Artificial Intelligence in Supply Chain Risk Management: A Systematic Literature Review

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Abstract

The increasing complexity and uncertainty in global supply chains have intensified the need for effective risk management strategies. In recent years, Artificial Intelligence (AI) has emerged as a transformative technology capable of enhancing the identification, prediction, and mitigation of supply chain risks. This study conducts a systematic review of existing literature to examine the role of AI in supply chain risk management. Using a structured review approach, relevant research articles published between 2015 and 2025 were collected from major academic databases and screened based on predefined inclusion and exclusion criteria. The review aims to synthesize the existing body of knowledge on how AI technologies such as machine learning, predictive analytics, and big data analytics are applied to manage disruptions and uncertainties in supply chains. Furthermore, the study identifies the dominant research themes, technological applications, and methodological approaches adopted in previous studies. The findings highlight the growing integration of AI-driven tools in areas such as demand forecasting, disruption prediction, supplier risk evaluation, and decision support systems. Despite the increasing attention to AI-based solutions, the review also reveals several research gaps related to implementation challenges, data quality issues, and integration with traditional risk management practices. The study provides a comprehensive understanding of the current research landscape and offers directions for future studies in AI-enabled supply chain risk management.

Keywords: Machine Learning, Artificial Intelligence, Technological, Supply Chain, Risk

Introduction

Supply chain management has emerged as a critical competitive differentiator in the globally interconnected economy, yet organizations face unprecedented complexity in managing supply chain risks. The rapid evolution of global markets, combined with geopolitical tensions, climate-related disruptions, and unexpected crises such as the COVID-19 pandemic, has exposed vulnerabilities in traditional supply chain models (Sharma et al., 2026). Modern supply chains operate within an environment characterized by demand fluctuations, supplier unreliability, transportation delays, and the persistent challenge of maintaining visibility across multi-tier networks (Chatterjee & Rane, 2026). These challenges have catalyzed a fundamental shift in how organizations approach supply chain risk management, moving away from reactive approaches toward proactive, data-driven strategies enabled by advanced technologies. The digital transformation of supply chains has been fundamentally reshaped by the convergence of Artificial Intelligence (AI), Blockchain, Internet of Things (IoT), and advanced analytics technologies (Samuels, 2025). Organizations are increasingly recognizing that managing supply chain risks effectively requires more than incremental improvements to existing processes; it demands a paradigm shift in how data is collected, analyzed, and transformed into actionable insights. Artificial Intelligence, in particular, offers transformative potential through machine learning

algorithms, deep learning architectures, and predictive analytics capabilities that enable organizations to anticipate disruptions before they occur, optimize inventory positions dynamically, and make data-driven decisions in real-time (Yusuf et al., 2025). The application of AI technologies spans multiple dimensions of supply chain risk management, from demand forecasting and inventory optimization to predictive maintenance, supplier risk assessment, and sustainability monitoring (Borah et al., 2024).

This comprehensive literature review examines the existing body of research on the application of Artificial Intelligence in supply chain risk management. The review synthesizes findings from over 40 peer-reviewed studies published primarily between 2020 and 2026, identifying major research themes, technological approaches, and critical research gaps. Through systematic analysis of the literature, this review reveals that while AI offers substantial opportunities for enhancing supply chain resilience and risk mitigation, the field is characterized by fragmented research efforts, limited integration frameworks, and persistent barriers to practical implementation. The review is structured to first establish the foundational concepts and context, then explore the major research themes including machine learning applications, predictive analytics, technology integration frameworks, and sustainability considerations, before finally addressing research gaps and future directions.

Literature Review

Major Research Themes and Technological Approaches in AI-Driven Supply Chain Risk Management
Machine Learning and Deep Learning Applications in Supply Chain Optimization
Machine learning has emerged as a foundational technology for addressing supply chain risk management challenges through its capacity to identify patterns in complex datasets and make accurate predictions under uncertainty (Chatterjee & Rane, 2026). The literature reveals that machine learning algorithms have demonstrated superior performance in critical supply chain functions including demand forecasting, inventory optimization, and predictive maintenance. These algorithms enable organizations to move beyond static forecasting models toward dynamic, adaptive systems that continuously learn from incoming data and adjust predictions in response to changing market conditions (Alonge et al., 2021). Deep learning architectures, including artificial neural networks (ANN) and deep convolutional neural networks (DCNN), have proven particularly effective in complex pattern recognition tasks that traditional statistical methods struggle to handle (Lakhan et al., 2025).

Empirical studies demonstrate quantifiable improvements in supply chain performance through the application of machine learning techniques. For instance, research employing Genetic Algorithm (GA) optimization has achieved 23% savings in operational costs, while Artificial Neural Networks (ANN) have delivered 18% improvements in demand forecasting accuracy (Borah et al., 2024). Support Vector Machines (SVM) have reduced lead times by 15%, and Particle Swarm Optimization (PSO) algorithms have enhanced supply chain flexibility by 20% (Borah et al., 2024). These results underscore the practical value of machine learning in translating raw supply chain data into competitive advantages. The integration of machine learning with other technologies further amplifies these benefits; when AI is integrated with blockchain technology, supply chain resilience increases significantly, with disruptions decreasing by approximately 30% (Borah et al., 2024).

The application of machine learning extends beyond performance optimization to address fundamental supply chain visibility challenges. Real-time data analytics platforms leverage machine learning algorithms for anomaly detection, identifying potential disruptions such as supplier delays, equipment failures, and demand fluctuations before they cascade through the supply chain (Alonge et al., 2021). This capability represents a fundamental shift from reactive problem-solving to proactive risk mitigation. Deep learning models have also demonstrated effectiveness in demand planning and inventory management optimization, enabling organizations to minimize both stockouts and excess inventory simultaneously (Serrano-Torres et al., 2025). However, the literature also identifies significant implementation challenges, including data quality constraints, model reliability concerns, and the requirement for specialized expertise in algorithm development and deployment (Kommula, 2025).

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Predictive Analytics for Risk Anticipation and Early Warning Systems

Predictive analytics has emerged as a critical capability for transforming supply chains from reactive to proactive risk management paradigms (Kommula, 2025). Rather than merely responding to disruptions after they occur, organizations leveraging predictive analytics can anticipate disruptions by deploying machine learning algorithms, IoT-enabled data collection systems, and advanced computational frameworks that identify emerging risks before they materialize (Kommula, 2025). This capability is particularly valuable in supply chain contexts where the cost of disruptions can be exponential, affecting not only direct operations but also downstream customer satisfaction and brand reputation.

The implementation of predictive analytics systems involves sophisticated modeling approaches that integrate multiple data sources and analytical techniques to forecast supply chain disruptions with high accuracy (Ike et al., 2024). These systems combine machine learning algorithms with ensemble modeling and deep learning to enhance predictive accuracy, while adaptive algorithms accommodate evolving market trends and new types of disruptions (Ike et al., 2024). Quantitative measurements from organizations implementing predictive analytics demonstrate significant improvements in resilience metrics and return on investment compared to traditional reactive approaches (Kommula, 2025). The applications encompass multiple critical supply chain functions: enhanced demand forecasting accuracy enables better inventory positioning, improved logistics planning optimizes transportation routes and reduces fuel consumption, and proactive supplier risk management enables organizations to diversify sourcing strategies before supplier disruptions occur.

The integration of IoT-enabled data collection systems with predictive analytics creates powerful early warning systems that monitor supply chain conditions in real-time (Kommula, 2025). IoT sensors deployed at multiple points in the supply chain generate continuous streams of data on equipment performance, product condition, location, and environmental factors (Ikevuje et al., 2024). This real-time data, when processed through machine learning algorithms, enables organizations to identify subtle patterns that precede disruptions, allowing intervention before problems escalate (Alonge et al., 2021). However, the literature also identifies significant challenges in implementing predictive analytics, including data quality issues that can undermine model accuracy, organizational resistance to replacing intuition-based decisions with algorithm-driven recommendations, and concerns about model reliability when deployed in novel situations (Kommula, 2025). Additionally, the cost-benefit equation varies significantly across different business scales and supply chain types, requiring organizations to carefully evaluate whether predictive analytics investments will deliver appropriate returns.

Integration of Artificial Intelligence with Blockchain and IoT Technologies

The convergence of Artificial Intelligence, Blockchain, and Internet of Things technologies represents a significant evolution in supply chain risk management capabilities (Sharma et al., 2026). While each technology offers distinct benefits—Blockchain provides immutable ledgers for trust and traceability, IoT enables real-time asset monitoring, and AI provides predictive analytics for optimized decision-making—their integrated application creates synergistic effects that exceed the capabilities of any individual technology (Sharma et al., 2026). This recognition has prompted substantial research into integrated architectures that leverage the complementary strengths of these technologies to create more transparent, resilient, and efficient supply chains.

Blockchain technology has been specifically designed to address transparency and trust challenges in multi-stakeholder supply chain environments (Owusu-Berko, 2025). The decentralized, immutable nature of blockchain ledgers ensures data integrity, prevents fraud and manipulation, and enables all supply chain participants to access accurate, tamper-proof information (Igwe et al., 2024). When integrated with smart contracts—self-executing code stored on blockchain networks—organizations can automate compliance verification, trigger payment releases based on predefined conditions, and ensure that quality and sustainability criteria are met throughout the supply chain (Prova et al., 2025).

The combination of blockchain's trust infrastructure with IoT sensors creates particularly powerful applications for supply chain transparency; IoT devices provide real-time data on product location, condition, and handling, while blockchain ensures this data cannot be retroactively altered or falsified (Ojadi et al., 2025).

Integrated frameworks that combine AI, Blockchain, and IoT create comprehensive solutions for supply chain risk management that address multiple dimensions simultaneously (Chatterjee & Rane, 2026). The Blockchain-Based Supply Chain Optimization (BISCON) framework exemplifies this integration, incorporating blockchain technology for transparent data management, Intelligent Edge Computing (IEC) for low-latency processing, and Evolutionary Algorithms for optimization of logistics parameters (Islam, 2025). Implementation of such frameworks has demonstrated substantial improvements in operational performance: a 32% decrease in computational delay, a 25% increase in supply chain throughput, and increased resilience to cyber attacks (Islam, 2025). Similarly, sustainable blockchain-assisted AIoT and green multiconstraint supply chain systems have been developed to simultaneously optimize multiple performance dimensions including time, energy, cost, and carbon dioxide emissions through genetic algorithm and deep convolutional neural network integration (Lakhan et al., 2025).

The literature emphasizes that successful integration of these technologies requires not merely implementing individual solutions but rather designing coherent frameworks in which the technologies reinforce each other's capabilities (Samuels, 2025). Data fusion techniques that merge information from multiple sources including IoT devices, operational databases, and external environmental factors can be integrated within Distributed Ledger Technology (DLT) infrastructure to ensure both data integrity and comprehensive visibility (Igwe et al., 2024). The challenge identified in the literature is that while individual technology implementations are becoming increasingly mature, the field lacks sufficiently developed integration frameworks that address interoperability, standardization, and coordinated optimization across multiple technologies (Chatterjee & Rane, 2026).

Demand Forecasting and Inventory Optimization Through AI

Demand forecasting represents one of the most critical applications of AI in supply chain risk management, as inaccurate forecasts cascade through supply chains, creating bullwhip effects that amplify inventory imbalances and operational inefficiencies (Alonge et al., 2021). Traditional statistical forecasting methods often fail to capture the complex, nonlinear relationships in demand data, particularly during periods of high volatility or when introducing new products with limited historical data (Borah et al., 2024). Machine learning algorithms and deep learning architectures overcome these limitations by learning directly from historical patterns and adapting to changing market conditions. The superior performance of AI-based forecasting is well-documented in the literature, with neural network-based approaches consistently outperforming traditional time-series forecasting methods in both accuracy and adaptability (Alonge et al., 2021).

The integration of AI-driven demand forecasting with real-time data collection creates closed-loop systems that continuously improve forecasting accuracy (Alonge et al., 2021). As new demand data is collected through point-of-sale systems, IoT sensors, and customer engagement platforms, machine learning models are retrained, allowing the forecasting system to adapt to shifting market conditions, seasonal patterns, and emerging trends (Alonge et al., 2021). This capability is particularly valuable in highly volatile industries such as fashion and food production, where demand uncertainty creates substantial risk of either stockouts that lose sales or excess inventory that leads to markdowns or spoilage. The dairy supply chain literature provides specific examples of how AI-enabled forecasting using algorithms such as SARIMA can optimize both production planning and inventory management across temperature-controlled supply chains where spoilage risk is particularly high (Serrano-Torres et al., 2025).

Inventory optimization through AI extends beyond simple demand forecasting to encompass dynamic optimization that considers multiple constraints including inventory carrying costs, stockout risks, production capacity limits, and supplier lead time variability (Alonge et al., 2021). Machine learning algorithms can learn the cost structure associated with different inventory positions and automatically optimize stock levels to minimize total costs while maintaining service level targets (Borah et al., 2024). Advanced approaches incorporate scenario analysis and stress testing, using historical disruption data to identify inventory positions that would prove robust across multiple potential disruption scenarios (Kommula, 2025). However, the literature identifies important challenges in inventory optimization including the need for high-quality, comprehensive data across multiple supply chain tiers, the difficulty of capturing all relevant constraints in optimization models, and the need for organizational processes that allow rapid implementation of algorithmically-determined inventory positions (Alonge et al., 2021).

Real-Time Supply Chain Visibility and Monitoring Systems

Real-time visibility throughout supply chain networks has emerged as a foundational requirement for effective risk management, yet achieving end-to-end visibility across complex, multi-tier supply networks remains a substantial challenge (Yusuf et al., 2025). IoT technologies enable this visibility through the deployment of smart sensors, RFID trackers, and connected devices that continuously monitor product location, condition, and environmental factors (Ikevuje et al., 2024). When integrated with cloud-based data platforms and AI-powered analytics, these IoT systems transform raw sensor data into actionable insights that enable real-time decision-making (Owusu-Berko, 2025). Real-time visibility systems have demonstrated particular value in temperature-controlled supply chains such as pharmaceuticals and food distribution, where maintaining product integrity requires continuous monitoring of environmental conditions (Mellah et al., 2025). Digital Twin technology represents an advanced approach to supply chain visualization and risk assessment, creating virtual replicas of physical supply chain processes that can be used for simulation, scenario analysis, and optimization (Owusu-Berko, 2025). Digital twins leverage real-time data from IoT sensors and other sources to continuously update virtual models of supply chain operations, enabling organizations to model the impact of potential disruptions before they occur in the physical world (Owusu-Berko, 2025). This capability has particular value for supply chain network design and resilience assessment; organizations can simulate the impact of supplier disruptions, transportation delays, or demand shocks and identify vulnerabilities before they are exposed by actual disruptions. The literature indicates that digital twins, combined with AI-driven optimization algorithms, enable organizations to transition from reactive firefighting to proactive optimization of supply chain operations (Owusu-Berko, 2025).

The integration of real-time visibility systems with AI-powered analytics creates sophisticated supply chain control systems that support both strategic and operational decision-making (Ikevuje et al., 2024). Edge computing approaches, which process data close to where it is generated rather than transmitting all data to centralized cloud servers, reduce latency and enable faster response to emerging disruptions (Islam, 2025). However, implementing comprehensive real-time visibility systems requires substantial infrastructure investment, integration with legacy systems that may not have been designed for data sharing, and development of organizational processes that can act on real-time insights (Yusuf et al., 2025). Data standardization remains a persistent challenge; supply chain ecosystems typically involve multiple independent organizations using different systems, data formats, and communication protocols, making integrated data flow difficult (Samuels, 2025).

Sustainability, Environmental Impact, and Risk Management Integration

Sustainability has evolved from a peripheral corporate responsibility concern to a central supply chain risk management imperative, driven by regulatory requirements, investor pressure, and customer expectations (Sagar et al., 2025). AI technologies enable supply chains to simultaneously optimize economic performance and environmental sustainability by providing real-time monitoring of carbon emissions, energy consumption, waste generation, and resource utilization (Ojadi et al., 2025). Blockchain and IoT technologies integrated with AI create systems that can track

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environmental impact with transparency and accuracy, enabling organizations to identify hotspots where environmental performance can be improved and to substantiate sustainability claims to stakeholders (Ojadi et al., 2025).

Carbon tracking and emissions management has become a critical application of integrated AI, Blockchain, and IoT systems in supply chains (Kirui et al., 2024). Smart contracts deployed on blockchain networks can automatically verify carbon credits, enforce sustainability requirements, and trigger actions based on predefined sustainability metrics (Igwe et al., 2024). IoT sensors provide real-time data on energy consumption, transportation distances, and supply chain activities, while AI algorithms analyze this data to identify opportunities for emissions reduction and to model the impact of alternative supply chain designs on carbon footprint (Ojadi et al., 2025). The integration of data fusion techniques within distributed ledger infrastructure ensures that environmental data cannot be manipulated and is accessible to all supply chain stakeholders including regulators (Igwe et al., 2024). The literature emphasizes that effective sustainability monitoring requires not only accurate data collection but also meaningful metrics that reflect actual environmental impact rather than merely documenting activities (Sagar et al., 2025).

Supply chain resilience and environmental sustainability have been shown to reinforce each other through AI-enabled transparency and collaboration (Sagar et al., 2025). Research on the fashion supply chain in Bangladesh demonstrates that visibility, agility, and collaboration core resilience constructs positively influence both waste management and pollution/emissions reduction (Sagar et al., 2025). Digital tools including AI, IoT, blockchain, and big data predictive analytics moderate these relationships, strengthening the impact of visibility while creating opportunities to identify win-win strategies that simultaneously improve resilience and environmental performance (Sagar et al., 2025). However, the literature identifies substantial barriers to achieving sustainability through supply chain optimization, including the complexity of measuring actual environmental impact across global supply networks, the difficulty of establishing accountability when environmental responsibility is distributed across multiple independent organizations, and the need for supply chain redesign to achieve fundamental sustainability improvements rather than mere incremental efficiency gains (Kirui et al., 2024).

Specific Applications and Industry-Focused Implementations

Healthcare and Pharmaceutical Supply Chains

The healthcare supply chain presents particularly acute challenges for risk management due to the critical nature of pharmaceutical products, the complexity of temperature-controlled logistics, the widespread geographic distribution of demand, and the high cost of supply disruptions (Rasel et al., 2022). COVID-19 exposed significant vulnerabilities in healthcare supply chains, including inefficiencies in demand forecasting that led to simultaneous shortages and surpluses, delays in procurement processes that prevented rapid response to changing needs, and insufficient visibility across multi-tier networks to identify and resolve bottlenecks (Rasel et al., 2022). AI and advanced analytics have emerged as critical tools for addressing these challenges, enabling healthcare organizations to improve demand forecasting accuracy, optimize inventory positioning across multiple sites, and enhance the resilience of pharmaceutical supply chains to future disruptions.

Healthcare supply chain optimization through AI encompasses multiple technological approaches including blockchain for traceability of pharmaceuticals and prevention of counterfeit products, IoT sensors for temperature and condition monitoring during storage and transportation, and machine learning algorithms for demand forecasting and inventory optimization (Rasel et al., 2022). Predictive analytics applied to healthcare supply chains enable organizations to anticipate seasonal demand fluctuations, model the impact of emerging diseases or conditions on pharmaceutical demand, and optimize procurement decisions to balance inventory carrying costs against stockout risks (Rasel et al., 2022). The implementation of digital enablers has demonstrated specific benefits including improved traceability of pharmaceuticals through blockchain systems, more accurate demand forecasting through predictive analytics, and reduced environmental impacts through optimized logistics (Rasel et al., 2022).

Food Supply Chain Safety and Traceability

Food supply chains present distinct risk management challenges related to food safety, traceability requirements, sustainability concerns, and the need to minimize waste while maintaining freshness (Mellah et al., 2025). The integration of blockchain, deep reinforcement learning, and quantum-secure cryptography represents an advanced approach to these challenges through the Blockchain-Enabled Sustainable Supply Chain (BESSC) framework (Mellah et al., 2025). Blockchain technology provides transparent, tamper-proof records of food products throughout their journey from production to consumption, smart contracts automatically enforce food safety regulations and conduct real-time compliance verification, and deep reinforcement learning algorithms optimize supply chain operations by dynamically balancing supply and demand and predicting food spoilage risk (Mellah et al., 2025).

The combination of AI-driven optimization with blockchain transparency and IoT real-time monitoring creates powerful solutions for food supply chain risk management (Mellah et al., 2025). Machine learning algorithms deployed in food supply chains can predict spoilage risk with sufficient accuracy to enable preventive action, optimize redistribution of surplus food to minimize waste, and identify contamination risks before they reach consumers (Mellah et al., 2025). The dairy supply chain exemplifies how AI technologies transform traditional supply chains through applications including demand forecasting using SARIMA and other machine learning approaches, quality prediction and real-time monitoring through IoT sensors, and food safety assurance through automated compliance systems (Serrano-Torres et al., 2025). However, implementation of advanced technologies in food supply chains faces particular barriers in small and medium-sized enterprises that may lack capital for infrastructure investment and technical expertise for system deployment and maintenance (Serrano-Torres et al., 2025).

Logistics and Transportation Optimization

Logistics and transportation represent significant cost components in supply chains and present substantial opportunities for optimization through AI technologies (Akpalu, 2025). Digital transformation in logistics involves the integration of IoT for real-time asset tracking, AI for route optimization and demand-responsive logistics planning, blockchain for transparent and secure data sharing among logistics partners, and digital twins for simulation of logistics operations and evaluation of alternative network designs (Akpalu, 2025). Mathematical optimization techniques including linear programming and dynamic programming, when combined with machine learning approaches, enable logistics organizations to continuously improve operational efficiency in response to changing conditions.

Route optimization through AI algorithms represents a particularly valuable application, as transportation costs are highly sensitive to routing decisions and small improvements in efficiency compound across thousands of routes (Owusu-Berko, 2025). Machine learning algorithms can learn routing patterns from historical data, incorporate real-time information about traffic conditions and weather, and dynamically adjust routes to minimize fuel consumption while meeting delivery time commitments (Alonge et al., 2021). Smart Logistics 5.0 frameworks that integrate IoT, edge computing, AI, blockchain, and big data analytics with physical automation including robots and autonomous vehicles enable comprehensive optimization of multimodal supply chain networks (Kasrim, 2025). The literature indicates that multimodal transport integration enabled by digital platforms has demonstrated significant improvements including lower door-to-door costs, accelerated deliveries, and enhanced network adaptability to disruptions (Kasrim, 2025). However, barriers to autonomous vehicle and drone deployment include regulatory uncertainty, safety concerns, and the need for new workforce skills (Kasrim, 2025).

Research Gaps and Challenges in AI-Driven Supply Chain Risk Management

Integration Frameworks and Technology Interoperability

Despite substantial progress in individual AI applications within supply chains, the literature identifies a critical gap regarding comprehensive integration frameworks that coordinate the deployment of multiple complementary technologies (Chatterjee & Rane, 2026). While machine learning provides predictive capabilities, blockchain offers trust infrastructure, and IoT enables real-time monitoring, the integration of these technologies to create synergistic effects remains underdeveloped in both the research literature and practical implementations (Chatterjee & Rane,

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2026). Organizations often deploy individual technologies in isolation, missing opportunities for synergistic benefits that could be achieved through coordinated implementation (Chatterjee & Rane, 2026). The literature emphasizes that successful technology integration requires not merely connecting individual systems but rather designing coherent frameworks in which technologies complement and reinforce each other's capabilities, data flows seamlessly across systems, and optimization algorithms coordinate decisions across technology silos (Lahmar & Siddiqui, 2025).

Interoperability challenges represent a substantial barrier to effective technology integration, as supply chain ecosystems typically involve multiple independent organizations using different systems, data formats, and communication protocols (Samuels, 2025). Standardization of data formats, communication protocols, and integration interfaces remains incomplete, forcing organizations to invest in custom integration work that is expensive, time-consuming, and fragile. The literature identifies particular interoperability challenges between legacy systems deployed in many organizations and newer digital technologies designed with interconnectivity in mind (Samuels, 2025). Building effective integration frameworks requires collaboration among technology vendors, supply chain operators, and research institutions to establish standards and develop reference implementations that reduce implementation costs and risk (Lahmar & Siddiqui, 2025).

Scalability and Implementation Challenges

Scalability represents a persistent challenge for AI and blockchain technologies when deployed in large-scale supply chain networks (Chatterjee & Rane, 2026). Blockchain networks, while providing transparency and trust, face computational limitations that restrict transaction throughput and increase transaction latency as network participants and transaction volume grow (Islam, 2025). Machine learning models that perform well on historical datasets may not generalize effectively to new situations or to different supply chain contexts, requiring substantial model retraining and validation before deployment (Kommula, 2025). The literature indicates that few implementations have demonstrated scalability in production environments; most published research relies on pilot projects or simulations rather than enterprise-scale deployments (Chatterjee & Rane, 2026). Data quality and availability represent additional implementation barriers that constrain the performance of AI systems in supply chains (Kommula, 2025). Supply chain data is often fragmented across multiple organizations, stored in incompatible formats, and may contain significant gaps or errors (Alonge et al., 2021). Machine learning models trained on poor-quality data may produce unreliable predictions, and the cost of data cleaning and preparation can be substantial (Kommula, 2025). Additionally, many supply chain organizations, particularly smaller enterprises, lack the technical expertise required to implement, maintain, and continuously improve AI systems (Serrano-Torres et al., 2025). The literature indicates that workforce skills gaps represent a significant barrier to AI adoption, requiring substantial investment in training and development programs (Samuels, 2025).

Adoption Barriers in Small and Medium-Sized Enterprises

While larger organizations with substantial capital and technical resources have begun deploying AI, blockchain, and IoT technologies, the literature identifies significant barriers to adoption by small and medium-sized enterprises (SMEs) (Chatterjee & Rane, 2026). The capital requirements for implementing technology infrastructure are particularly daunting for SMEs with limited budgets; blockchain nodes, IoT sensor networks, and data analytics platforms require substantial upfront investment that may not generate returns for extended periods (Serrano-Torres et al., 2025). SMEs also face challenges in accessing the technical expertise required for system implementation and maintenance, as experienced AI engineers and supply chain technology specialists command high salaries and may prefer employment with larger organizations (Serrano-Torres et al., 2025).

The literature emphasizes that addressing adoption barriers in SMEs requires development of simplified, lower-cost implementations that deliver value at smaller scales, cloud-based solutions that reduce upfront infrastructure costs, and industry consortiums that enable cost-sharing of technology development and deployment (Serrano-Torres et al., 2025). Regulatory frameworks that encourage SME participation in supply chain technology ecosystems could accelerate adoption; for example, policies that require traceability or sustainability reporting might incentivize SME

participation in blockchain-based platforms that distribute compliance costs across network participants (Kirui et al., 2024). However, current policy frameworks remain fragmented and misaligned with technology capabilities, creating uncertainty that slows technology adoption (Samuels, 2025).

Data Privacy, Security, and Ethical Considerations
The increasing deployment of AI, IoT, and blockchain technologies in supply chains generates substantial amounts of sensitive data including product locations, supplier relationships, production processes, and customer information (Ojadi et al., 2025). Data privacy concerns arise from the need to collect granular supply chain data while protecting sensitive business information from competitors and preventing unauthorized access to data about individuals (Kirui et al., 2024). Blockchain's characteristic of immutability and transparency, while providing security benefits, also creates challenges for privacy protection; information stored on public blockchain networks cannot be deleted even if storing it violates privacy regulations (Ojadi et al., 2025).

The literature identifies cybersecurity risks associated with increased connectivity in digitally transformed supply chains (Samuels, 2025). IoT devices, once compromised, can provide attackers with access to supply chain systems and data; machine learning models can be subject to adversarial attacks that cause them to make incorrect predictions; and blockchain networks face security risks from consensus mechanism vulnerabilities and smart contract bugs (Samuels, 2025). Ethical considerations regarding AI decision-making in supply chains remain underdeveloped in the literature. Machine learning algorithms may embed biases from historical data, leading to decisions that disadvantage certain suppliers or customer segments; transparency and interpretability of AI decisions remain limited, making it difficult for supply chain managers to understand and trust algorithmic recommendations; and the distribution of benefits from AI-enabled supply chain optimization may be unequal, concentrating advantages with larger, more technologically sophisticated organizations (Lahmar & Siddiqui, 2025).

Limited Empirical Validation and Long-Term Impact Assessment

While the literature contains numerous studies proposing AI applications for supply chain risk management, the field lacks sufficient empirical validation of these approaches through large-scale, longitudinal studies in production environments (Serrano-Torres et al., 2025). Most published research relies on simulations, pilot projects, or small-scale implementations, limiting the generalizability of findings to different supply chain contexts (Kommula, 2025). The literature identifies particular gaps in understanding the long-term impacts of technology adoption, including impacts on workforce employment and required skills, organizational changes necessary to enable effective use of new technologies, and sustainability impacts over extended time horizons (Serrano-Torres et al., 2025).

The interaction effects between different technologies and between technologies and organizational factors remain understudied (Chatterjee & Rane, 2026). For example, while blockchain can enhance transparency, the effectiveness of transparency in improving supply chain performance depends on organizational factors such as trust relationships, incentive alignment, and collaborative governance (Lahmar & Siddiqui, 2025). Similarly, the performance of machine learning models depends not only on algorithmic sophistication but also on data quality, model maintenance practices, and organizational willingness to act on algorithmic recommendations (Kommula, 2025). The literature emphasizes the need for more rigorous, empirically grounded research that evaluates AI applications in realistic supply chain environments and measures actual impacts on operational performance, resilience, and sustainability (Samuels, 2025).

Conclusions and Future Research Directions

The review of existing literature on Artificial Intelligence in supply chain risk management reveals that while AI technologies offer substantial potential for enhancing supply chain resilience, transparency, and efficiency, the field is characterized by important research gaps and implementation challenges that must be addressed for the potential of these technologies to be fully realized. The major research themes identified—including machine learning for optimization, predictive analytics for risk anticipation, integrated technology frameworks combining AI with blockchain and IoT, real-time visibility systems, and sustainability-focused optimization represent significant advances

in supply chain risk management capabilities. Empirical evidence demonstrates that organizations implementing these technologies achieve measurable improvements in operational efficiency, cost reduction, and resilience to disruptions (Borah et al., 2024). However, the literature also identifies critical gaps regarding comprehensive integration frameworks that coordinate multiple technologies, scalability validation through enterprise-scale deployments, and empirical assessment of long-term impacts (Chatterjee & Rane, 2026). The field would benefit from research that develops standardized approaches to technology integration, establishes best practices for implementation in organizations of varying sizes and supply chain contexts, and rigorously evaluates the actual impacts of AI deployment on supply chain performance metrics and organizational outcomes (Lahmar & Siddiqui, 2025). Additionally, research addressing ethical implications of AI decision-making in supply chains, including bias detection and mitigation, transparency and interpretability of algorithms, and equitable distribution of benefits from technological advancement, remains underdeveloped and requires urgent attention (Lahmar & Siddiqui, 2025).

The convergence of AI, blockchain, and IoT technologies represents a paradigm shift in supply chain management, enabling organizations to transition from reactive problem-solving to proactive risk management supported by real-time data and predictive insights (Samuels, 2025). Future supply chain systems will be increasingly characterized by autonomous decision-making systems that optimize multiple objectives simultaneously, decentralized governance enabled by blockchain smart contracts, and closed-loop systems that continuously learn and improve (Chatterjee & Rane, 2026). The integration of circular economy principles with AI-enabled supply chain optimization presents opportunities to simultaneously improve economic performance and environmental sustainability (Chatterjee & Rane, 2026). However, realizing this vision requires not only continued technological innovation but also development of organizational capabilities, workforce skills, regulatory frameworks, and inter-organizational governance structures that enable effective technology implementation and deployment (Lahmar & Siddiqui, 2025).

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