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Review Article

Enhancing Supply Chain Management Using Machine Learning Techniques: A Comprehensive Review, Gap Analysis, and Strategic Framework

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KEYWORDS

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ABSTRACT

In the Industry 4.0 era, Supply Chain Management (SCM) is being transformed by digitalization and advanced analytics, with Machine Learning (ML) emerging as a pivotal driver of efficiency, resilience, and intelligent decision-making. This study reviews ML applications across major SCM domains, demonstrating their potential to enhance predictive accuracy, operational agility, and competitiveness. However, adoption remains constrained by persistent challenges, including data quality, model interpretability, scalability, and integration with legacy systems. A structured gap analysis highlights priority areas for advancement, such as explainable ML, real-time analytics, sustainability-oriented applications, and human–machine collaboration. To address these gaps, a strategic framework is proposed, comprising four interdependent pillars: Data and Systems Foundations, Algorithmic Intelligence, Organizational and Human Integration, and Strategic and Sustainability Alignment. This framework provides a roadmap for embedding ML into supply chains by reinforcing data ecosystems, advancing adaptive and interpretable algorithms, fostering human-centered adoption, and aligning digital transformation with ethical and sustainability imperatives. The study concludes that ML adoption represents a socio-technical transformation rather than a technical upgrade, offering both theoretical insights and practical guidance for building intelligent, resilient, and sustainable SCM.

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1. Introduction

Supply Chain Management (SCM) involves the strategic coordination of an organization's core business functions—including procurement, production, inventory management, logistics, and distribution—to optimize processes, reduce costs, and enhance overall performance. By ensuring the smooth flow of goods, services, and information from suppliers to end-users, SCM is essential for achieving high customer satisfaction and sustaining competitive advantage. Its effectiveness depends on accurate, timely, and consistent data, as even small errors or inconsistencies can propagate through the supply chain, leading to delays, higher costs, and service disruptions. To address these challenges, modern SCM increasingly leverages advanced technologies such as data analytics, machine learning, and digital twins to support informed decision-making, improve visibility, and create agile, resilient, and responsive supply chains [1-3]. Table 1 provides a comprehensive framework of the ten core functions of Supply Chain Management (SCM), their associated domains or activities, and their primary strategic objectives [4-6].

1) Supply Chain Planning – This function includes demand forecasting, demand and supply planning, production scheduling, inventory optimization, and logistics and financial planning. Its primary objective is to align supply with demand, optimize resources, minimize costs, and ensure timely fulfillment, forming the foundation of an efficient and responsive supply chain.
2) Procurement & Sourcing – Key activities involve supplier selection and evaluation, strategic sourcing, contract management, purchase order management, and supplier relationship management. The goal is to secure a high-quality, cost-effective, and reliable supply while building and maintaining strategic supplier partnerships.
3) Production & Manufacturing – This area encompasses capacity planning, production scheduling, quality assurance and control, work-in-progress monitoring, and lean and agile manufacturing practices. Its objective is to maximize operational efficiency, minimize waste, maintain product quality, and reliably meet customer demand.
4) Inventory Management – Activities include stock level optimization, safety stock management, reorder point calculation, and warehouse inventory control. The goal is to balance inventory costs with availability, prevent stockouts or overstocking, and maintain consistent service levels.
5) Logistics & Transportation – Key domains cover transportation planning, route optimization, fleet management, carrier selection, and distribution network design. Its objective is to ensure the timely, cost-efficient, and reliable movement of goods across the supply chain.
6) Warehousing & Storage – This function involves warehouse layout optimization, material handling, order picking and fulfillment, and inventory accuracy and control. The goal is to enhance storage efficiency, minimize handling costs, and expedite order fulfillment.
7) Order Management & Fulfillment – Activities include order processing, order tracking, backorder management, returns handling, and service level monitoring. The objective is to deliver accurate, on-time orders while maintaining high customer satisfaction.
8) Supply Chain Risk & Compliance – Key domains include risk assessment, regulatory compliance, supplier audits, and contingency planning. The goal is to mitigate supply chain disruptions, ensure regulatory adherence, and safeguard operational continuity.
9) Performance Management & Analytics – This function includes KPI monitoring, supply chain analytics, reporting and visualization, and continuous improvement initiatives. Its objective is to support data-driven decision-making, optimize performance, and drive continuous improvement.

10) Customer Relationship Management – Activities involve customer demand analysis, collaborative planning, service level management, and feedback integration. The goal is to strengthen customer relationships, enhance responsiveness, and align supply chain operations with customer expectations.

The Industry 4.0 era is transforming industrial and business processes through digitalization, advanced analytics, and interconnected systems. Supply Chain Management (SCM) is shifting from traditional operational models to intelligent, data-driven, and adaptive networks. Increasing global complexity, market volatility, heightened customer expectations, and sustainability pressures require more efficient, resilient, and agile approaches to planning, execution, and monitoring. Figure 1 illustrates the core technologies driving Industry 4.0, including: IoT for connectivity; smart sensors for real-time monitoring; advanced robotics for precision; AI for intelligent automation; cyber-physical systems (CPS) for real-time control; AR/VR for design, training, and maintenance; cloud computing and ML for scalable processing and predictive analytics; digital twins for system replication and optimization; 3D printing for rapid prototyping; big data analytics for actionable insights; blockchain for secure transactions; and GPS/RFID for enhanced tracking. Collectively, these technologies establish the foundation for smart, adaptive, and interconnected supply chain ecosystems [7-8].

Machine learning has become a transformative enabler in supply chain management, enhancing both operational performance and strategic foresight. Analyzing vast volumes of structured and unstructured data it improves decision-making, demand forecasting, inventory optimization, logistics, and risk management. It enables predictive inventory control, anticipates supplier and production dynamics, and reduces stockouts and excess inventory. Through real-time sensor analytics, machine learning supports predictive maintenance, minimizes downtime, and extends asset life. Moreover, it optimizes supply chain networks and dynamic routing, empowering organizations to build agile, resilient, and highly competitive supply chains capable of adapting to rapidly evolving markets.

A general structure of a machine learning-based predictive model is shown in Figure 2. The workflow begins with data acquisition, collecting high-resolution information from sensors, IoT devices, machine logs, and historical records to capture equipment behavior under diverse operational conditions. This is followed by data preprocessing, which includes cleaning, normalization, feature extraction, and handling missing or noisy data to ensure robust and reliable inputs. During model development, advanced machine learning algorithms—spanning supervised learning for fault prediction, unsupervised learning for anomaly detection, and reinforcement learning for dynamic maintenance scheduling—are trained to detect complex patterns, anticipate failures, and forecast remaining useful life. The models undergo rigorous validation and testing to ensure accuracy, robustness, and generalizability. Upon deployment, real-time predictions guide proactive maintenance decisions, optimize scheduling, and support resource allocation. Finally, continuous monitoring and refinement allow the models to adapt to evolving conditions, incorporate new data, and sustain predictive performance. This workflow underpins intelligent, adaptive maintenance strategies that enhance reliability, reduce lifecycle costs, and drive operational excellence in modern industrial environments [9-11].

Machine learning (ML), a branch of artificial intelligence, enables systems to learn from data and make predictions or decisions without explicit programming. Table 2 categorizes ML algorithms based on the type of data and learning approach. Supervised learning uses labeled data to map inputs to outputs, employing algorithms such as Linear Regression, Decision Trees, and Neural Networks, and is applied in spam detection, medical diagnosis, and stock prediction. Unsupervised learning analyzes unlabeled data to reveal hidden patterns or clusters, using methods like K-Means, PCA, and DBSCAN, often for customer segmentation or anomaly detection. Semi-supervised learning combines a small set of labeled data with large unlabeled datasets to improve performance, using techniques such as Semi-supervised SVM and Label Propagation, commonly in web content classification and medical imaging. Reinforcement learning trains agents through trial-and-error interactions with an environment to maximize cumulative reward, using algorithms like Q-Learning and Deep Q-Networks, with applications in robotics, autonomous vehicles, and game AI. This classification provides a comprehensive overview of ML approaches, their objectives, key algorithms, and typical applications [9,11].

Despite increasing interest, research on ML in SCM remains fragmented. Most studies focus on specific applications without providing a holistic perspective of ML's potential across the supply chain. Furthermore, integration challenges, strategic alignment, and practical implementation in real-world contexts are rarely addressed.

This paper addresses existing gaps by providing a comprehensive review of machine learning (ML) applications in supply chain management (SCM), performing a systematic gap analysis, and proposing a strategic framework for researchers and practitioners. The framework focuses on aligning ML initiatives with organizational objectives, fostering data-driven decision-making, and enabling agile, intelligent, and sustainable supply chains, offering a practical roadmap for implementation.

The paper is structured as follows: Section 2 reviews state-of-the-art ML applications in SCM; Section 3 analyzes research gaps; Section 4 explores ML applications across core SCM domains; Section 5 introduces the proposed strategic framework; and Section 6 concludes with key insights and future research directions.

Table 1. Key Supply Chain Management (SCM) Functions, Domains, and Strategic Objectives

#	SCM Function	Key Domains / Activities	Primary Objective
1	Supply Chain Planning	Demand forecasting, demand & supply planning, production scheduling, inventory optimization, logistics & financial planning	Synchronize supply and demand, optimize resources, reduce costs, and ensure timely fulfillment.
2	Procurement & Sourcing	Supplier selection & evaluation, strategic sourcing, contract management, purchase order management, supplier relationship management	Ensure high-quality, cost-effective, and reliable supply while building strategic supplier partnerships.
3	Production & Manufacturing	Capacity planning, production scheduling, quality assurance & control, work-in-progress monitoring, lean & agile manufacturing	Maximize operational efficiency, minimize waste, maintain product quality, and reliably meet customer demand.
4	Inventory Management	Stock level optimization, safety stock management, reorder point calculation, and warehouse inventory control	Balance inventory costs and availability, prevent stockouts or overstocking, and maintain service levels.
5	Logistics & Transportation	Transportation planning, route optimization, fleet management, carrier selection, distribution network design	Enable timely, cost-efficient, and reliable movement of goods across the supply chain.
6	Warehousing & Storage	Warehouse layout optimization, material handling, order picking & fulfillment, inventory accuracy & control	Improve storage efficiency, reduce handling costs, and accelerate order fulfillment.
7	Order Management & Fulfillment	Order processing, order tracking, backorder management, returns handling, service level monitoring	Deliver accurate, on-time orders while maintaining high customer satisfaction.
8	Supply Chain Risk & Compliance	Risk assessment, regulatory compliance, supplier audits, contingency planning	Mitigate supply chain disruptions, ensure compliance, and safeguard operational continuity.
9	Performance Management & Analytics	KPI monitoring, supply chain analytics, reporting & visualization, continuous improvement initiatives	Support data-driven decisions, optimize performance, and drive continuous improvement.

10	Customer Relationship Management	Customer demand analysis, collaborative planning, service level management, and customer feedback integration	Strengthen customer relationships, enhance responsiveness, and align operations with customer expectations.

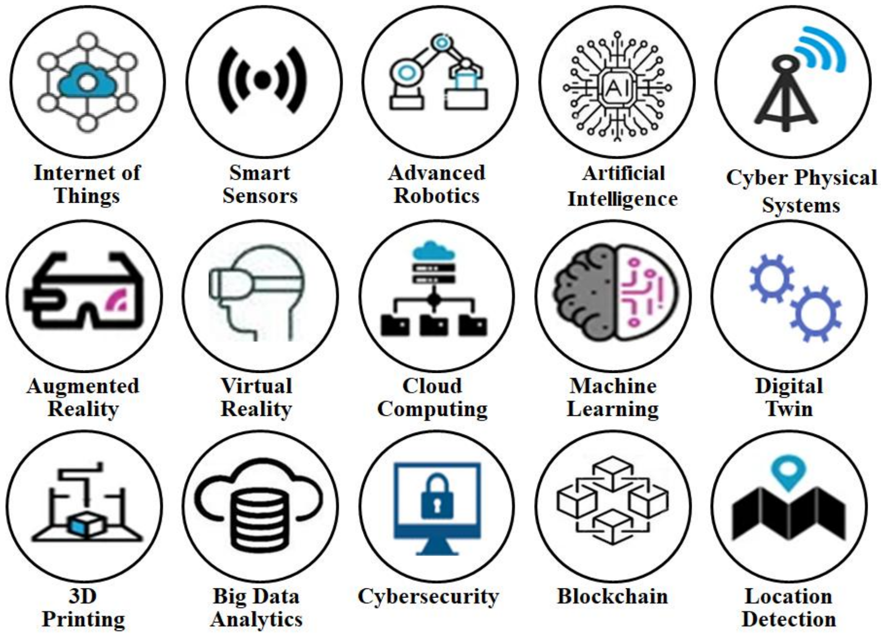

Figure 1. Main Technologies of Industry 4.0.

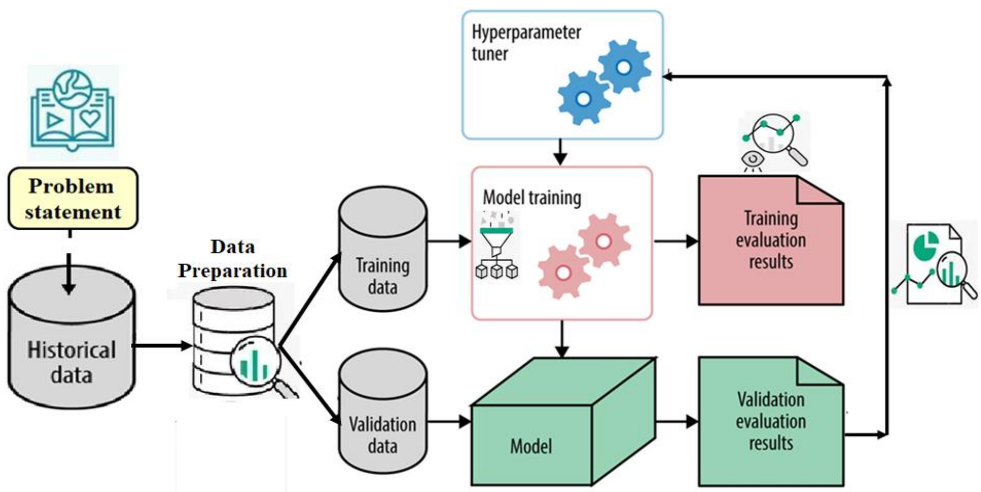

Figure 2. ML-Driven Workflow.

Table 2. Main Categories of Machine Learning Algorithms.

#	Category	Data Type	Goal / Task	Key Algorithms / Examples	Typical Applications
1	Supervised Learning	Labeled	Learn a predictive mapping from input features to outputs	Linear Regression, Logistic Regression, Decision Tree, Random Forest, SVM, KNN, Neural Networks	Spam detection, medical diagnosis, stock price prediction

2	Unsupervised Learning	Unlabeled	Discover hidden patterns, clusters, or structures	K-Means, Hierarchical Clustering, DBSCAN, PCA, Apriori	Customer segmentation, anomaly detection, market basket analysis
3	Semi-Supervised Learning	Partially labeled	Combine a small set of labeled data with large unlabeled datasets	Semi-supervised SVM, Label Propagation, Graph-based algorithms	Web content classification, medical imaging
4	Reinforcement Learning	Feedback / reward-based	Learn optimal actions via trial-and-error to maximize cumulative reward	Q-Learning, Deep Q-Networks (DQN), Policy Gradient, Actor-Critic	Robotics, autonomous vehicles, game AI

2. Literature Review

Industry 4.0 (I4.0) is profoundly reshaping Supply Chain Management (SCM) through the integration of advanced digital technologies, including the Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), blockchain, cloud computing, and cyber-physical systems (CPS). These technologies provide unprecedented opportunities for real-time visibility, predictive analytics, automation, and intelligent decision-making, thereby enhancing efficiency, agility, and resilience across global supply networks. At the same time, they enable more sustainable practices by improving traceability, reducing waste, and optimizing resource utilization [8]. Collectively, these advancements underscore the transformative impact of digitalization in creating intelligent, adaptive, and sustainable supply chain ecosystems.

Despite the rapid growth of digital transformation research, explicit studies that directly connect ML techniques to core SCM practices remain comparatively limited [12]. The literature reveals significant potential but also fragmentation across domains, insufficient cross-industry validation, and gaps in integrating ML with complementary Industry 4.0 enablers. Existing contributions can be grouped into several key thematic clusters, as illustrated in Table 3, which summarizes representative applications of ML across forecasting, supplier management, logistics, hybrid optimization, sustainability, and sector-specific domains.
Demand forecasting remains the most extensively explored ML application in SCM. Babai et al. (2025) [13], using the SCOR framework, demonstrate how ML adoption has accelerated since 2019, particularly in demand prediction, inventory optimization, and transportation planning. Retail-focused studies, such as Samineni et al. (2025) [14], show that predictive analytics enhance sales forecasting, logistics efficiency, and inventory turnover. Similarly, Islam et al. (2021) [15] integrate ML-based forecasting with optimization techniques to improve supplier selection and order allocation in the Canadian food supply chain. These contributions highlight ML's strength in handling high-dimensional, volatile demand data, yet they also underline challenges related to model generalizability and data quality.

Supplier management is another area where ML demonstrates strong promise. Ali et al. (2023) [16] employ Random Forest classifiers to improve supplier evaluation accuracy, while Abdulla et al. (2023) [17] combine ML with the MARCOS method for supplier assessment in the oil and gas sector. Neural networks have been applied to classify supplier efficiency (Mitrovic et al., 2021) [18], while decision trees (Abdulla et al., 2019) [19], support vector machines (Zhao et al., 2021) [20], and hybrid multi-criteria decision-making frameworks (Wilson et al., 2020) [21] expand the methodological toolkit. However, most studies face difficulties with heterogeneous data sources, model interpretability, and scalability across industries—limiting broader adoption in practice.

Logistics optimization and disruption management also represent a major domain of ML application. Akbari and Do (2021) [22], in their review of 110 studies, emphasize the versatility of ML in logistics, while Breitenbach et al. (2021) [23] underline its importance in disruption detection and targeted operational improvements. Applications range from transportation cost reduction (Ali et al., 2023) [16] and risk prediction (Tirkolaee et al., 2021) [5] to enabling autonomous logistics systems (Gomaa, 2025d) [8]. Yet, while ML offers efficiency gains and resilience enhancements, the sector still struggles with issues such as real-time data integration, cybersecurity, and harmonization with global logistics platforms.

Hybrid models that combine ML with simulation are increasingly recognized for their ability to address uncertainty and complexity in SCM. Badakhshan et al. (2024) [24] propose a Sim-ML Classification Framework based on 99 studies, demonstrating how discrete-event simulation and reinforcement learning can improve resilience under uncertainty. Similarly, Bastani et al. (2021) [25] highlight reinforcement learning as a promising approach for adaptive, real-time SCM decision-making. While these approaches offer significant potential, they remain underexplored in terms of optimization capabilities, industrial scalability, and validation through real-world case studies.

Recent scholarship has increasingly turned toward ML's role in enabling sustainable and intelligent supply chains. Gomaa (2025d) [8] proposes an SCM 4.0 framework that integrates AI-driven forecasting, blockchain -enabled transparency, digital twins, and predictive maintenance within Lean and Agile paradigms. Khedr (2024) [26] emphasizes ML/DL and cloud-based analytics in advancing sustainability-focused SCM, while Feizabadi (2022) [27] links AI/ML adoption in manufacturing to sustainable production and smart factory ecosystems. Bibliometric analyses (Baziyad et al., 2024 [28]; Jahani et al., 2023 [29]) confirm growing adoption but reveal persistent gaps in embedding circular economy principles, resilience metrics, and real-time decision support into ML-enabled supply chains.

Sector-specific applications further demonstrate ML's versatility. In food supply chains, ML and DL are used for safety, quality assurance, and risk monitoring (Zhu et al., 2021 [30]; Zhou et al., 2019 [31]). Al-Sahaf et al. (2019) [32] apply evolutionary computation to optimize agri-food supply chains, while Nti et al. (2022) [33] explore AI applications in engineering and manufacturing, including fault detection, defect prediction, and cost optimization. These specialized applications illustrate the breadth of ML adoption but also reflect the fragmentation of research across isolated industry contexts.

Overall, the literature demonstrates that ML has advanced SCM capabilities in forecasting, supplier management, logistics, and hybrid modeling, providing significant improvements in efficiency, adaptability, and decision quality. However, several critical gaps remain. Many ML applications are highly context-specific and lack transferability across industries. Limited synergy with digital twins, IoT, blockchain, and cloud computing restricts the development of fully autonomous, real-time supply chain ecosystems. Persistent challenges with fragmented, siloed, and low-quality data hinder model robustness and broader adoption. Furthermore, while sustainability is gaining attention, most studies address it superficially, with limited integration of circular economy principles, carbon footprint reduction, or life-cycle optimization.

In conclusion, the literature confirms that ML significantly enhances SCM by strengthening forecasting accuracy, supplier evaluation, logistics optimization, and adaptive decision-making. Nevertheless, existing contributions remain fragmented, industry-specific, and insufficiently integrated within broader Industry 4.0 ecosystems. These limitations underscore the urgent need for a unified, scalable, and sustainability-oriented strategic framework that consolidates ML applications into holistic, intelligent, and resilient supply chain systems.

Table 3. Key Applications of Machine Learning Across Supply Chain Management Domains.

Theme	Key Studies	Methods / Technologies	Main Contributions	Research Gaps
Forecasting & Inventory	Babai et al. (2025); Samineni et al. (2025); Islam et al. (2021)	ML (SCOR classification), predictive analytics, regression models	Improved demand forecasting accuracy, inventory optimization, and logistics responsiveness	Limited real-time integration; insufficient validation in diverse industries
Supplier Selection & Evaluation	Ali et al. (2023); Abdulla et al. (2023, 2019); Mitrovic et al. (2021); Zhao et al. (2021); Wilson et al. (2020)	Random Forest (RF), MARCOS–ML, Decision Trees (DT), MLP, SVM	Enhanced supplier evaluation, interpretable decision-making, higher classification accuracy	Data quality limitations; lack of hybrid/multi-criteria models; weak cross-sector generalization
Logistics & Transportation	Akbari & Do (2021); Breitenbach et al. (2021); Tirkolaee et al. (2021)	ML classifiers, SCOR -aligned models, disruption detection	Optimized transport flows, improved risk prediction, enhanced responsiveness to disruptions	Low adoption of IoT, blockchain, and digital twins in logistics optimization
Hybrid & Simulation Approaches	Badakhshan et al. (2024); Bastani et al. (2021)	Sim-ML frameworks, discrete-event simulation, reinforcement learning	Addressed supply chain complexity and uncertainty; developed classification frameworks	Limited focus on optimization; restricted real-world validation; underexplored industry-specific use
Sustainability & I4.0 Integration	Gomaa (2025d); Khedr (2024); Feizabadi (2022); Jahani et al. (2023); Baziyad et al. (2024)	AI/ML, blockchain, digital twins, bibliometric mapping	Proposed SCM 4.0 frameworks, sustainability-oriented models, and mapped intellectual structure	Weak sustainability integration: interoperability, cybersecurity, and governance challenges
Specialized Applications	Zhu et al. (2021); Zhou et al. (2019); Al -Sahaf et al. (2019); Nti et al. (2022)	ML/DL for food supply chains, evolutionary computation, AI in engineering	Enhanced food safety/quality, process control, packaging, cost, and energy reduction	Narrow domain focus; limited scalability and cross-industry applicability

3. Challenges and Research Gaps Analysis

In today's volatile, uncertain, complex, and ambiguous (VUCA) environment, supply chains face unprecedented pressure to balance efficiency, resilience, and sustainability. While digital technologies such as machine learning (ML), artificial intelligence (AI), and the Internet of Things (IoT) offer transformative potential, organizations continue to encounter systemic barriers that constrain competitiveness. These challenges extend across operational, financial, technological, and strategic domains, while encompassing broader concerns such as resilience, sustainability, human capital, customer-centricity, cybersecurity, and geopolitics. Table 4 categorizes these challenges, outlining their causes, implications, and strategic significance [32-40].

1) Operational Efficiency: Supply chains continue to struggle with resource inefficiencies, inventory imbalances, and systemic bottlenecks. Globalized networks are particularly vulnerable to disruptions at critical nodes such as ports, where congestion and backlogs have worsened during crises like the COVID

-19 pandemic. Balancing inventory excess—tying up working capital—with shortages—causing stockouts and service failures—remains a persistent challenge. Capacity constraints in transportation, container availability, and warehouse space further restrict agility and responsiveness.

2) Financial Pressures: Rising costs for raw materials, energy, and logistics have heightened financial strain across supply chains. Freight price volatility, largely shaped by fuel fluctuations and shipping demand, compounds these pressures. Broader macroeconomic instability—including inflation, exchange rate movements, and interest rate volatility—further complicates sourcing and procurement strategies, eroding margins and reducing financial predictability.
3) Technological Challenges: Although digital transformation offers significant promise, adoption remains uneven. Organizations face difficulties in managing fragmented, large-scale datasets and achieving real-time visibility. Integration of IoT, AI, and automation is often hampered by legacy infrastructure, siloed processes, and incompatible systems, resulting in limited data-driven decision-making.
4) Strategic & Relational Challenges: Supplier collaboration is vital for resilience, yet many firms suffer from weak relationship management, trust deficits, and insufficient information sharing. Over-reliance on a narrow supplier base or specific regions amplifies vulnerability, where disruptions at a single source can destabilize entire supply networks. Building diversified, trust-based, and strategically aligned supplier partnerships is therefore essential.
5) Resilience & Risk: Resilience has become a defining supply chain capability. The pandemic revealed forecasting and planning failures, as organizations struggled to match supply with volatile demand. Ongoing disruptions—from labor shortages to transportation bottlenecks—continue to expose vulnerabilities. Climate-induced disasters and extreme weather events further compound systemic risks, highlighting the need for robust, proactive risk management frameworks.
6) Quality & Compliance: Meeting speed-to-market demands while ensuring product quality and regulatory compliance presents a dual challenge. Accelerated production cycles increase the risk of defects, while global supply chains must navigate complex regulations covering labor, safety, customs, and environmental standards. Compliance failures carry not only financial penalties but also reputational damage.
7) Sustainability: Sustainability is both a regulatory requirement and a competitive differentiator. Firms face growing pressure to reduce carbon emissions, minimize waste, and adopt circular economy practices. The expansion of e-commerce introduces additional complexity, particularly reverse logistics involving product returns, recycling, and remanufacturing. Achieving both environmental responsibility and cost-effectiveness requires innovative supply chain design.
8) Human Capital: A skilled workforce is central to digital supply chain transformation, yet the skills gap persists. Shortages in analytics, digital tools, and Industry 4.0 expertise constrain innovation and slow technology adoption. Without sustained investment in workforce development, organizations risk losing their competitive edge.
9) Customer-Centric Challenges: Modern consumers demand speed, personalization, and transparency. They expect faster deliveries, tailored services, and real-time tracking. Meeting these expectations requires integrated customer analytics, flexible distribution models, and digitally enabled visibility. However, these capabilities must be balanced against cost control and operational efficiency.
10) Security & Governance: Digitalization increases exposure to cyber threats, data breaches, and governance failures. Protecting data integrity, ensuring compliance with global privacy regulations, and maintaining cybersecurity resilience are now essential for safeguarding supply chain trust and continuity.
11) Geopolitical Challenges: Global supply chains are increasingly affected by trade wars, sanctions, and shifting trade policies. These forces disrupt sourcing strategies, logistics flows, and market access,

introducing uncertainty that requires firms to pursue diversification, regionalization, and contingency planning.

In conclusion, modern supply chains face an intricate set of interdependent challenges spanning efficiency, cost, sustainability, resilience, and governance. Addressing them demands more than incremental adjustments; it requires adaptive, digitally enabled, and data-driven strategies. Machine learning, AI, and digital twins can play a pivotal role in enhancing visibility, resilience, and intelligence across supply chains. Ultimately, organizations that proactively address these barriers will be better positioned to build future-ready, sustainable, and competitive ecosystems.

Table 4. Current and Emerging Challenges in Supply Chain Management (SCM).

Category	Challenge	Description
1. Operational Efficiency	Resource Management	Ineffective use of materials, labor, and equipment leads to delays, higher costs, and productivity losses.
	Unexpected Delays	Multi-stage global networks are highly exposed to disruptions and extended lead times.
	Port Congestion	Inefficiencies in loading and unloading—intensified during COVID-19—created congestion and delivery backlogs.
	Inventory Management	Balancing excess stock (capital lock-up) with shortages (stockouts) remains a critical challenge.
	Capacity Constraints	Shortages of transport, containers, and warehousing reduce operational flexibility and responsiveness.
2. Financial Pressures	Cost Escalation	Rising raw material and logistics costs demand stronger cost-control mechanisms.
	Freight Price Volatility	Fluctuating fuel prices and global shipping demand significantly increase freight expenses.
	Macroeconomic Instability	Currency shifts, inflation, and interest rate volatility amplify sourcing and financial risks.
3. Technological	Data Management & Collaboration	Handling fragmented, large-scale datasets is essential for visibility, transparency, and informed decisions.
	Digital Transformation	Adoption of IoT, AI, and automation remains uneven across supply chain functions.
	System Integration	Achieving interoperability between new digital solutions and legacy infrastructure is a persistent barrier.
4. Strategic & Relational	Supplier Relationship Management	Weak supplier collaboration undermines reliability, flexibility, and long-term performance.
	Supplier Dependence	Over-reliance on specific suppliers or regions increases disruption vulnerability.
5. Resilience & Risk	Demand Forecasting	The pandemic exposed weaknesses in predicting demand and synchronizing supply with market shifts.
	End-to-End Uncertainty	Labor shortages, bottlenecks, and limited equipment access sustain global unpredictability.
	Disaster & Climate Risks	Extreme weather, natural disasters, and pandemics expose supply chains to large-scale disruptions.
6. Quality & Compliance	Product Quality & Safety	Speed-to-market pressures often conflict with rigorous quality and safety requirements.
	Regulatory Complexity	Diverse international regulations on labor, safety, customs, and environment complicate compliance efforts.
7. Sustainability	Environmental Responsibility	Reducing carbon emissions, waste, and environmental footprints while meeting sustainability goals remains challenging.

	Reverse Logistics	The growth of e-commerce intensifies challenges in managing returns, recycling, and remanufacturing.
8. Human Capital	Skills and Talent Shortages	Limited expertise in digital technologies, analytics, and advanced SCM slows transformation.
9. Customer-Centric	Rising Service Expectations	Customers demand faster, more personalized, and transparent services, intensifying performance pressures.
10. Security & Governance	Cybersecurity & Data Privacy	Greater reliance on digital systems exposes supply chains to cyberattacks and data breaches.
11. Geopolitical	Political & Trade Instability	Trade wars, sanctions, and shifting trade policies disrupt sourcing, logistics, and global market access.

Despite its transformative potential, the adoption of Machine Learning (ML) in Supply Chain Management (SCM) remains constrained by challenges that limit reliability, scalability, and strategic impact, including fragmented data, insufficient integration, and limited real-time visibility. Nevertheless, ML is reshaping SCM by enabling predictive, data-driven, and optimized decision-making across all core functions, from supply chain planning and procurement to production, inventory, logistics, risk management, and customer engagement. Table 5 highlights the critical research gaps in ML-driven SCM, identifies their underlying causes, and suggests strategic directions to enhance performance. By addressing these gaps, ML can improve demand forecasting accuracy, optimize operational efficiency, proactively manage risks, strengthen supplier and customer relationships, and support data-driven strategic decision-making, ultimately transforming traditional supply chains into predictive, resilient, and highly responsive systems.

1) Supply Chain Planning faces challenges in long-term and multi-echelon demand forecasting due to high volatility, fragmented data, and limited integration of market intelligence. Research should focus on hybrid ML models that combine time-series forecasting, causal analysis, and real-time IoT and market data, alongside scenario-based predictive simulations to enhance planning accuracy, responsiveness, and operational resilience.
2) Procurement and Sourcing suffers from incomplete predictive analytics for supplier risk and performance, caused by fragmented supplier data, insufficient real-time monitoring, and limited ESG integration. Strategic research can explore ML-driven real-time supplier scoring, risk prediction, and sustainability-focused analytics to strengthen supplier relationships and improve sourcing decisions.
3) Production and Manufacturing faces inefficiencies in predictive maintenance and production scheduling due to variable machine conditions, limited sensor coverage, and incomplete process monitoring. Reinforcement learning, digital twin simulations, and anomaly detection can optimize maintenance planning, scheduling, and defect prevention while supporting lean and agile manufacturing practices.
4) Inventory Management experiences suboptimal multi-echelon stock and safety stock optimization due to demand uncertainty and limited visibility. ML applications using predictive and prescriptive analytics can dynamically balance stock levels, reduce holding costs, and maintain service levels across the supply chain.
5) Logistics and Transportation struggles with dynamic routing and fleet optimization due to traffic variability, fuel fluctuations, operational disruptions, and fragmented data. Research should focus on ML-powered real-time routing, fleet management, and cost optimization leveraging IoT and predictive traffic analytics to enhance delivery efficiency and reliability.
6) Warehousing and Storage is challenged by inefficient order picking, slotting, and task allocation due to manual processes and siloed data. ML-driven robotic automation, adaptive slotting, predictive picking optimization, and dynamic workload allocation can improve warehouse efficiency, reduce errors, and accelerate order fulfillment.

7) Order Management and Fulfillment faces delays and high backorder risks due to inaccurate forecasts and limited supply chain visibility. Predictive AI models for order prioritization, backorder risk mitigation, and dynamic fulfillment optimization can improve timeliness, reliability, and customer satisfaction.
8) Supply Chain Risk and Compliance shows limited proactive risk detection due to fragmented datasets, insufficient scenario modeling, and weak early-warning systems. ML-based risk scoring, anomaly detection, and scenario simulations can enable proactive risk management, compliance monitoring, and operational continuity.
9) Performance Management and Analytics often provides reactive insights due to fragmented KPIs, poor data integration, and insufficient real-time analytics. ML-driven predictive dashboards combining KPI monitoring, anomaly detection, trend forecasting, and decision-support analytics can enable timely, data-informed decision-making and continuous improvement.
10) Customer Relationship Management struggles with demand personalization and churn prediction because of limited behavioral data and weak real-time feedback integration. ML models combining sentiment analysis, behavioral insights, real-time feedback, and predictive demand forecasting can strengthen engagement, responsiveness, and alignment with customer expectations.

In summary, ML addresses critical gaps across all SCM functions, transforming traditional supply chains into predictive, resilient, and highly efficient systems. Implementing these research directions enhances forecasting accuracy, operational efficiency, risk management, and customer satisfaction, fostering agile, responsive, and competitive supply chains capable of thriving in dynamic and complex business environments.

Table 5. Key Research Gaps in ML–Driven SCM and Strategic Research Directions.

#	SCM Function	Identified Gap	Underlying Cause	Strategic Research Direction
1	Supply Chain Planning	Limited accuracy in long-term and multi-echelon demand forecasting	High demand volatility, fragmented and siloed data, insufficient market intelligence	Develop hybrid ML models combining time-series, causal analysis, and real-time IoT and market data; implement scenario-based predictive simulations to enhance planning resilience
2	Procurement & Sourcing	Incomplete prediction of supplier risk and performance	Fragmented supplier data, lack of real-time monitoring, limited ESG integration	Research ML-driven real-time supplier risk scoring and performance forecasting; integrate sustainability, resilience, and ethical metrics into sourcing decisions
3	Production & Manufacturing	Inefficient predictive maintenance and production scheduling	Variable machine conditions, limited sensor coverage, incomplete process monitoring	Apply reinforcement learning and digital twin simulations to optimize maintenance, scheduling, defect detection, and process efficiency
4	Inventory Management	Suboptimal multi-echelon stock and safety stock optimization	Demand uncertainty, lack of end-to-end visibility, limited predictive insights	Develop AI-driven multi-echelon inventory optimization using predictive and prescriptive analytics to dynamically balance stock, reduce costs, and maintain service levels
5	Logistics & Transportation	Limited dynamic routing and fleet optimization	Traffic variability, fuel cost fluctuations, unexpected disruptions, fragmented transport data	Investigate ML-powered real-time routing and fleet optimization integrating IoT, predictive traffic, and cost analytics

6	Warehousing & Storage	Ineffective order picking, slotting, and task allocation	Manual operations, siloed data, inefficient resource utilization	Apply ML-driven robotic automation, adaptive slotting, predictive picking, and dynamic workload assignment to improve warehouse efficiency and accuracy
7	Order Management & Fulfillment	Fulfillment delays and high backorder risk	Inaccurate demand forecasts, limited end-to-end visibility, reactive planning	Develop predictive AI models for order prioritization, backorder risk mitigation, and dynamic fulfillment optimization
8	Supply Chain Risk & Compliance	Limited proactive risk detection and mitigation	Fragmented risk datasets, insufficient scenario modeling, lack of early-warning systems	Implement ML-based risk scoring, anomaly detection, and scenario simulation frameworks for proactive disruption management and continuity planning
9	Performance Management & Analytics	Delayed or reactive performance insights	Fragmented KPIs, insufficient real-time analytics, poor data integration	Create predictive dashboards integrating KPIs with anomaly detection, trend forecasting, and decision-support analytics for continuous improvement
10	Customer Relationship Management	Poor demand for personalization and churn prediction	Limited behavioral data, weak real-time feedback integration, and insufficient analytics	Develop ML models combining sentiment analysis, behavioral insights, real-time feedback, and predictive demand modeling to enhance customer engagement and responsiveness

4. Strategic Framework for ML-Driven SCM

Machine learning (ML) is increasingly transforming Supply Chain Management (SCM) by enhancing predictive accuracy, operational agility, and competitive advantage. Table 6 illustrates the diverse applications of ML across core SCM functions and highlights the strategic and operational value each application delivers. By enabling data-driven decision-making, predictive insights, and process optimization, ML is reshaping traditional supply chain operations into highly responsive and efficient systems.

1) Supply Chain Planning leverages ML for predictive demand modeling, inventory optimization, production scheduling, scenario simulation, and financial risk forecasting. These applications align supply with demand, reduce operational costs, and improve planning accuracy, enhancing overall operational efficiency.
2) In Procurement and Sourcing, ML supports supplier risk scoring, cost and price prediction, contract analytics, spend analysis, and supplier performance forecasting. These tools enable informed sourcing decisions, reduce procurement costs, and strengthen supplier relationships, improving reliability and strategic alignment.
3) Production and Manufacturing benefits from ML through predictive maintenance, defect detection, bottleneck prediction, process optimization, and anomaly detection. These applications increase efficiency, minimize downtime, and maintain consistent product quality, supporting lean and agile manufacturing practices.
4) For Inventory Management, ML enables inventory forecasting, stockout prediction, replenishment optimization, and demand-supply alignment modeling. This ensures optimal inventory levels, reduces holding costs, prevents stockouts, and maintains service levels, balancing efficiency with responsiveness.
5) In Logistics and Transportation, ML applications such as route optimization, delivery time prediction, dynamic fleet management, and transportation cost forecasting improve delivery efficiency, reduce costs, and enhance shipment reliability and responsiveness.

6) Warehousing and Storage benefit from ML through automated storage and retrieval, slotting optimization, picking route optimization, and inventory accuracy prediction. These applications increase warehouse productivity, accelerate order fulfillment, and reduce handling errors, improving overall operational performance.
7) Within Order Management and Fulfillment, ML supports order demand prediction, fulfillment prioritization, backorder risk prediction, and returns analytics. These capabilities ensure timely, accurate, and reliable order fulfillment, enhancing customer satisfaction.
8) Supply Chain Risk and Compliance utilizes ML for risk detection and scoring, anomaly detection, compliance monitoring, and disruption prediction. This proactive approach mitigates potential risks, ensures regulatory compliance, and safeguards supply chain continuity.
9) Performance Management and Analytics relies on ML for predictive KPI modeling, performance anomaly detection, trend forecasting, and decision-support analytics. These tools enable data-informed decision-making, identify performance gaps, and support continuous improvement initiatives.
10) Finally, Customer Relationship Management leverages ML for demand prediction, churn analysis, sentiment analysis, and service level optimization. These applications strengthen customer relationships, improve responsiveness, and align supply chain operations with customer expectations.

In conclusion, ML is transforming SCM by enabling predictive, data-driven, and optimized decision-making across all core functions. From planning and procurement to production, inventory, logistics, and customer management, ML improves operational efficiency, reduces costs, mitigates risks, and enhances service quality. By harnessing predictive analytics, anomaly detection, optimization algorithms, and real-time insights, organizations can anticipate demand fluctuations, proactively manage disruptions, and strengthen supplier and customer relationships. Ultimately, ML fosters agile, resilient, and customer-centric supply chains, providing a sustainable competitive advantage in today's dynamic business environment.

Table 6. Machine Learning Applications Across SCM Domains.

#	SCM Function	Key Domains / Activities	Key Machine Learning (ML) Applications	Strategic / Operational Value
1	Supply Chain Planning	Demand forecasting, supply & demand planning, production scheduling, inventory optimization, logistics & financial planning	Predictive demand modeling, inventory optimization, production scheduling, scenario simulation, and financial risk forecasting	Aligns supply with demand, reduces costs, enhances planning accuracy and operational efficiency
2	Procurement & Sourcing	Supplier selection & evaluation, strategic sourcing, contract management, purchase order management, supplier relationship management	Supplier risk scoring, cost & price prediction, contract analytics, spend analysis, supplier performance forecasting	Supports data-driven sourcing, reduces procurement costs, and strengthens supplier relationships
3	Production & Manufacturing	Capacity planning, production scheduling, quality assurance, work-in-progress monitoring, lean & agile manufacturing	Predictive maintenance, defect detection, bottleneck prediction, process optimization, anomaly detection	Increases efficiency, minimizes downtime, and ensures consistent product quality
4	Inventory Management	Stock level optimization, safety stock management, reorder point calculation, warehouse inventory control	Inventory forecasting, stockout prediction, replenishment optimization, demand-supply alignment modeling	Optimizes inventory levels, reduces holding costs, prevents stockouts, and maintains service levels

5	Logistics & Transportation	Transportation planning, route optimization, fleet management, carrier selection, distribution network design	Route optimization, delivery time prediction, dynamic fleet management, transportation cost forecasting	Enhances delivery efficiency, reduces costs, and improves shipment reliability
6	Warehousing & Storage	Warehouse layout optimization, material handling, order picking & fulfillment, inventory accuracy & control	Automated storage & retrieval, slotting optimization, picking route optimization, and inventory accuracy prediction	Boosts warehouse productivity, accelerates fulfillment, reduces errors, and handling costs
7	Order Management & Fulfillment	Order processing, order tracking, backorder management, returns handling, service level monitoring	Order demand prediction, fulfillment prioritization, backorder risk prediction, returns analytics	Ensures timely, accurate order fulfillment and enhances customer satisfaction
8	Supply Chain Risk & Compliance	Risk assessment, regulatory compliance, supplier audits, contingency planning	Risk detection & scoring, anomaly detection, compliance monitoring, disruption prediction	Mitigates risks proactively, ensures compliance, and safeguards continuity
9	Performance Management & Analytics	KPI monitoring, supply chain analytics, reporting & visualization, continuous improvement initiatives	Predictive KPI modeling, performance anomaly detection, trend forecasting, decision-support analytics	Drives data-informed decisions, identifies gaps, and supports continuous improvement
10	Customer Relationship Management	Customer demand analysis, collaborative planning, service level management, and feedback integration	Customer demand prediction, churn analysis, sentiment analysis, service level optimization	Strengthens customer relationships, improves responsiveness, and aligns operations with customer expectations

To address the challenges of ML adoption in supply chains, this study introduces a strategic framework designed to align ML integration with organizational objectives, strengthen data-driven decision-making, and foster agile, intelligent, and sustainable supply chains. The framework is structured around four interdependent pillars: Data and Systems Foundations, Algorithmic Intelligence, Organizational and Human Integration, and Strategic and Sustainability Alignment. The overall structure of the proposed framework is summarized in Table 7.

1) Pillar 1: Data and Systems Foundations: Reliable ML adoption begins with robust data quality, interoperability, and security. Supply chains often face fragmented and inconsistent data across legacy systems, limiting scalability. To overcome these barriers, organizations require standardized governance models, interoperable architectures, and secure data-sharing platforms. Technologies such as IoT, cloud–edge computing, and blockchain enable real-time, trusted, and privacy-preserving data exchange. Strengthening this foundation enhances visibility, traceability, and predictive capabilities across the supply chain.
2) Pillar 2: Algorithmic Intelligence: Data must be complemented by interpretable and adaptive ML models. Opaque “black-box” algorithms limit managerial trust, while static models underperform in volatile contexts. Incorporating explainable AI (XAI), reinforcement learning, and digital twins allows supply chains to adapt dynamically, simulate disruptions, and balance competing objectives. Moving beyond cost efficiency, ML-driven optimization should integrate resilience, service excellence, and sustainability to create future-ready decision frameworks.
3) Pillar 3: Organizational and Human Integration: Technology adoption depends on people, leadership, and culture. Resistance to change, skill shortages, and low digital maturity are major barriers. Effective adoption requires leadership-driven transformation, hybrid skill development, and human–machine

collaboration platforms. Decision-support systems that translate ML outputs into actionable insights enhance managerial trust and encourage adoption. Embedding ML as a partner to human judgment fosters a culture of collaboration, agility, and innovation.

4) Pillar 4: Strategic and Sustainability Alignment: For lasting impact, ML adoption must align with long-term strategy and sustainability goals. Current applications often operate in silos and neglect ESG objectives, circular economy practices, and lifecycle optimization. ML can enable carbon tracking, waste reduction, and reverse logistics, creating measurable environmental and social value. At the same time, ethical AI governance is essential to mitigate bias, ensure accountability, and safeguard cybersecurity. This pillar ensures that ML not only improves efficiency but also drives responsible, resilient, and sustainable supply chains.

Integrative Implications: These four pillars provide a holistic roadmap for ML-driven SCM. Data foundations enable reliable insights, algorithmic intelligence drives adaptability, organizational integration fosters adoption, and strategic alignment ensures resilience and sustainability. Collectively, they establish a pathway for building intelligent, adaptive, and future-ready supply chains in the Industry 4.0 era and beyond.

Table 7. Strategic Framework for ML-Driven SCM

#	Pillar	Focus Area	Key Challenges Addressed	Strategic Directions
1	Data and Systems Foundations	Data governance, interoperability, security	Poor data quality, fragmented systems, and privacy risks	Establish robust data governance and stewardship; adopt standardized taxonomies; enable interoperable infrastructures via IoT, cloud–edge, and blockchain; integrate privacy-preserving approaches such as federated learning
2	Algorithmic Intelligence	Model transparency, adaptability, and multi-objective optimization	Opaque ML models (“black boxes”); static, disruption-prone models; efficiency-only focus	Deploy explainable AI (XAI) for interpretability; integrate reinforcement learning and digital twins for real-time adaptability; advance multi-objective optimization, balancing cost, resilience, sustainability, and service
3	Organizational and Human Integration	Leadership, culture, skills, human–machine collaboration	Resistance to change, lack of cross-disciplinary skills, and limited digital maturity	Foster executive leadership and change management; invest in digital upskilling and hybrid training; build human–machine decision-support platforms that augment managerial judgment
4	Strategic and Sustainability Alignment	ESG integration, ethics, resilience, ecosystem collaboration	Short-term functional focus; lack of circularity; weak ethical governance	Align ML adoption with ESG and circular economy goals; apply ML to carbon footprint reduction, waste minimization, reverse logistics; establish ethical AI governance (bias, fairness, accountability); enable secure cross-partner data sharing

5. Conclusion and Future Work

This study examined the transformative role of Machine Learning (ML) in Supply Chain Management (SCM) within the Industry 4.0 era, where digitalization and advanced analytics are reshaping efficiency, resilience, and competitiveness. A comprehensive review of ML applications across core SCM functions—including demand forecasting, inventory management, logistics, procurement, and risk management—demonstrated their potential to enhance predictive accuracy, operational agility, and strategic decision-making.

Despite these advances, adoption remains constrained by persistent challenges such as data quality and interoperability, model interpretability, scalability, and integration with legacy systems. A structured gap analysis highlighted key opportunities in explainable ML, real-time adaptive analytics, sustainability-driven applications, and human–machine collaboration, underscoring the need for more holistic and adaptive approaches.

To address these gaps, the study proposed a strategic framework structured around four interdependent pillars: Data and Systems Foundations, Algorithmic Intelligence, Organizational and Human Integration, and Strategic and Sustainability Alignment. This framework provides a roadmap for embedding ML into supply chains by establishing robust data ecosystems, developing adaptive and interpretable algorithms, fostering human-centered adoption, and aligning digital transformation with ethical and sustainability imperatives.

The study concludes that ML adoption constitutes a socio-technical transformation rather than a mere technical upgrade, requiring alignment with organizational culture, governance, and long-term strategy. Future research should validate the proposed framework across industries, explore integration with emerging technologies such as digital twins, edge computing, and generative AI, and develop metrics to evaluate the sustainability and resilience impact of ML-enabled supply chains. By consolidating current knowledge, identifying critical gaps, and offering actionable directions, this study provides both theoretical insights and practical guidance for advancing intelligent, resilient, and sustainable supply chains.

Theoretical Implications: This framework advances SCM theory by integrating technological, organizational, and strategic perspectives into a unified model. It shifts the discourse beyond efficiency toward resilience, sustainability, and ethical governance, enriching the understanding of intelligent, data-driven ecosystems.

Practical Implications: For practitioners, the framework provides guidance on overcoming adoption challenges through data governance, explainable AI, digital twins, and collaborative platforms. These insights support improved forecasting, risk management, logistics optimization, and supplier collaboration.

Managerial Implications: The framework emphasizes leadership's role in shaping ML adoption. Managers are encouraged to cultivate a digital culture, invest in workforce reskilling, and embed ethics and sustainability into decisions, thereby positioning ML as a strategic capability for competitiveness and long-term value creation.

Study Limitations: As a conceptual study, the framework requires empirical validation. Its applicability may differ across industries, contexts, and maturity levels, while rapid technological change may demand ongoing adaptation.

Future Research Directions: Future research should validate, refine, and extend the proposed ML-driven SCM framework across diverse industries and global contexts. Experimental designs may include pilot studies, controlled trials, and cross-industry benchmarking to assess ML's impact on key SCM functions, such as demand forecasting, inventory optimization, logistics, procurement, and risk management. Key research propositions include:

1) Predictive Performance: ML-enabled analytics can enhance accuracy, responsiveness, and operational efficiency compared to traditional methods. Experiments could examine performance under varying data quality and system complexity.
2) Human–Machine Collaboration: Collaborative ML systems can improve workforce efficiency, adoption, and decision quality. Longitudinal studies may track user interactions, trust, and decision outcomes.

3) Technology Integration: Combining ML with emerging technologies—blockchain, IoT, digital twins, and quantum computing—can strengthen supply chain resilience, transparency, and sustainability. Scenario-based simulations or pilot deployments can test these integrations.
4) Sustainability and Circular Economy: ML can optimize resource use, reduce waste, and support circular economy practices. Research could integrate life-cycle assessment metrics with ML-driven decision models.
5) Governance and Ethics: Robust governance frameworks are essential to ensure fairness, transparency, accountability, and ethical compliance. Comparative studies could evaluate governance approaches across organizational and regulatory contexts.

By pursuing these directions, researchers and practitioners can advance adaptive, responsible, and future-ready supply chains that align with Industry 4.0 principles and long-term sustainability goals.

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Data Availability

Data supporting reported results can be found in the links to publicly archived datasets analyzed.

Conflicts of Interest

The authors declare no conflict of interest.

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