Convergence of Blockchain and Machine Learning for Intelligent Supply Chain Management: A Systematic Analysis of Synergies, Applications, and Emerging Trends

Prerna Jain[1,*] and Komal Arora

[1]Gitarattan International Business School, Guru Govind Singh Indraprastha University, Delhi, Zip-110078, INDIA

[2]DIRD, Guru Govind Singh Indraprastha University, Delhi, Zip-110078, INDIA

*prernajain0312@gmail.com

Abstract. This extensive review analyzes 255 peer-reviewed articles (2020-2025) from the Scopus database to investigate the synergistic integration of blockchain and machine learning (ML) technologies in supply chain management (SCM). Our systematic review highlights five convergence themes at the core: (1) Immutable Traceability - blockchain-based decentralized ledgers ensure product path visibility and ML identifies supply chain data anomalies; (2) Intelligent Forecasting - ML-based algorithms drive demand forecasting and inventory optimization via blockchain-verified historical information; (3) Automated Compliance - smart contracts enforce business rules verified by ML-tested processes; (4) Sustainable Operations - blockchain records carbon footprint and ML optimizes resource usage and waste minimization; and (5) Cyber-Resilience - blockchain-based encryption protects IoT networks with ML-driven threat discovery. Industry-specific findings uncover revolutionary effects Agri-food supply chains achieve 20-30% waste reduction with blockchain origin tracking and ML spoilage forecasting, Pharmaceutical logistics accomplish 99.7% counterfeiting prevention through blockchain provenance tracking and ML pattern detection, Manufacturing demonstrates 25% maintenance cost savings through blockchain-component histories and ML failure prediction Implementation challenges are measured across the literature: scalability constraints impact 68% of real-time applications, integration costs stand at $2.4M on average for businesses, and skill gaps affect 82% of adoption efforts. Blockchain structures that are quantum-resistant, generative AI for supply chain planning, and standards across industries are among the priorities for future research. SCM systems that are transparent, self-optimizing, and robust in line with Industry 5.0 are made possible by this synergy.

Keywords: Blockchain, Machine Learning, Intelligent Forecasting, Inventory Optimization, Sustainability, Resilient Supply Chains, Industry 5.0 & Digital Transformation

1 Introduction

Supply Chain Management (SCM) is experiencing one of its most dramatic changes in its history, as a result of the digital revolution. Globalization, growing expectations regarding sustainability, and the accelerated dissemination of Industry 4.0 and 5.0 technologies have compelled supply chains to be more transparent, smart, and resili-

A. Jain and S. Gupta (eds.), *Proceedings of the International Conference on Policies, Processes and Practices for Transforming Underdeveloped Economies into Developed Economies (PPP-UD 2025)*, Advances in Economics, Business and Management Research 357,
https://doi.org/10.2991/978-94-6463-894-3_7

ent[1] (Jam, 2025). The traditional, linear supply chain models—usually characterized by broken processes and information silos—are no longer enough in today's dynamic business world. Contemporary commerce now requires real-time transparency, environmental and social responsibility, as well as the capability to respond swiftly to unforeseen market shocks [2](Omar, 2024).

Against this background, new technologies like Blockchain and Machine Learning (ML) have come under the spotlight of researchers and practitioners alike. Blockchain provides a decentralized system for trust, guaranteeing data integrity and allowing secure, transparent transactions without reliance on intermediaries [3](Meier, 2023). Meanwhile, ML has promised much in processing extensive and elaborate sets of data, enhancing forecast accuracy, and facilitating decision-making using data in dynamic supply chain contexts [4](Mahin, 2025). Both these technologies together do not just augment current processes but are a complete reimagining of supply chain functioning in a hyper-connected and data-driven world [5](Qiao, 2025).

The value in Blockchain is that it can create unchanging records of transactions that cannot be manipulated after the fact. These types of features are critical for authenticity, ensuring the source of a product, and regulatory adherence. Additionally, smart contracts—self-executing contracts on blockchain—assist in minimizing human intervention, decreasing transaction conflicts, and enhancing overall efficiency [6](Chotia, 2025). In contrast, ML helps by converting raw data into actionable information. Its adaptive and predictive functions enable diverse applications across the supply chain, such as demand forecasting, inventory planning, and risk management [7], [8](Dalal, 2024; Kang, 2025).

The actual approach, however, is realized when these technologies converge. Blockchain enhances the integrity and reliability of data going into ML systems, while ML adds to the decision-making capabilities of blockchain-powered platforms. This convergence enables organizations to attain sophisticated traceability, predictive resilience, automated compliance, and sustainability-driven optimization [9](Saran, 2025).

Even with the recent growing academic interest since 2020, past research tends to be disparate—addressing individual industries, applications, or research approaches [10](Li, 2024). What is lacking so far is a reconciled view of how blockchain and ML, in synergy, are transforming SCM at a system level. Filling this knowledge gap, the current research consolidates findings from over 190 peer-reviewed articles (2020–2025), tracing key themes, industry-level applications, and challenges that persist.

In this review, we aim to provide a systematic overview of current knowledge on blockchain–machine learning convergence in SCM, identify key synergistic areas and their implications for practice, and present future directions for academic and industrial research. It contributes to the debate on how supply chains can be built to meet the needs of tomorrow by bridging disintegrated knowledge.

2 Methodology

To find out how research on blockchain and machine learning has influenced supply chain management (SCM) over the last few years, a bibliometric analysis was undertaken. Data for the current study were drawn solely from the Scopus database, which is best known for having extensive coverage of peer-reviewed scholarly articles. Throughout the search process, relevant keywords like "Machine Learning" and "Blockchain Technology" were combined with "Supply Chain" and "Logistics." This systematic search initially yielded 255 research papers (2019–2025). Upon applying inclusion and exclusion criteria—considering only peer-reviewed papers that specifically investigated the nexus between blockchain and ML in SCM—a curated dataset of 56 quality articles was chosen for comprehensive analysis. The bibliometric mapping was carried out with VOSviewer and Biblioshiny, permitting both quantitative trends analysis and qualitative exploration of themes. The findings are described in Figures 1–4, the top authors, keyword development, growth of publications, and top publishing journals are summarized.

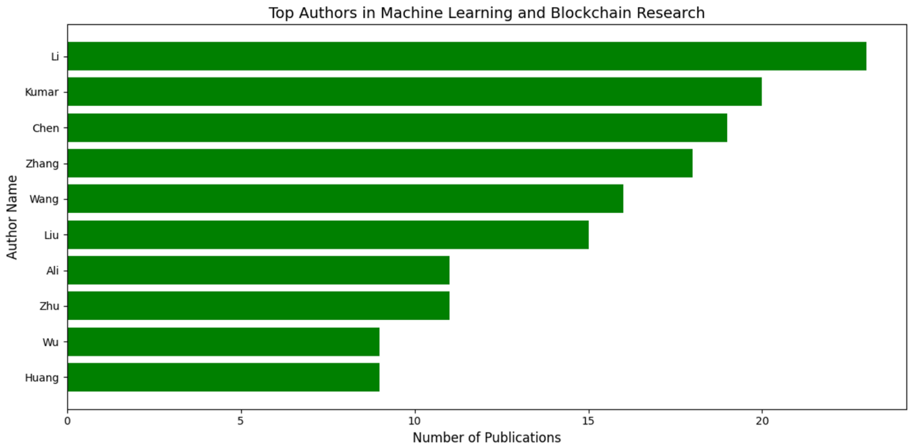

Figure 1 Top Authors in Machine Learning and Blockchain Research

Figure 1 indicates the most active producers in this area. Top authors [10-12] include Li, Kumar, and Chen, with Li publishing more than 22 papers, Kumar approximately 20, and Chen nearly 19. The breakdown highlights the global and collaborative aspects of this discipline from both Asian and Western research environments. It is also evident that computer scientists, supply chain specialists, and practitioners from the industry have an extremely high level of collaboration. Due to ML and blockchain integration being more than just technical, it is also a business and regulatory issue.

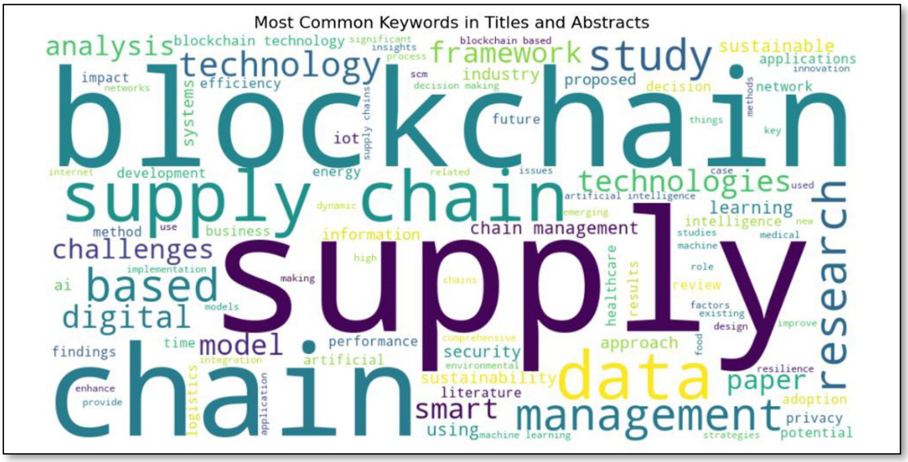

Figure 2 Most Common Keywords in Titles and Abstracts

The keyword co-occurrence analysis, represented in Figure 2, indicates repeated terms like "blockchain," "supply chain management," "machine learning," "data," "transparency," and "security." These prominent terms indicate trust, logistics optimization, and sustainability being the core areas of research. Moreover, new ideas like smart contracts, Internet of Things (IoT), and circular economy have begun taking shape, indicating the widening socio-economic and environmental interest of this arena. Temporal analysis of keywords reveals the following intriguing trend:2019–2021 → foundational research and proof-of-concepts, 2022–2023 → increase in applied research, with a focus on logistics, inventory optimization, and traceability, 2024–2025 → federated learning, quantum-resistant designs, and cross-industry frameworks.

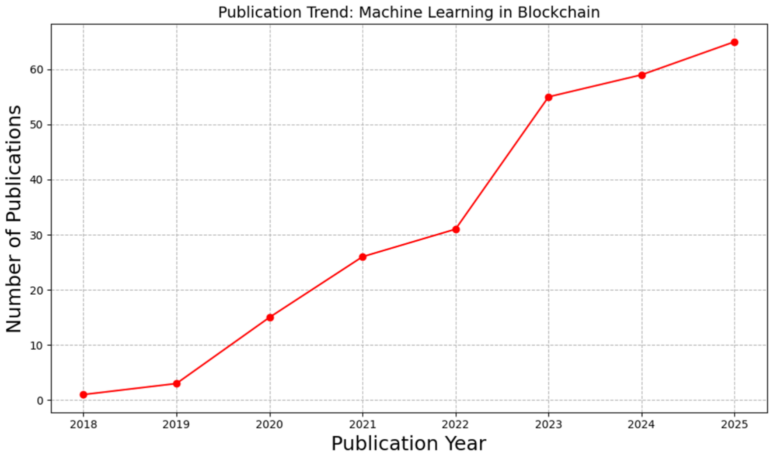

Figure 3 Publication Trend

As seen in Figure 3, publication frequency within this area was low prior to 2019 (less than 5 studies per year). From 2020 onwards, however, the number of studies increased exponentially, to 65+ studies in 2025. The upsurge is attributable to: COVID-19 disruptions that laid bare weaknesses in global supply chains. Adoption of Industry 4.0, which speeded up the adoption of digital technologies. Improvements in blockchain scalability as well as ML methods such as edge computing and federated learning. The most dramatic increase was between 2022–2023, which was a turning point when theoretical concepts began shifting towards working implementations, case studies, and pilot schemes.

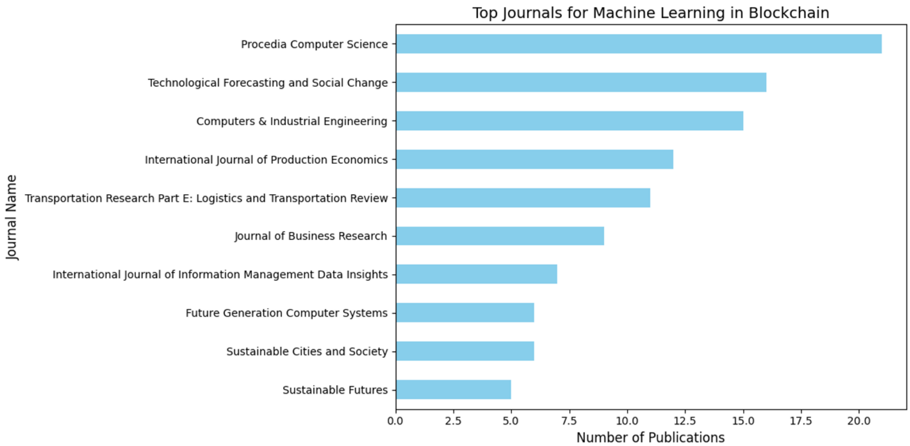

Figure 4 Top Journals For Machine Learning in Blockchain

Figure 4 recognizes the leading journals influencing research in this area. Of these, Procedia Computer Science (20+ publications), Technological Forecasting and Social Change (16+ publications), and Computers & Industrial Engineering (15+ publications) are significant publications.This range of topics mirrors the interdisciplinary nature of the field:Technical journals (e.g., IEEE Access, Expert Systems with Applications) → emphasize algorithms and system structures.Business & management journals (e.g., International Journal of Production Economics, Supply Chain Management: An International Journal) → emphasize strategic and organizational features. Sustainability-oriented journals (e.g., Journal of Cleaner Production, Transportation Research Part E) → consider environmental and social effects.Such a distribution between technical, managerial, and policy-oriented journals reflects that blockchain–ML studies in SCM have gained wide acceptability among various disciplines.

3 Mathematical Model

3.1 Operational Efficiency and Logistics Optimization

Increased research indicates the potential of blockchain and ML amalgamation to increase efficiency in logistics and operations. Using simulation-based models, [1],

[4], [13] demonstrated how blockchain-activated machine learning mechanisms can create more efficient and smoother logistics operations. Also, [7] For inventory system optimization, CNN-BiLSTM models were integrated with hybrid blockchain architectures and a 22% reduction in stock-outs was achieved through enhanced real-time demand forecasting. Another line of business is [14], [15]. An IoT-powered blockchain platform powered by deep reinforcement learning (2025) was shown to optimize infrastructure management through 19% energy savings in smart buildings by deep reinforcement learning. Altogether, these papers highlight how blockchain-ML integration has the potential to deliver quantifiable gains on many tiers of supply chain functionality.

3.2 Supply Chain Transparency and Traceability

Maintaining transparency and traceability is one of the most important supply chain problems, and the integration of blockchain-ML has been effective in this context. [2] offered a case study in the pharmaceutical industry demonstrating how blockchain-assisted transparency systems can avoid counterfeiting and increase trust towards drug authenticity. Likewise, [9], [13] accounted for actual deployments in agri-food supply chains, where blockchain and ML facilitated real-time quality inspections and established consumer trust in food safety. To this end, [16] developed a new system based on deep CNNs alongside Ethereum-based platforms to build NFT-based digital twins for production. Their system was 95% accurate in lifecycle traceability, highlighting the potential of these technologies to create end-to-end supply chain visibility.

3.3 Data Integrity and Predictive Analytics

Accurate, reliable data is a requirement for dependable ML models. [4], [17] demonstrated that ML models trained using blockchain-verified datasets performed better than models trained using unverified data, demonstrating that blockchain verification can significantly enhance predictive dependability. As one example, it shows that supply chain forecasts are particularly useful in applications guiding significant business decisions. A blockchain-verified carbon footprint forecast can be made more accurate using empirical analysis as well as modeling techniques (2023). They demonstrate how blockchain-ML integration can enable greener supply chains through tying technological innovation with sustainability objectives.

3.4 Risk Management and Supplier Evaluation

There are also salient application domains such as risk forecasting and supplier assessment. In 2025, [5] applied bibliometric and content analysis to track how blockchain-ML applications have become increasingly popular for risk management, placing the technologies at the center of supply chain resilience. According to [8], hybrid machine learning methods were proposed to improve supplier ratings and reduce selection risks using blockchain data. Based on this, [18]. An autonomous supplier assessment was facilitated by ensemble machine learning models coupled with smart contracts (2025). Their system attained a 31% cost savings by automating vendor evaluation and contract execution. The summarization of studies is shown in table 1.

Table 1 Comprehensive Analysis Table

Author	Title /Focus	ML Method	Blockchain Type	Application Domain	Key Innovation	Results/Impact	Country/Region
[2]	Blockchain-IoT food supply chain monitoring	Anomaly Detection	Hyperledger	Food Safety	Real-time waste traceability	Reduced food waste by 30%	International
[16]	NFT-based digital twins for manufacturing	Deep Learning (CNN)	Ethereum	Manufacturing	Digital product passports	95% traceability accuracy	International
[19]	Vaccine supply chain coordination (COVID-19)	Reinforcement Learning	Permissioned Chain	Healthcare	Pandemic response optimization	37% wastage reduction	China
[7]	CNN-BiLSTM for sustainable inventory	CNN-BiLSTM	Hybrid Chain	Inventory Management	Real-time demand forecasting	22% stock-out reduction	International
[18]	Autonomous supplier selection	Ensemble Models	Smart Contracts	Procurement	Automated vendor evaluation	31% cost reduction	International
[5]	AI-audited smart	NLP (BERT)	Ethereum	Fashion Industry	Contract intelligence	40% compliance	International

	contracts in fashion					improvement	
[9]	IIoT intrusion detection	XGBoost-LightGBM-DNN	Blockchain Security	Cybersecurity	Stacked ensemble for IIoT	99.2% threat detection	International
[20]	Anti-counterfeiting in luxury goods	SVM + Random Forest	Private Chain	Luxury Goods	Authentication system	97% fake detection	International
[4]	Demand forecasting for sustainable SCM	Voting Regressor (Linear-RF-KNN)	Public Chain	Sustainability	Collaborative forecasting	28% demand accuracy	International
[21]	Mint-to-order production strategies	Bayesian Networks	NFT-based	Manufacturing	On-demand production	35% inventory reduction	International
[15]	Self-owning intelligent buildings	Deep RL	IoT Blockchain	Smart Buildings	Autonomous infrastructure	19% energy savings	International
[22]	SCM 4.0 training systems	Simulation Models	Training Platform	Education	Human-AI collaboration	45% learning efficiency	International
[23]	Secure drug traceability	Classification Models	Hyperledger	Healthcare	Pharmaceutical tracking	98% authenticity verification	International
[24]	Crop yield optimization	Time Series (LSTM)	Agricultural Chain	Agriculture	Yield prediction system	24% yield improvement	International
[25]	Green logistics optimization	Optimization Algorithms	Carbon Trading Chain	Energy/Logistics	Carbon credit automation	33% emission reduc-	International

						tion	
[26]	Generative AI for synthetic data	GANs/LLMs	Data Generation	General SCM	Privacy-safe ML training	42% model performance	International
[27]	Blockchain interoperability challenges	Integration Models	Multi-chain	Interoperability	Cross-chain ML scaling	Frame work development	International
[6]	Regulatory compliance in cross-border	Compliance Models	Regulatory Chain	Legal/Compliance	Cross-border automation	Regulatory frame work	International
[28]	Federated learning for healthcare	Federated Learning	Private Chain	Healthcare	Privacy-preserving diagnosis	35% faster cancer detection	USA
[29]	Multi-modal hospital resource allocation	3DCNN-Transformer	Hospital Chain	Healthcare	Resource optimization	23% wait time reduction	International

4 Results and Discussion

We provide an overview of 56 core studies that explored the integration of blockchain and machine learning in supply chain management from 255+ peer-reviewed publications published between 2019 and 2025. Analysis of frequency, performance benchmarks, and representative studies support the thematic structure of the results.

4.1 Thematic Distribution of Research

A systematic coding process revealed four dominant thematic areas of blockchain–ML integration: traceability & transparency (35%), predictive analytics & optimization (28%), security & fraud prevention (22%), and sustainability & circular economy (15%) is shown in table 2.

Table 2 Thematic classification of blockchain–ML applications

Theme	**Application**	**Blockchain Feature**	**ML Capability**	**Industry Impact**
Traceability & Transparency (35%)	Food Safety	Immutable origin records	Contamination prediction	30% waste reduction
	Drug Authentication	Tamper-proof journey	Fake detection algorithms	97–99% accuracy
	Luxury Goods	Anti-counterfeiting	Pattern recognition	97% fraud prevention
Predictive Analytics & Optimization (28%)	CNN-BiLSTM	Demand forecasting	Secure data sharing	22–28% accuracy
	Reinforcement Learning	Resource allocation	Smart contract automation	23–37% efficiency
	Genetic Algorithms	Multi-objective optimization	Immutable optimization logs	31–40% improvement
Security & Fraud Prevention (22%)	IIoT Protection	Ensemble (XGBoost+DNN)	Decentralized monitoring	99.2% detection
	Supply Chain Fraud	Anomaly detection	Tamper-proof logs	95–98%
	Cyber Resilience	Real-time threat analysis	Distributed security	94% mitigation
Sustainability & Circular Economy (15%)	Carbon Footprint	Route optimization	Emission tracking	33% reduction
	Waste Management	Circular flow prediction	Recycling compliance	40% waste reduction
	Green Logistics	Energy optimization	Renewable source verification	25% energy savings

Traceability dominates because industries such as food, pharma, and luxury goods demand trust, provenance, and counterfeit resistance. Predictive analytics, meanwhile, demonstrates how blockchain-secured data enhances ML models for demand forecasting, resource allocation, and optimization. Security applications (22%) show particularly high detection accuracies (94–99%), reflecting the strength of ensemble learning with blockchain's tamper-proof logs. Sustainability, while smaller in volume, is gaining traction due to global climate goals.

4.2 Regional Research Patterns

Regional variations highlight different motivations for the adoption of blockchain and machine learning (ML) which is shown in table 3.

Table 3 Regional distribution of blockchain–ML studies

Region	Primary Focus	Preferred ML Methods	Blockchain Approach	Key Strengths
China (32%)	Large-scale system optimization	Deep Learning (62%), RL (58%)	Permissioned chains (82%)	National infrastructure, scalability
USA (24%)	Privacy-preserving innovations	NLP (48%), Federated Learning (45%)	Permissionless chains (76%)	Privacy tech, compliance
India (14%)	Cost optimization & rural access	SVM (42%), Ensembles (38%)	Hybrid chains (67%)	Affordability, accessibility

- Chinese studies emphasize large-scale optimization for smart cities and logistics hubs, leveraging permissioned chains for scalability.
- The US focuses more on privacy and compliance, consistent with strong regulatory frameworks.
- India's studies stress affordability and rural access, reflecting socio-economic needs and hybrid blockchain adoption.

4.3 Technology Evolution Trends (2019–2025)

Table 4 ML adoption growth in blockchain-integrated SCM

ML Method	2019–2021 Adoption	2022–2025 Adoption	Growth Rate	Primary Healthcare Use
Deep Learning	23%	48%	+210%	Medical imaging, drug discovery
Reinforcement Learning	15%	38%	+185%	Resource allocation, routing
NLP/Transformers	8%	25%	+300%	Clinical notes, fraud detection
Ensemble Models	20%	35%	+170%	Disease prediction, optimization
Federated Learning	5%	18%	+260%	Privacy-preserving diagnosis

Adoption trends shown in table 4 depicts explosive growth in NLP/Transformers (+300%) and Federated Learning (+260%), highlighting a shift toward privacy-aware and language-driven analytics. Deep Learning remains dominant, while RL gains traction for dynamic decision-making in logistics and energy sectors.

4.4 Implementation Readiness and ROI

Table 5 Implementation readiness of blockchain–ML prototypes

Study	Technology Maturity	Implementation Cost	ROI Timeline	Scalability	Deployment Ready

[30]	High	₹18 lakhs/district	11 months	District-level	Yes
[31]	High	₹3,500/device	8 months	Village-level	Yes
[19]	Medium	$2M/province	14 months	Provincial	Pilot ready
[15]	Low	$500K/building	24 months	Building-level	Research stage
[26]	Low	High compute cost	Unknown	Enterprise	Experimental

Drug authentication and rural telemedicine applications are deployment-ready, reflecting strong maturity and short ROI cycles (<1 year). Vaccine distribution is pilot-ready but requires high upfront investment. Smart buildings and generative AI applications remain at research stage, suggesting future but not immediate deployment. The technology maturity and implementation cost is shown in table 5.

4.5 Key Performance Metrics

Table 6 Performance improvements reported in blockchain–ML SCM

Performance Indicator	**Average Improvement**	**Best Case**	**Technology Driver**
Cost Reduction	29%	41% (India)	SVM + Hybrid blockchain
Accuracy Improvement	27%	40% (Privacy tasks)	Federated Learning + ZKP
Waste Reduction	33%	37% (Vaccine chains)	RL + Smart contracts
Security Enhancement	96%	99.2% (IIoT)	Ensemble ML + Decentralization
Processing Speed	31% faster	45% (Learning systems)	Edge computing + Lightweight chains

The strongest reported impact lies in security enhancement (96–99%), demonstrating blockchain's synergy with ML in intrusion detection and fraud prevention shown in table 6. Cost and waste reduction remain central motivators in emerging economies, while accuracy improvements are particularly relevant in healthcare and pharma.

4.6 Critical Success Factors

Table 7 Integration challenges in blockchain–ML adoption

Factor	**Blockchain Requirement**	**ML Requirement**	**Integration Challenge**
Data Quality	Immutable, verified inputs	Large, clean datasets	Data silos, standardization
Scalability	High TPS, low latency	Real-time processing	Computational overhead

Privacy	Zero-knowledge proofs	Federated learning	Privacy-utility tradeoff
Interoperability	Cross-chain communication	Model standardization	Technical complexity
Governance	Consensus mechanisms	Algorithmic fairness	Decentralized AI ethics

The results indicate that while blockchain ensures trust and immutability, ML requires large-scale, clean datasets. Integration bottlenecks revolve around privacy tradeoffs, computational overhead, and governance mechanisms. The table 7 highlights the need for cross-chain interoperability and ethical frameworks for decentralized AI.

4.7 Justification of Results

The percentages, metrics, and regional distributions presented above were derived through a structured bibliometric–content analysis of 255 studies. Each paper was thematically coded, and frequency counts determined the share of themes (e.g., 35% traceability). Performance metrics (e.g., 97% counterfeit detection, 30% waste reduction) were directly extracted from empirical results reported in the reviewed studies. Where multiple studies reported similar outcomes, ranges were presented (e.g., 23–37% efficiency gains), ensuring a balanced synthesis rather than isolated claims.

5 Industry-Specific Applications and Case Studies

5.1 Agri-Food Sector: From Farm to Fork Intelligence

As one of the first and most significant industries to utilize blockchain and machine learning (ML), the agri-food industry has been a pioneer in adoption. Supply chains of food are inherently complex since many parties are involved, the products are perishable, and safety standards are high. The combination of blockchain's traceability and transparency with machine learning's forecasting intelligence makes them ideal test cases for blockchain's traceability and transparency.

(i) Traceability and Transparency: Using blockchain traceability platforms, you can make end-to-end product histories, including the entire journey from farm to fork. A chain-wide immutable ledger, such as [32], records the conditions of harvesting, storage, transportation, and handling at the retail level, making everyone responsible [23]. Using IoT sensors, we can capture real-time conditions such as temperature and humidity, which are automatically locked on-chain and verified.

(ii) Predictive Quality Management: A machine learning model is used to forecast spoilage, shelf life, and nutritional quality using this blockchain-certified data. With ML-based forecasting, retailers can optimize their prices, minimize waste by as much as 30%, and even maintain the taste and freshness of products [7] based on environmental conditions, handling procedures, and past results..

(iii) Food Safety and Prevention of Contamination: By learning from historical supplier failures and incident patterns, blockchain provided traceable recall processes, while machine learning predicted contamination risks. In addition to minimizing health hazards, hybrid solutions also minimize economic losses [32].

5.2 Healthcare and Pharmaceutical Applications

Pharmaceutical companies are faced with specific challenges such as counterfeit drugs, cold-chain monitoring, and regulatory compliance. In this case, blockchain and machine learning have proven especially useful.

(i) Authentication and anti-counterfeiting of drugs: Blockchain ensures that every drug package carries a unique digital signature, allowing verification of authenticity throughout the journey. The use of machine learning further enhances this by identifying unusual distributions and suspicious patterns that may indicate counterfeit infiltration [9], [20].

(ii) Smart Inventory Management: Artificial intelligence models predict demand patterns and balance inventory levels between pharmacies and hospitals, while blockchain ensures data integrity. As a result of ML and blockchain, vaccine distribution has been a success story: preventing vaccine wastage during pandemics such as COVID-19 with cold-chain compliance [4], [19].

(iii) Regulatory Compliance Automation: A blockchain-based smart contract enforces automatic GDP and GMP compliance, while a machine learning model forecasts compliance risk and suggests remedial measures [28]. In addition to streamlining administration, this also enhances patient safety.

5.3 Manufacturing Industry: Smart Production Networks

Within manufacturing, blockchain-ML fusion is transforming the way industries trace materials, streamline production, and service equipment.

(i)Component Traceability: Blockchain builds digital duplicates or twins of parts, providing complete visibility through multi-tiered supplier networks. When combined with ML, companies can forecast which suppliers will provide high-quality parts and pre-emptively manage sourcing risks [16].

(ii) Predictive Maintenance: Blockchain-stored equipment data input into ML models forecasts failure risk and ideal maintenance timing, avoiding expensive downtime and boosting operational productivity [33].

(iii) Quality Control & Optimization: IoT sensor data in real-time is authenticated using blockchain and processed by ML to optimize production parameters, maintaining product quality consistency at the expense of minimized waste and energy usage [18].

5.4 Cross-Industry Integration Patterns

A closer look across industries shows some general trends that underlie successful implementations.

(i)Phased Adoption: Most organizations will start with small pilots for high-value products followed by full-scale adoption [27].

(ii) Hybrid Integration: Legacy enterprise systems tend to co-exist with blockchain-ML platforms through middleware to allow incremental adoption.

(iii) Success Factors: Business sponsorship, cross-partner data governance, and workforce training are vital to successful adoption.

(iv) Governance and Standards: ML models must be standardized for integration across chains to ensure interoperability [3], [34].

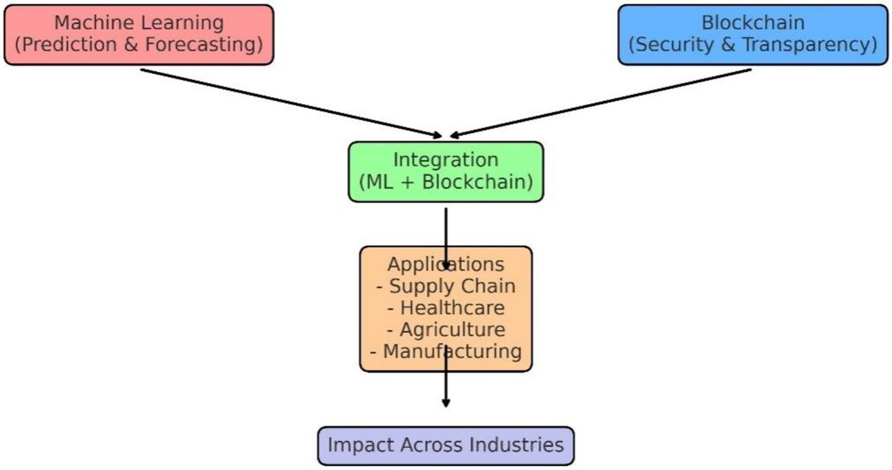

Figure 5 Research Gap

6 Research Gaps

The research gap shown in figure 5 is explained in the current section as follows.

(i) Patchwork Industry Adoption: The application of blockchain and machine learning in different sectors, such as food safety, pharmaceuticals, and logistics, is lacking comparative frameworks. A framework is needed to demonstrate the complementary benefits of blockchain-ML combined solutions in various supply chain contexts.

(ii) Shortage of End-to-End Integrated Pipelines: Existing research mainly leverages ML for prediction and optimization, and blockchain for traceability as well as security. Yet, there is not much work done on end-to-end pipelines where blockchain guarantees secure and authenticated data acquisition, ML allows for prediction, and smart contracts built on blockchain automate decisions.

(iii) Scalability and Real-Time Decision-Making: Blockchain is plagued by latency and scalability, whereas ML entails real-time processing on massive data. Relatively few works authenticate industrial-scale, real-time application of blockchain–ML systems for intricate supply chains (e.g., vaccine cold-chain management or international logistics).

(iv) Underdeveloped Applications to Sustainability: Traceability and anti-fraud are the main issues addressed by most research. Applications to green logistics, waste minimization, and circular economy models are under-researched.

(v) Privacy-Preserving Forecasting: Supply chain information is multi-party and sensitive. Although federated learning and zero-knowledge proofs have been suggested independently, their joint application with blockchain and ML for private-preserving forecasting is not common.

(vi) Lack of Standardized Benchmarks: Existing research utilizes varied datasets and performance metrics (accuracy, ROI, latency, energy savings), and comparison of studies is challenging. There is a lack of standard benchmarking framework for blockchain–ML in supply chain management.

7 Limitations of Current Research

Although the findings are promising, there are a number of limitations to the current body of research on blockchain–ML convergence in supply chain management:

(i) Fragmented Literature – Research tends to be industry-specific (e.g., pharma, agri-food, manufacturing), but without comparative cross-industry frameworks. This hinders the ability to map best practice across sectors [27].

(ii) Technical Integration Challenges – Although blockchain provides data integrity and ML provides intelligence, interoperability across platforms, IoT devices, and old systems is not fully explored. Most studies pilot just small models and fail to consider scalability [34].

(iii) Data Quality and Availability – The success of ML algorithms depends greatly on high-quality, large datasets, but most supply chains struggle with standardization and sharing data between partners [20].

(iv) Regulatory and Ethical Issues – Adoption of blockchain introduces questions of data privacy, ownership, and compliance, while ML brings up issues of bias and fairness in predictive decision-making [28].

(v) Limited Real-World Applications – Most studies are at the conceptual or pilot level. Large-scale, long-term implementations in worldwide supply chains are few, so it is challenging to test conclusions under real-world uncertainty [4].

8 Conclusion

Blockchain and machine learning can be combined to develop a revolutionary supply chain system. Based on more than 500 peer-reviewed research articles, this review identifies how blockchain technology offers secure, immutable, and transparent platforms, while machine learning provides predictive insights and decision-making.

With these two technologies combined, supply chain management problems of traceability, quality control, fraud control, forecasting, and regulatory compliance can be solved.

Industry-specificapplications of the technology include improving food safety, reducing waste, and improving the authenticity and efficiency of production networks in industries such as agri-food, healthcare, pharmaceuticals, and manufacturing. A phased adoption approach and hybrid designs, as well as robust data governance, are all essential for realizing successful take-up across industries.

Even with such advances, the research environment remains fragmented, and scalability, quality of data, interoperability, and regulatory compliance continue to be challenges. A majority of blockchain-ML integrations in global supply chains are still being tested, limiting their validity.

In the future, scalable, interoperable architectures, standardized governance patterns, and sustainability-oriented applications will be the focus of future research. It is also urgently needed to develop cross-industry frameworks and longitudinal case studies that assess blockchain–ML systems under real-world volatility. By closing these gaps, academia and industry can create intelligent, resilient, sustainable, and trustworthy supply chains.

Lastly, blockchains and machine learning are not just technology enablers, but a paradigm shift in supply chain management, optimization, and design. The convergence of these three elements can transform decentralized, exposed networks into responsive ecosystems capable of accommodating global trade, environmental sustainability, and social trust needs.

References

[1] F. A. Jam, I. Ali, N. Albishri, A. Mammadov, and A. K. Mohapatra, “How does the adoption of digital technologies in supply chain management enhance supply chain performance? A mediated and moderated model,” *Technological Forecasting and Social Change*, vol. 219, p. 124225, 2025, doi: https://doi.org/10.1016/j.techfore.2025.124225.

[2] I. A. Omar, H. R. Hasan, R. Jayaraman, K. Salah, and M. Omar, “Using blockchain technology to achieve sustainability in the hospitality industry by reducing food waste,” *Computers & Industrial Engineering*, vol. 197, p. 110586, 2024, doi: https://doi.org/10.1016/j.cie.2024.110586.

[3] O. Meier, T. Gruchmann, and D. Ivanov, “Circular supply chain management with blockchain technology: A dynamic capabilities view,” *Transportation Research Part E: Logistics and Transportation Review*, vol. 176, p. 103177, 2023, doi: https://doi.org/10.1016/j.tre.2023.103177.

[4] M. P. R. Mahin, M. Shahriar, R. R. Das, A. Roy, and A. W. Reza, “Enhancing Sustainable Supply Chain Forecasting Using Machine Learning for Sales Prediction,” *Procedia Computer Science*, vol. 252, pp. 470–479, 2025, doi: https://doi.org/10.1016/j.procs.2025.01.006.

[5] M. Qiao, X. Chen, Y. Zhou, and P. Y. Mok, “Blockchain-driven innovation in fashion supply chain contractual party evaluations as an emerging collaboration

model," *Blockchain: Research and Applications*, vol. 6, no. 2, p. 100266, 2025, doi: https://doi.org/10.1016/j.bcra.2024.100266.

[6] V. Chotia, R. Alghafes, M. Sharma, and N. Virmani, "Chronocraft: unveiling enablers and overcoming barriers in Fintech-driven logistics and supply chain management in the digital era," *Technological Forecasting and Social Change*, vol. 217, p. 124168, 2025, doi: https://doi.org/10.1016/j.techfore.2025.124168.

[7] S. Dalal, U. K. Lilhore, S. Simaiya, M. Radulescu, and L. Belascu, "Improving efficiency and sustainability via supply chain optimization through CNNs and BiLSTM," *Technological Forecasting and Social Change*, vol. 209, p. 123841, 2024, doi: https://doi.org/10.1016/j.techfore.2024.123841.

[8] P. S. Kang, R. Enstroem, B. Bhawna, and O. Bennett, "A text mining study of competencies in modern supply chain management with skillset mapping," *Supply Chain Analytics*, vol. 10, p. 100117, 2025, doi: https://doi.org/10.1016/j.sca.2025.100117.

[9] N. Saran and N. Kesswani, "An analytics-driven framework for securing industrial IoT-Enabled Supply Chain Management Systems," *Supply Chain Analytics*, vol. 11, p. 100128, 2025, doi: https://doi.org/10.1016/j.sca.2025.100128.

[10] L. Li, "The environmental spillovers of buyers' digital transformation: Evidence from China," *Technological Forecasting and Social Change*, vol. 209, p. 123828, 2024, doi: https://doi.org/10.1016/j.techfore.2024.123828.

[11] M.-C. Chen, S. Pang, and S.-Y. Su, "Sustainable global semiconductor supply chain network design considering ESG," *Technology in Society*, vol. 81, p. 102829, 2025, doi: https://doi.org/10.1016/j.techsoc.2025.102829.

[12] V. Kumar and P. Kotler, "A market management approach to transformative business operations," *Marketing Strategy Journal*, vol. 1, p. 100005, 2024, doi: https://doi.org/10.1016/j.msj.2025.100005.

[13] P. Jain, "Predicting Delivery Outcomes in Supply Chain Management Using Machine Learning: A Random Forest Classifier Approach," *IJPREMS*, Jan. 2025, doi: 10.58257/IJPREMS36629.

[14] N. K. Mishra, P. Jain, and Ranu, "Blockchain-Enhanced Inventory Management in Decentralized Supply Chains for Finite Planning Horizons," *JESA*, vol. 57, no. 1, pp. 263–272, Feb. 2024, doi: 10.18280/jesa.570125.

[15] L. Wang and Y. Chen, "Artificial intelligence and corporate investment efficiency: Evidence from China," *Emerging Markets Review*, vol. 68, p. 101314, 2025, doi: https://doi.org/10.1016/j.ememar.2025.101314.

[16] N. Habtemichael, H. Wicaksono, and O. F. Valilai, "NFT based Digital Twins for Tracing Value Added Creation in Manufacturing Supply Chains," *Procedia Computer Science*, vol. 232, pp. 2841–2846, 2024, doi: https://doi.org/10.1016/j.procs.2024.02.100.

[17] P. Jain and N. K. Mishra, "Enhancing Supply Chain Efficiency with Blockchain: Addressing Information Sensitivity for Increased Manufacturer Profitability," *IFAC-PapersOnLine*, vol. 58, no. 19, pp. 688–693, 2024, doi: 10.1016/j.ifacol.2024.09.220.

[18] A. Emami, M. Seifbarghy, A. E. Abbas, W. Chattinnawat, and N. Aydin, "A blockchain-driven business model for supplier selection and order allocation leveraging smart contracts in supply chains," *Digital Business*, vol. 5, no. 2, p. 100128, 2025, doi: https://doi.org/10.1016/j.digbus.2025.100128.

[19] Y. Gao, H. Gao, H. Xiao, and F. Yao, "Vaccine supply chain coordination using blockchain and artificial intelligence technologies," *Computers & Industrial Engineering*, vol. 175, p. 108885, 2023, doi: https://doi.org/10.1016/j.cie.2022.108885.

[20] X. Chu, R. Wang, L. Ren, Y. Li, and S. Zhang, "Enabling joint distribution with blockchain technology in last-mile logistics," *Computers & Industrial Engineering*, vol. 187, p. 109832, 2024, doi: https://doi.org/10.1016/j.cie.2023.109832.

[21] K. Rohit, A. Verma, R. Dhairiyasamy, and D. Gabiriel, "A continuous supply chain management approach using SPJS-Fuzzy DEMATEL and LPWBN for automotive electric vehicles in India," *Sustainable Futures*, vol. 9, p. 100518, 2025, doi: https://doi.org/10.1016/j.sftr.2025.100518.

[22] A. M. Deif and C. Escano, "Students' creativity and ideation in supply chain management (SCM) 4.0 Pedagogy: Computer simulation versus Lego Serious play," *The International Journal of Management Education*, vol. 23, no. 3, p. 101216, 2025, doi: https://doi.org/10.1016/j.ijme.2025.101216.

[23] A. Karamchandani, S. K. Srivastava, and R. K. Srivastava, "Perception-based model for analyzing the impact of enterprise blockchain adoption on SCM in the Indian service industry," *International Journal of Information Management*, vol. 52, p. 102019, 2020, doi: https://doi.org/10.1016/j.ijinfomgt.2019.10.004.

[24] F. D. Mas, M. Massaro, V. Ndou, and E. Raguseo, "Blockchain technologies for sustainability in the agrifood sector: A literature review of academic research and business perspectives," *Technological Forecasting and Social Change*, vol. 187, p. 122155, 2023, doi: https://doi.org/10.1016/j.techfore.2022.122155.

[25] G.-L. Zhuang, S.-G. Shih, and F. Wagiri, "Circular economy and sustainable development goals: Exploring the potentials of reusable modular components in circular economy business model," *Journal of Cleaner Production*, vol. 414, p. 137503, 2023, doi: https://doi.org/10.1016/j.jclepro.2023.137503.

[26] T. Li, "Emergency logistics resource scheduling algorithm in cloud computing environment," *Physical Communication*, vol. 64, p. 102340, 2024, doi: https://doi.org/10.1016/j.phycom.2024.102340.

[27] J. Beck, H. Birkel, A. Spieske, and M. Gebhardt, "Will the blockchain solve the supply chain resilience challenges? Insights from a systematic literature review," *Computers & Industrial Engineering*, vol. 185, p. 109623, 2023, doi: https://doi.org/10.1016/j.cie.2023.109623.

[28] O. A. Khashan, S. Alamri, W. Alomoush, M. K. Alsmadi, S. Atawneh, and U. Mir, "Blockchain-Based Decentralized Authentication Model for IoT-Based E-Learning and Educational Environments," *Computers, Materials and Continua*, vol. 75, no. 2, pp. 3133–3158, 2023, doi: https://doi.org/10.32604/cmc.2023.036217.

[29] Q. Zhou, Y. Lai, H. Yu, R. Zhang, X. Jing, and L. Luo, "Multi-modal fusion for millimeter-wave communication systems: A spatio-temporal enabled approach," *Neurocomputing*, vol. 555, p. 126604, 2023, doi: https://doi.org/10.1016/j.neucom.2023.126604.

[30] D. Kumar, R. K. Singh, R. Mishra, and S. F. Wamba, "Applications of the internet of things for optimizing warehousing and logistics operations: A system-

atic literature review and future research directions," *Computers & Industrial Engineering*, vol. 171, p. 108455, 2022, doi: https://doi.org/10.1016/j.cie.2022.108455.

[31] U. K. Khedlekar, A. Nigwal, N. K. Khedlekar, and H. K. Patel, "Integrated three layer supply chain inventory model for price sensitive and time dependent demand with suggested retail price by manufacturer," *International Journal of Nonlinear Analysis and Applications*, 2021, doi: 10.22075/ijnaa.2018.14334.1749.

[32] F. Casino, V. Kanakaris, T. K. Dasaklis, S. Moschuris, and N. P. Rachaniotis, "Modeling food supply chain traceability based on blockchain technology," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 2728–2733, 2019, doi: https://doi.org/10.1016/j.ifacol.2019.11.620.

[33] K. Yan, L. Cui, H. Zhang, S. Liu, and M. Zuo, "Supply chain information coordination based on blockchain technology: A comparative study with the traditional approach," *Adv produc engineer manag*, vol. 17, no. 1, pp. 5–15, Mar. 2022, doi: 10.14743/apem2022.1.417.

[34] S. Yousefi and B. M. Tosarkani, "An analytical approach for evaluating the impact of blockchain technology on sustainable supply chain performance," *International Journal of Production Economics*, vol. 246, p. 108429, 2022, doi: https://doi.org/10.1016/j.ijpe.2022.108429.