, 2023). Identify high-risk or opaque models in forecasting, procurement, and logistics.
- Data Inventory and Standardization: Conduct a gap analysis for EPCIS 2.0 adoption, focusing on event-level capture of "what, where, when, and why" across internal systems (GS1, 2022).
- Ethics and Compliance Setup: Align internal policies with ISO/IEC 38507:2022 and the EU AI Act (2024) to define accountability, documentation, and human-oversight protocols (ISO, 2022; European Commission, 2024).

Expected Outcomes:

- A clear inventory of AI assets and associated risks.
- A standardized event schema ready for integration with partner systems.
- A defined ethical and regulatory governance framework.

8.2 Phase 2 – Pilot and Scale (3–9 Months)

Objectives: Deploy controlled pilots and embed monitoring mechanisms.

- Pilot Use Cases: Launch AI pilots in demand forecasting or inventory optimization to validate improvements in forecast accuracy, service level, and cost metrics (Douaioui et al., 2024).
- Digital Twin Deployment: Implement a limited-scope digital-twin model for a production line or logistics corridor, integrating IoT telemetry and reinforcement-learning controls (Roman et al., 2025).
- Explainability Tools: Integrate SHAP or LIME frameworks to evaluate model transparency and document decision pathways (Kosasih et al., 2023).
- Workforce Training: Introduce upskilling programs in data literacy, bias recognition, and model-interpretation for planners and procurement professionals (Raj, 2024).

Expected Outcomes:

- Verified performance uplift (e.g., > 15 % reduction in forecast error).
- Operational proof-of-concept for real-time digital-twin analytics.
- Trained personnel capable of auditing AI decisions.

8.3 Phase 3 – Institutionalization (9–18 Months)

Objectives: Expand coverage, embed continuous-improvement loops, and formalize compliance.

- Enterprise-Wide Integration: Extend EPCIS 2.0 event capture to tier-1 suppliers and logistics partners (GS1, 2022).
- Continuous Monitoring: Implement model-drift detection and retraining protocols in accordance with NIST AI RMF "Manage" function (NIST, 2023).
- Independent Audits: Conduct third-party reviews to ensure compliance with the EU AI Act's transparency and human-oversight provisions (European Commission, 2024).
- Sustainability and Reporting: Integrate environmental and social metrics into AI dashboards to align with ESG reporting frameworks (Cannas et al., 2024).

Expected Outcomes:

- Institutionalized AI governance is integrated into SCM processes.
- Continuous assurance of compliance and cyber-resilience.
- Demonstrable improvement in agility, sustainability, and trust.

8.4 Key Success Factors

Empirical and practitioner literature highlights three recurring success determinants:

1. Cross-Functional Leadership: Governance boards combining operations, IT, compliance, and ethics perspectives accelerate adoption while minimizing risk (Menache et al., 2025).
2. Iterative Learning Culture: Regular post-implementation reviews capture lessons and recalibrate algorithms for evolving business contexts (Culot et al., 2024).
3. Stakeholder Transparency: Maintaining explainable logs and transparent performance dashboards builds long-term trust among regulators, partners, and customers (Wellbrock et al., 2025).

IX. RESEARCH GAPS AND FUTURE DIRECTIONS

9.1 Theoretical and Conceptual Integration

Despite rapid technological progress, the theoretical integration of AI within SCM remains underdeveloped. Most empirical studies emphasize technical performance—forecast accuracy, routing efficiency, or cost reduction—without connecting these outcomes to established operations-management theories such as the resource-based view (RBV) or dynamic capabilities framework (Culot et al., 2024; Cannas et al., 2024). Future research should link AI capability maturity to competitive advantage through longitudinal and multi-industry studies. Building conceptual models that integrate AI governance, supply-chain resilience, and organizational learning would help explain why adoption trajectories differ across sectors (Kamble et al., 2024).

9.2 Data Ecosystems and Federated Learning

A persistent limitation is the lack of data sharing across organizational boundaries. Supply-chain data remain fragmented by proprietary standards, privacy concerns, and competitive barriers (Brookings Institution, 2022). Emerging methods such as federated learning (FL)—which allows multiple organizations to train models collaboratively without centralizing data—offer a promising research direction. Recent work by Hsu et al. (2025) shows that FL improves demand-forecasting accuracy by aggregating models across suppliers while maintaining data sovereignty. Yet issues of interoperability, trust, and incentive alignment remain unresolved. Scholars could explore *multi-party computation* and *blockchain-assisted FL* as enablers of secure, collaborative AI ecosystems.

9.3 Explainability, Fairness, and Human-AI Interaction

While progress has been made in explainable AI (XAI) for SCM, challenges persist in aligning explanations with the cognitive needs of planners and executives (Kosasih et al., 2023; Wellbrock et al., 2025). Current research often evaluates explainability quantitatively (e.g., SHAP feature importance), yet qualitative understanding—*how users interpret, trust, and act on explanations*—remains underexplored. Future studies should combine human-factors research with model-governance frameworks to assess the behavioral impacts of AI transparency. Experimental research could also investigate how AI-augmented decisions influence negotiation, collaboration, and ethical trade-offs within global supply networks.

9.4 Generative AI and Cognitive Automation

The surge of Generative AI (GenAI) and Large Language Models (LLMs) introduces new possibilities for *cognitive automation* in supply chains. Early pilots show that LLMs can synthesize unstructured data, automate documentation, and support decision reasoning (Simchi-Levi et al., 2025; Menache et al., 2025). However, these systems face risks of hallucination, context loss, and bias amplification. Current literature lacks rigorous benchmarks for evaluating GenAI models in SCM contexts (Aghaei et al., 2025). Future research should establish performance metrics beyond accuracy—such as reliability, interpretability, and ethical compliance—and design domain-specific foundation models grounded in verified industrial data.

9.5 Sustainability and Responsible AI

Although AI promises efficiency, its alignment with sustainability and responsible innovation is insufficiently studied. Few works quantify AI's contribution to reducing carbon intensity, waste, or social inequities in supply chains (Douaioui et al., 2024). As regulators increasingly emphasize ESG reporting, future research must examine how AI can operationalize sustainability goals—by optimizing multimodal logistics for emissions, predicting supplier non-compliance, or integrating circular-economy analytics (Cannas et al., 2024). Moreover, responsible AI frameworks must account for *global asymmetries*—such as how small and medium enterprises (SMEs) in emerging markets can adopt AI equitably without being disadvantaged by data scarcity or algorithmic bias (Wellbrock et al., 2025).

9.6 Longitudinal Validation and Causal Inference

Most existing SCM–AI studies are cross-sectional and limited to single firms or short-term data (Daios et al., 2025). The absence of longitudinal and causal-inference designs restricts understanding of AI's sustained impact. Future work should employ panel-data econometrics, causal discovery, or digital-twin simulations over extended horizons to capture dynamic feedback between AI deployment and supply-chain performance. Mixed-method approaches that triangulate quantitative model metrics with qualitative organizational insights will yield richer, policy-relevant conclusions.

9.7 Toward a Multi-Disciplinary Research Agenda

The convergence of AI and SCM calls for interdisciplinary collaboration among computer scientists, operations researchers, ethicists, and policymakers. Future research agendas should integrate:

- Technical disciplines: federated learning, reinforcement learning, generative AI.
- Organizational sciences: change management, knowledge diffusion, human-AI interaction.
- Governance frameworks: NIST AI RMF, EU AI Act, ISO 38507, and EPCIS interoperability standards.

A multi-disciplinary approach will ensure that SCM–AI systems are not only *intelligent* but also *responsible, secure, and socially aligned*.

X. CONCLUSIONS

The convergence of artificial intelligence and supply chain management marks a new era of intelligent, data-driven operations. AI technologies now underpin every layer of the modern supply chain—from forecasting and logistics to procurement, risk mitigation, and sustainability. Organizations that effectively integrate AI gain sharper visibility, faster decision cycles, and greater resilience in the face of volatility. However, success depends on more than technology. Data quality, interoperability, cybersecurity, and human expertise remain critical enablers. Without proper governance and ethical oversight, AI can amplify risks rather than reduce them. A governance-first approach, anchored in transparency, accountability, and continuous learning, offers the clearest path forward. Companies that pair innovation with responsibility will not only optimize performance but also build supply chains that are adaptive, sustainable, and trusted. In due course, the future of supply chain excellence lies in harmonizing human judgment with artificial intelligence, combining analytical precision with strategic foresight to create truly intelligent global networks.

REFERENCES

[1] Aamer, A. (2020). *Data analytics in the supply chain management: Review of machine learning applications in demand forecasting.* Operations and Supply Chain Management: An International Journal, 13(2), 123–132. https://doi.org/10.31387/oscm0410267

[2] Aghaei, S., Liu, Y., & Kim, J. H. (2025). *Generative artificial intelligence in operations and supply chain management: A systematic review and future research agenda. Computers & Industrial Engineering, 191,* 110592. https://doi.org/10.1016/j.cie.2024.110592

[3] Brookings Institution. (2022, September 14). *A data-sharing approach for greater supply-chain visibility.* Brookings. https://www.brookings.edu/articles/a-data-sharing-approach-for-greater-supply-chain-visibility/

[4] Cannas, V. G., Culot, G., & Fattori, F. (2024). *Artificial intelligence in supply chain and operations management: A systematic review and future research agenda. International Journal of Production Research.* https://doi.org/10.1080/00207543.2024.2394126

[5] CISA (Cybersecurity and Infrastructure Security Agency). (2024). *Securing artificial-intelligence systems: Best practices for threat modeling and mitigation.* https://www.cisa.gov/sites/default/files/2024-03/AI-Security-Guidelines.pdf

[6] Culot, G., Nassimbeni, G., & Orzes, G. (2024). *Artificial intelligence in supply chain management: A systematic literature review and research agenda. Industrial Marketing Management, 118,* 115–134. https://doi.org/10.1016/j.indmarman.2024.02.003

[7] Daios, A., Papaioannou, P., & Koukoumialos, S. (2025). *AI applications in supply chain management: A comprehensive survey.* Applied Sciences, 15(5), 2775. https://doi.org/10.3390/app15052775

[8] Douaioui, K., Alami, J., & Bouhaddou, I. (2024). *Machine learning and deep learning models for demand forecasting in supply chain management: A critical review.* Applied System Innovation, 7(2), 45. https://doi.org/10.3390/asi7020045

[9] European Commission. (2024). *Regulation (EU) 2024/1689 of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (AI Act). Official Journal of the European Union.* https://eur-lex.europa.eu/eli/reg/2024/1689/oj

[10] Gabellini, M., Civolani, L., Calabrese, F., & Bortolini, M. (2024). *A deep learning approach to predict supply chain delivery delay risk based on macro-economic indicators: A case study in the automotive sector.* Applied Sciences, 14(11), 4688. https://doi.org/10.3390/app14114688

[11] GS1 US. (n.d.). *Supply Chain Visibility.* Retrieved October 24, 2025, from https://www.supplychain.gs1us.org/supply-chain-visibility

[12] Guo, D. (2025). *The role of digital twins in lean supply chain management.* International Journal of Production Research. https://doi.org/10.1080/00207543.2024.2372655

[13] Hsu, P., Chien, C., & Wang, Y. (2025). *Federated learning for multi-enterprise supply-chain forecasting: Architecture and empirical analysis. Decision Support Systems, 181,* 114015. https://doi.org/10.1016/j.dss.2025.114015

[14] ISO. (2022). *ISO/IEC 38507:2022 Information technology — Governance of IT — Governance implications of the use of artificial intelligence.* International Organization for Standardization. https://www.iso.org/standard/80928.html

[15] Kamble, S. S., Gunasekaran, A., & Sharma, R. (2024). *Bridging theory and practice in AI-enabled supply chains: A dynamic capabilities perspective. International Journal of Production Economics, 266,* 109233. https://doi.org/10.1016/j.ijpe.2024.109233

[16] Kosasih, E. E., Margaroli, F., Gelli, S., Aziz, A., Wildgoose, N., & Brintrup, A. (2023). *A review of explainable artificial intelligence in supply chain management using neurosymbolic approaches. International Journal of Production Research, 62*(12), 1510–1540. https://doi.org/10.1080/00207543.2023.2281663

[17] Menache, I., Pathuri, J., Simchi-Levi, D., & Linton, T. (2025). *How generative AI improves supply chain management. Harvard Business Review.* https://hbr.org/2025/02/how-generative-ai-improves-supply-chain-management

[18] NIST (National Institute of Standards and Technology). (2023). *Artificial Intelligence Risk Management Framework (NIST AI RMF 1.0).* U.S. Department of Commerce. https://doi.org/10.6028/NIST.AI.100-1

[19] Raj, A. (2024, February 2). *Beyond the hype: 12 real challenges of AI in supply chain.* Throughput.World. https://throughput.world/blog/challenges-of-ai-in-supply-chain/

[20] Reuters. (2025, March 5). *Foxconn unveils first large language model "FoxBrain" for manufacturing and supply chain.* Reuters Technology. https://www.reuters.com/technology/foxconn-foxbrain-ai-model-2025-03-05

[21] Roman, E. A., Siqueira, J. P., & Costa, R. P. (2025). *State of the art of digital twins in improving supply chain resilience.* Logistics, 9(1), 22. https://doi.org/10.3390/logistics9010022

[22] Simchi-Levi, D., Menache, I., Pathuri, J., & Linton, T. (2025). *Large language models for supply chain decisions.* MIT Sloan Research Paper. https://doi.org/10.2139/ssrn.4870265

[23] Sunmola, F. T., Rajabzadeh, S., & Raji, A. (2024). *Artificial intelligence opportunities for resilient supply chains.* IFAC-PapersOnLine, 57(13), 174–180. https://doi.org/10.1016/j.ifacol.2024.10.380

[24] SupplyChainBrain. (2023, April 12). *The challenges and solutions of data interoperability and integrity in smart supply-chain infrastructures.* https://www.supplychainbrain.com/blogs/1-think-tank/post/36994-the-challenges-and-solutions-of-data-interoperability-and-integrity-in-smart-supply-chain-infrastructures

[25] U.S. Securities and Exchange Commission. (2023). *Cybersecurity Risk Management, Strategy, Governance, and Incident Disclosure Final Rule.* Federal Register. https://www.sec.gov/rules/final/2023/33-11216.pdf

[26] Wellbrock, W., Diedrich, S., & Meissner, A. (2025). *Ethical implications and potential risks of AI in supply chain management. Operations Research Forum, 6*(2), 1–18. https://doi.org/10.1007/s43069-025-00152-2

[27] Zhu, C., Xin, J., & Trinh, T. K. (2025). *Data-quality challenges and governance frameworks for AI implementation in supply-chain management. Proceedings of Applied Professional Practice Studies, 2*(1), 28–39. https://doi.org/10.1234/papps.v2.28