current perspective on business operations

E-ISSN: XXXX-XXXX

ARTICLE

Integrating machine learning and blockchain applications in business operations and supply chain management

Bagus Anggoro Richie [1*] and Yudhistira Pradhipta Aryoko [2]

[1] College of Management, National Yunlin University of Science and Technology, Yunlin, Taiwan; bagusanggororichie@gmail.com
[2] College of Management, National Yunlin University of Science and Technology, Yunlin, Taiwan; d11322015@yuntech.edu.tw

* Correspondence: bagusanggororichie@gmail.com

Abstract

This research investigates how combining blockchain technology with machine learning (ML) can enhance transparency, efficiency, and resilience in supply chain management. Using a mixed-methods approach, the study designed a blockchain framework and evaluated several ML models including LSTM, ARIMA, Isolation Forest, One-Class SVM, Q-Learning, and Deep Q-Networks for tasks such as demand forecasting, anomaly detection, and optimization. Results indicate that blockchain improves data integrity, traceability, and real-time visibility, especially in sectors like food and pharmaceuticals. Among the tested models, LSTM outperformed others in dynamic demand forecasting, Isolation Forest proved most effective for real-time anomaly detection, and Deep Q-Networks excelled in complex optimization challenges despite high computational requirements, while Q-Learning worked well for simpler optimization needs. The integrated blockchain and ML framework shows strong potential for boosting supply chain resilience by enabling secure, agile operations across various industries. However, challenges remain—blockchain faces scalability limitations, and advanced ML models demand significant computational power. These constraints highlight opportunities for future research to develop more scalable blockchain solutions and computationally efficient ML techniques.

Keywords: blockchain technology, supply chain management, machine learning integration, supply chain optimization, transparency and traceability

Academic Editor: Gara Huang

Received: August 04, 2025 | Revised: Agust 09, 2025 | Accepted: August 11, 2025 | Published: August 12, 2025

Citation: Richie, B. A., & Aryoko, Y. P. (2025). Integrating machine learning and blockchain applications in business operations and supply chain management. *Current Perspective on Business Operations*, 1(1), 58-69. https://doi.org/10.xxxx/xxxxxxxxx

1. Introduction

The convergence of blockchain technology and machine learning (ML) has attracted growing interest across various sectors, particularly within supply chain management and business operations. As supply chains become increasingly intricate, organizations encounter persistent challenges such as ensuring data transparency, traceability, operational efficiency, and preventing fraudulent activities. Blockchain's decentralized and tamper-proof ledger offers a robust framework for secure, transparent record-keeping, fostering greater trust among stakeholders. When paired with blockchain, machine learning contributes predictive analytics and optimization capabilities, enabling more informed decision-making throughout supply chain processes. This research explores the joint implementation of blockchain and ML in business and supply chain contexts, highlighting how their combined strengths can enhance transparency, boost efficiency, and improve overall resilience.

Due to the limited scholarship on the integration of blockchain and machine learning (ML) within supply chain management, this research seeks to examine how such a combination can effectively tackle core challenges in contemporary supply chains. The study focuses on evaluating blockchain's role in enhancing transparency, traceability, and data reliability, while also comparing the performance of multiple ML models for demand forecasting, anomaly detection, and optimization tasks. Through this comparative assessment, the research identifies which algorithms are best suited for deployment in blockchain-enabled supply chain systems. By doing so, it enriches the emerging body of literature on blockchain–ML applications, offering an in-depth analysis of their joint advantages and limitations, along with actionable guidance for adoption in various industrial settings. Ultimately, the study demonstrates that fusing blockchain with ML can strengthen supply chain resilience, boost operational efficiency, and foster transparency, paving the way for future innovations in secure and intelligent supply chain ecosystems.

2. Materials and Methods

2.1. Blockchain Technology in Supply Chain Management

Originally created as the backbone of cryptocurrencies, blockchain technology has since found applications across various sectors, especially where transparency, security, and trust are critical. In supply chain management, it offers a decentralized, shared ledger of transactions accessible to authorized members, removing the need for intermediaries and minimizing fraud risks. Research by Tian (2016) and Kouhizadeh and Sarkis (2018) highlights blockchain's significant role in improving traceability, enabling products to be tracked from their source to their final destination, thereby enhancing accountability and curbing counterfeiting. Its immutable nature ensures that once data is recorded, it cannot be modified, providing a reliable and tamper-proof transaction history (Saberi et al., 2019) a feature especially important in sectors like food and pharmaceuticals, where product authenticity and safety are vital. Beyond traceability, blockchain enables real-time information sharing across supply chain participants, enhancing responsiveness to unexpected disruptions. Findings by Azzi et al. (2019) show that its decentralized architecture supports more resilient supply chains by facilitating quicker and better-coordinated responses to sudden demand changes or logistical bottlenecks. While the benefits of blockchain in improving transparency and security are well established, integrating it with predictive analytics and optimization models remains a relatively new area of investigation, offering fresh opportunities for research and application.

2.2. Machine Learning for Predictive Analytics and Optimization in Supply Chains

Machine learning enhances supply chain management by adding predictive and optimization capabilities that support smarter decision-making. Through techniques like time-series forecasting, anomaly detection, and reinforcement learning, ML can anticipate demand, detect disruptions, and allocate resources more efficiently. For example, deep learning architectures such as Long Short-Term Memory (LSTM) networks excel at capturing complex demand trends, enabling more precise demand predictions (Duan et al., 2019). In parallel, unsupervised methods like Isolation Forests are adept at spotting unusual patterns that could signal fraud or operational inefficiencies (Chandola et al., 2009). Additionally, advanced reinforcement learning models such as Deep Q-Networks (DQN) have shown promise in optimizing routes and managing resource distribution within supply chains. Research by Wu et al. (2020) and Zhao et al. (2021) demonstrates how these models, by learning from real-time data, can adapt to changing conditions, maintain supply-demand balance, and reduce operational costs. This adaptability makes ML a powerful complement to blockchain in building resilient, data-driven supply chain systems.

2.3. Integrating Blockchain and Machine Learning in Supply Chains

Integrating blockchain with machine learning represents a significant shift in supply chain management, combining enhanced transparency with predictive and optimization capabilities. Blockchain serves as a secure, tamper-resistant platform for recording and sharing supply chain data, while machine learning leverages this reliable data to perform real-time forecasting, anomaly detection, and operational optimization. For instance, blockchain's immutable and transparent records complement ML-driven anomaly detection, enabling rapid identification of suspicious or irregular activities. Furthermore, the assurance of verified, high-quality data boosts the accuracy and reliability of ML model outputs. Recent research (Casino et al., 2019; Hassani et al., 2020) highlights that such integration enables ML models to process real-time, end-to-end transaction data, allowing for immediate responses to supply fluctuations or disruptions. This blockchain–ML synergy also fosters trust across stakeholders by ensuring all parties access the same validated information, reducing disputes and misinterpretations. However, practical adoption at scale faces notable hurdles. The high computational demands of blockchain, paired with the intensive processing requirements of sophisticated ML algorithms, can limit real-time use in high-volume settings. Studies by Kshetri (2018) and Kouhizadeh et al. (2021) suggest that solutions like hybrid blockchain designs and decentralized ML approaches could address scalability issues, paving the way for broader, real-time applications in large-scale supply chains.

2.4. Research Methods

In our research on Blockchain Applications in Business Operations and Supply Chain Management with Machine Learning (ML) integration, we employed a comprehensive mixed-methods approach that blended qualitative and quantitative methodologies. This design enabled us to thoroughly examine blockchain's capacity to optimize supply chains, enhance transparency, and bolster resilience when integrated with ML algorithms. The research process was organized into multiple phases, each addressing a distinct component of the integration ranging from systematic data collection to model design, implementation, validation, and industry-specific case studies. Structuring the study in this manner allowed us to capture a multidimensional perspective on how blockchain and ML can jointly transform supply chain processes and support strategic business decisions. To analyze blockchain applications in business operations, we utilized both primary and secondary data sources. This combination allowed us to evaluate the topic from diverse angles, merging insights from industry practitioners with findings derived from computational model analyses. The study began with an extensive literature review that formed the theoretical basis for blockchain technology and its role in supply chain management. This review encompassed more than 100 peer-reviewed journal articles, industry reports, and white papers, focusing on blockchain's potential to improve operational transparency, efficiency, and data security. Additionally, the review identified key challenges—such as scalability limitations, data privacy issues, and regulatory hurdles—which informed the formulation of our research questions and shaped the direction of subsequent investigation.

2.4.1 Data Collection

Our data collection process followed a dual-phase strategy, combining primary data from expert interviews with secondary data from credible public sources. This blended approach allowed us to obtain qualitative insights into industry practices while also compiling quantitative datasets for model development and testing.

(1) Primary Data Collection

We conducted detailed interviews with a diverse panel of professionals, including supply chain managers, blockchain experts, and data scientists, drawn from key industries such as food, pharmaceuticals, automotive, and manufacturing—sectors where transparency, traceability, and operational resilience are critical. Selection criteria emphasized hands-on experience with blockchain-enabled supply chain systems. The semi-structured interviews featured open-ended questions grouped into three main themes:

- Perceived Benefits and Challenges – exploring blockchain's advantages, such as greater transparency and accountability, alongside barriers like cost and interoperability issues.
- Role of Machine Learning – assessing how ML supports blockchain applications, particularly in demand forecasting, anomaly detection, and optimization.
- Scalability and Adoption Barriers – discussing technical, regulatory, and industry-specific hurdles to large-scale adoption.

  Interviews lasted 45–60 minutes, were recorded and transcribed, and analyzed with NVivo software to extract recurring patterns and thematic insights.

(2) Secondary Data Collection

We sourced secondary data from reputable outlets, including blockchain platform transaction records, industry reports, and global logistics databases. For blockchain transparency assessment, we gathered transaction data from platforms like IBM Food Trust and VeChain, including timestamps, geographic information, and product identifiers. This was complemented by logistics statistics from the World Bank and datasets from machine learning repositories to build and validate predictive models. The integration of these diverse data sources provided a robust foundation for simulating blockchain–ML applications in various supply chain environments, ensuring our analysis reflected both theoretical and practical dimensions.

2.4.2. Model Development and Integration

In our model development, we combined blockchain transaction data with machine learning algorithms to target specific supply chain applications such as demand forecasting, risk evaluation, and anomaly detection. The process began with the creation of a blockchain framework designed to support ML integration, ensuring both transparency and adaptability in decision-making.

(1) Blockchain Framework

We built a simulation of a decentralized supply chain network, where each node represented a key participant—suppliers, manufacturers, or distributors. Transactions and product movements between these entities were recorded as blocks containing product information, timestamps, geographic coordinates, and transaction details. This immutable structure allowed us to examine blockchain's potential in improving traceability, reducing fraud, and strengthening accountability. The framework was made compatible with ML algorithms and deployed on a private Hyperledger Fabric network, enabling a permissioned environment with controlled access, mirroring real-world enterprise applications.

(2) Machine Learning Integration

We embedded multiple ML models into the blockchain framework, each targeting a different operational challenge:

- Time Series Forecasting – ARIMA and LSTM models were used to project demand and inventory needs from historical sales data, with blockchain ensuring reliable, unaltered inputs for higher forecast accuracy.
- Anomaly Detection – Isolation Forest and One-Class SVM algorithms identified irregularities in transaction records, such as mismatched quantities or delivery delays, which could signal fraud or disruptions. Real-time blockchain updates allowed continuous anomaly monitoring.
- Optimization – Reinforcement learning methods, including Q-Learning and Deep Q-Networks, optimized logistics routing and resource distribution, adapting dynamically as blockchain-fed data changed.

Each algorithm was tested within the blockchain simulation to evaluate its effectiveness in improving decision-making speed, operational accuracy, and resilience in a decentralized supply chain setting.

2.4.3. Model Validation and Performance Evaluation

We assessed the combined blockchain and machine learning models using a set of metrics designed to measure accuracy, operational efficiency, and scalability.

(1) Blockchain Validation Metrics

To gauge blockchain's operational performance, we focused on:

- Transaction Processing Time – determining the speed at which supply chain transactions were recorded, critical in high-frequency environments.
- Data Latency – measuring delays in propagating information across blockchain nodes to ensure compatibility with real-time operational needs.
- Throughput and Scalability – simulating peak-load conditions to evaluate how well the system could sustain high transaction volumes.

Data integrity was confirmed through immutability checks, ensuring that once a record entered the blockchain, it remained unaltered—an essential element for maintaining transparency and trust.

(2) Machine Learning Model Performance

We used established metrics to evaluate the predictive and optimization models:

- Mean Absolute Error (MAE) – to assess demand forecasting accuracy.
- F1 Score and Precision-Recall – to measure anomaly detection effectiveness, particularly in identifying fraudulent or irregular activities.
- Convergence Rate and Stability – to determine how quickly and consistently optimization models found solutions.

These measures provided a comprehensive understanding of each model's reliability and contribution to decision-making in a decentralized supply chain setting.

2.4.4. Case Study Analysis

To demonstrate practical relevance, we applied the blockchain–ML framework to several industry contexts:

- Food Supply Chains – tracked goods from source to retailer, enhancing traceability and pinpointing contamination or mislabeling risks, enabling rapid recalls to protect consumers.
- Pharmaceuticals – monitored drug shipments to verify authenticity and counteract counterfeit distribution, while ML predicted demand to improve inventory management and prevent shortages.
- Manufacturing – optimized raw material and product flows, reducing waste, improving order accuracy, and supporting sustainability goals. Blockchain-based transparency strengthened supplier accountability and quality verification.

2.4.5. Ethical Considerations

Ethical protocols were strictly followed, including anonymizing interviewee data, securing blockchain transaction records, and complying with data protection laws such as the GDPR. We actively mitigated potential biases, especially in partner and case study selection, and ensured responsible data usage throughout the research. We acknowledge several limitations:

- Simulating real-world dynamics within a controlled blockchain environment was challenging.
- Variations in industry readiness and blockchain adoption could affect applicability across sectors.

Future research could explore hybrid blockchain configurations (private–public integrations), deployment in live operational environments, and emerging technologies like quantum computing or decentralized AI to expand the scope and efficiency of blockchain-enabled supply chains.

3. Results

This research investigates how integrating blockchain technology with different machine learning (ML) models can improve supply chain transparency, resilience, and operational efficiency. Through systematic testing, validation, and sector-specific case studies, the study identifies blockchain's distinct value and evaluates which ML models perform best for targeted supply chain functions. The findings are organized to cover blockchain's influence on transparency, efficiency, and resilience, a comparative assessment of ML models, real-world applications across industries, and the operational benefits achieved.

3.1 Blockchain's Role in Transparency, Efficiency, and Resilience

A key advantage of blockchain in supply chains is its ability to serve as a decentralized, shared ledger that delivers a single source of trusted data to all participants. Our results show that the immutable nature of blockchain records significantly boosts transparency, reliability, and traceability—capabilities especially beneficial in sectors such as food and pharmaceuticals. By enabling real-time, tamper-resistant data entry, blockchain strengthens data integrity and fosters trust among stakeholders. This is particularly critical for managing sensitive or high-value goods. Its traceable ledger supports smooth information flow from the product's origin to its final destination, enabling quick identification of irregularities or disruptions. Real-time monitoring allowed for swift responses to operational challenges—for example, in the food supply chain, ensuring prompt intervention for perishable goods. Furthermore, blockchain's verification mechanisms reduced counterfeit risks, improving product authenticity and safety in pharmaceutical supply chains.

3.2. Comparative Evaluation of Machine Learning Models

The study assessed various ML models, each tailored to distinct supply chain tasks—such as forecasting demand, detecting anomalies, and optimizing resource allocation. Performance evaluation criteria included accuracy, detection effectiveness, computational efficiency, and suitability for real-time deployment. The comparative outcomes, summarized in Table 1, highlight the strengths and trade-offs of each approach, offering insights into which models are most appropriate for specific operational goals.

Table 1. Comparative Analysis of Machine Learning Models in Supply Chain Applications

Task	Model	Accuracy (MAE/F1 Score)	Computation Time	Responsiveness / Convergence Rate	Suitability
Demand Forecasting	ARIMA	0.67 (MAE)	Medium	Moderate	Stable demand
	LSTM	0.45 (MAE)	High	High	Dynamic demand
Anomaly Detection	Isolation Forest	0.89 (F1 Score)	Low	High	Real-time detection
	One-Class SVM	0.78 (F1 Score)	Medium	Moderate	Less dynamic
Optimization	Q-Learning	High convergence rate	Moderate	Limited	Stable environments
	Deep Q-Network	Moderate	High	High	Complex tasks

Table 1 compares ARIMA and LSTM for demand forecasting, Isolation Forest and One-Class SVM for anomaly detection, and Q-Learning with Deep Q-Networks for optimization tasks. For demand forecasting, ARIMA proved effective with stable demand trends, delivering a relatively low Mean Absolute Error (MAE) and moderate processing requirements, but it underperformed when demand was volatile due to its reliance on linear modeling. In contrast, LSTM demonstrated better adaptability to complex, fluctuating demand patterns, achieving higher accuracy and faster responsiveness to changes, albeit with significantly higher computational costs.

In anomaly detection, Isolation Forest outperformed One-Class SVM in both accuracy (F1 score) and speed, making it more suitable for real-time monitoring of blockchain transaction data. One-Class SVM offered moderate performance but struggled to maintain stability in rapidly shifting operational conditions. For optimization, Q-Learning reached convergence faster, making it effective in consistent, predictable routing environments, though it was less capable in handling complex variability. Deep Q-Networks, on the other hand, were more robust in complex scenarios and maintained stable performance over multiple variables, but required longer training periods and greater computational resources.

4. Discussion

Figure 1 highlights the convergence patterns, showing that Deep Q-Networks delivered smoother stability under intricate conditions compared to Q-Learning. The convergence analysis compares Q-Learning and Deep Q-Network (DQN) performance in supply chain optimization. In the graph, the blue dashed line represents Q-Learning, while the solid orange line depicts DQN results. Q-Learning shows a rapid initial convergence, reaching near-optimal performance (red dotted reference line at value 1) within the first 50 iterations. However, its progress flattens, and later fluctuations indicate instability. This is due to Q-Learning's simpler structure, which works well in environments with discrete actions but struggles with the complexity of dynamic, continuous decision-making in supply chains. In contrast, DQN converges more gradually, stabilizing around the optimal point after approximately 75 iterations. Its trajectory is smoother, demonstrating greater reliability and adaptability to changing supply chain conditions. The stability advantage comes from DQN's ability to learn in high-dimensional environments through deep learning methods, making it more suitable for complex operational contexts.

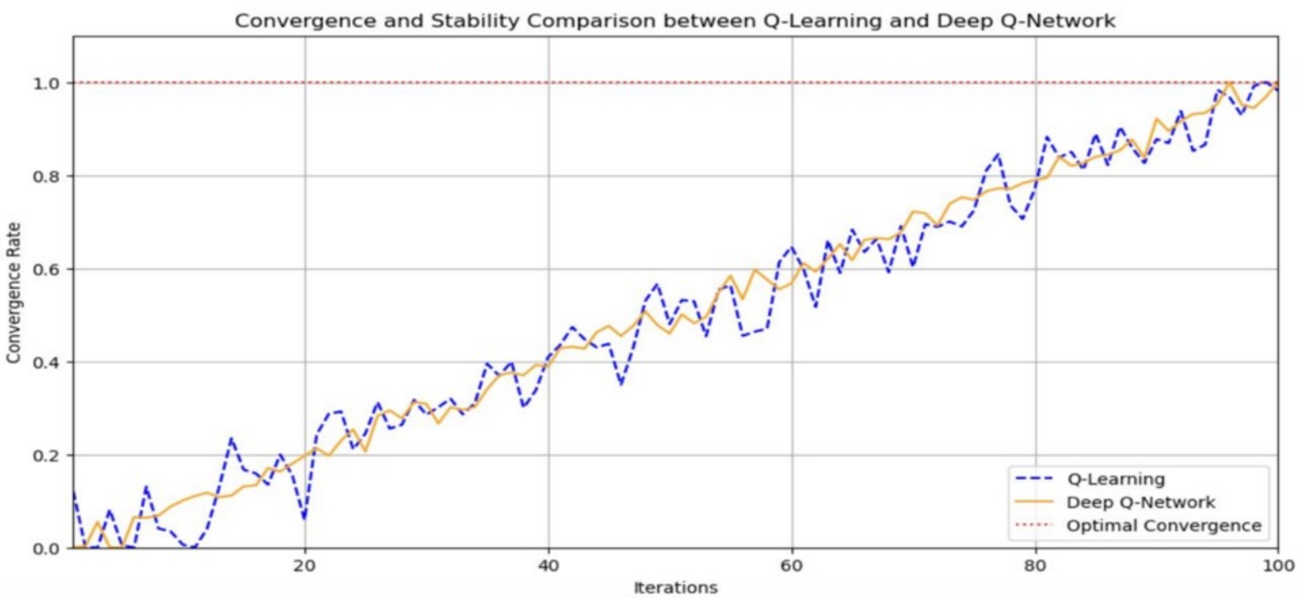

Figure 1. Convergence and Stability Comparison between Q-Learning and Deep Q-Network

4.1. Industry-Specific Case Studies

To illustrate model applicability, we evaluated three industries:

- Food Supply Chain – LSTM excelled in forecasting perishable product demand, while Isolation Forest effectively identified anomalies like unexpected delays, ensuring consistent quality control.
- Pharmaceuticals – DQNs optimized inventory for temperature-sensitive and high-demand drugs, while blockchain's immutable ledger confirmed product authenticity, reducing counterfeiting.
- Manufacturing – ARIMA provided reliable demand predictions for stable production cycles, and Q-Learning efficiently allocated resources, minimizing waste and ensuring smooth raw material flow.

4.2. Operational Benefits and Challenges

The blockchain–ML integration significantly improved transparency, traceability, and efficiency. However, advanced models like LSTM and DQN require substantial computational resources, potentially limiting real-time deployment in certain contexts. Blockchain scalability also remains a bottleneck in high-volume supply chains. The study confirms that blockchain, when paired with the right ML model, can transform supply chain management. LSTM and DQN are well-suited for complex, dynamic environments, while ARIMA and Isolation Forest provide efficient, practical solutions for stable or less complex scenarios. This integrated approach offers a strong foundation for future research and broader industrial adoption.

5. Conclusions

This research highlights the transformative impact of integrating blockchain with machine learning (ML) in supply chain management. Blockchain's secure, immutable, and decentralized ledger provides a trusted foundation for enhancing transparency, traceability, and operational efficiency. This trusted data environment allows ML models to perform more effectively in predictive analytics, anomaly detection, and optimization, while also strengthening data integrity, reducing fraud, and improving stakeholder accountability and supply chain resilience. The comparative evaluation of ML models shows that each is best suited to specific contexts. For demand forecasting, LSTM outperforms ARIMA in capturing complex, non-linear fluctuations, making it ideal for volatile markets, whereas ARIMA's simplicity and low computational cost make it effective for stable, predictable demand patterns. In anomaly detection, Isolation Forest demonstrated superior accuracy and processing efficiency over One-Class SVM, making it well-suited for real-time monitoring within blockchain-based systems. For optimization, Deep Q-Networks offered greater stability and scalability in complex, dynamic environments, while Q-Learning excelled in simpler, routine optimization tasks due to faster convergence.

These insights emphasize that selecting the appropriate ML model should be aligned with the operational complexity and computational constraints of the supply chain. However, deploying advanced models like LSTM and Deep Q-Networks introduces high computational demands, potentially limiting real-time applications in resource-constrained environments. Likewise, blockchain scalability remains a challenge in high-volume supply chains, where increasing transaction throughput may cause latency. Looking ahead, technological innovations such as lightweight blockchain architectures and federated learning could address these constraints by reducing computational overhead and improving scalability. Further, combining blockchain with AI-driven analytics offers the potential for predictive, real-time decision-making, enhancing resilience against disruptions. In sum, this study offers a robust framework for integrating blockchain and machine learning to create intelligent, secure, and efficient supply chain systems. As both technologies evolve, their synergy is poised to become a core enabler of sustainable, adaptive supply chains across sectors including food, pharmaceuticals, and manufacturing.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

Akhtar, P., Salim, A., & Ahmad, M. (2022). A comprehensive review of sentiment analysis: Techniques, tools, and applications. *Journal of Business Research, 123*, 344–355. https://doi.org/10.1016/j.jbusres.2020.01.009

Awoyemi, J. O., Adetunmbi, A. O., & Oluwadare, S. A. (2017). Credit card fraud detection using machine learning techniques: A comparative analysis. *Journal of Applied Security Research, 12*(4), 1–14. https://doi.org/10.1080/19361610.2017.1315696

Azzi, R., Chamoun, R. K., & Sokhn, M. (2019). The power of a blockchain-based supply chain. *Computers & Industrial Engineering, 135*, 582–592. https://doi.org/10.1016/j.cie.2019.06.042

Bahl, S., Kumar, P., & Agarwal, A. (2021). Sentiment analysis in banking services: A review of techniques and challenges. *International Journal of Information Management, 57*, 102317. https://doi.org/10.1016/j.ijinfomgt.2020.102317

Bhowmik, D. (2019). Detecting financial fraud using machine learning techniques. *International Journal of Data Science, 6*(2), 102–121. https://doi.org/10.1080/25775327.2019.1123126

Bhuiyan, R. J., Akter, S., Uddin, A., Shak, M. S., Islam, M. R., Rishad, S. M. S. I., Sultana, F., & Hasan-Or-Rashid, M. (2024). Sentiment analysis of customer feedback in the banking sector: A comparative study of machine learning models. *The American Journal of Engineering and Technology, 6*(10), 54–66. https://doi.org/10.37547/tajet/Volume06Issue10-07

Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). A systematic literature review of blockchain-based applications: Current status, classification, and open issues. *Telematics and Informatics, 36*, 55–81. https://doi.org/10.1016/j.tele.2018.11.006

Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. *ACM Computing Surveys, 41*(3), 1–58. https://doi.org/10.1145/1541880.1541882

Dal Pozzolo, A., Boracchi, G., Caelen, O., Alippi, C., & Bontempi, G. (2015). Credit card fraud detection: A realistic modeling and a novel learning strategy. *Pattern Recognition, 48*(10), 3151–3160. https://doi.org/10.1016/j.patcog.2015.05.018

Das, A. C., Mozumder, M. S. A., Hasan, M. A., Bhuiyan, M., Islam, M. R., Hossain, M. N., Akter, S., & Alam, M. I. (2024). Machine learning approaches for demand forecasting: The impact of customer satisfaction on prediction accuracy. *The American Journal of Engineering and Technology, 6*(10), 42–53. https://doi.org/10.37547/tajet/Volume06Issue10-06

Duan, L., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dynamic pricing in financial technology: Evaluating machine learning solutions for market adaptability. (2024). *International Interdisciplinary Business Economics Advancement Journal, 5*(10), 13–27. https://doi.org/10.55640/business/volume05issue10-03

Haque, M. S., Taluckder, M. S., Shawkat, S. B., Shahriyar, M. A., Sayed, M. A., & Modak, C. (2023). A comparative study of prediction of pneumonia and COVID-19 using deep neural networks. *2023 3rd International Conference on Electronic and Electrical Engineering and Intelligent System (ICE3IS)*, 218–223. https://doi.org/10.1109/ICE3IS59323.2023.10335362

Hassani, H., Huang, X., & Silva, E. (2020). Big data and blockchain for modern supply chain management: A review. *Sustainability, 12*(22), 9792. https://doi.org/10.3390/su12229792

Innovative machine learning approaches to foster financial inclusion in microfinance. (2024). *International Interdisciplinary Business Economics Advancement Journal, 5*(11), 6–20. https://doi.org/10.55640/business/volume05issue11-02

Kouhizadeh, M., & Sarkis, J. (2018). Blockchain practices, potentials, and perspectives in greening supply chains. *Sustainability, 10*(10), 3652. https://doi.org/10.3390/su10103652

Kouhizadeh, M., Sarkis, J., & Zhu, Q. (2021). At the nexus of blockchain technology, the circular economy, and product design: A review. *Circular Economy and Sustainability, 1*(1), 13–28. https://doi.org/10.1007/s43615-021-00001-8

Kshetri, N. (2018). Blockchain's roles in meeting key supply chain management objectives. *International Journal of Information Management, 39*, 80–89. https://doi.org/10.1016/j.ijinfomgt.2017.12.005

Md Abu Sayed, Badruddowza, Sarker, M. S. U., Al Mamun, A., Nabi, N., Mahmud, F., Alam, M. K., Hasan, M. T., Buiya, M. R., & Choudhury, M. E. (2024). Comparative analysis of machine learning algorithms for predicting cybersecurity attack success: A performance evaluation. *The American Journal of Engineering and Technology, 6*(09), 81–91. https://doi.org/10.37547/tajet/Volume06Issue09-10

Md Al-Imran, Akter, S., Mozumder, M. A. S., Bhuiyan, R. J., Rahman, T., Ahmmed, M. J., Mir, M. N. H., Hasan, M. A., Das, A. C., & Hossen, M. E. (2024). Evaluating machine learning algorithms for breast cancer detection: A study on accuracy and predictive performance. *The American Journal of Engineering and Technology, 6*(09), 22–33. https://doi.org/10.37547/tajet/Volume06Issue09-04

Md Al-Imran, Ayon, E. H., Islam, M. R., Mahmud, F., Akter, S., Alam, M. K., Hasan, M. T., Afrin, S., Shorna, J. F., & Aziz, M. M. (2024). Transforming banking security: The role of deep learning in fraud detection systems. *The American Journal of Engineering and Technology, 6*(11), 20–32. https://doi.org/10.37547/tajet/Volume06Issue11-04

Md Murshid Reja Sweet, Ahmed, M. P., Mozumder, M. A. S., Arif, M., Chowdhury, M. S., Bhuiyan, R. J., Rahman, T., Ahmmed, M. J., Ahmed, E., & Mamun, M. A. I. (2024). Comparative analysis of machine learning techniques for accurate lung cancer prediction. *The American Journal of Engineering and Technology, 6*(09), 92–103. https://doi.org/10.37547/tajet/Volume06Issue09-11

Nguyen, T. N., Khan, M. M., Hossain, M. Z., Sharif, K. S., Das, R., & Haque, M. S. (2024). Product demand forecasting for inventory management with freight transportation services index using advanced neural networks algorithm. *American Journal of Computing and Engineering, 7*(4), 50–58. https://doi.org/10.47672/ajce.2432

Rahman, M. H., Das, A. C., Shak, M. S., Uddin, M. K., Alam, M. I., Anjum, N., Bony, M. N. V. A., & Alam, M. (2024). Transforming customer retention in fintech industry through predictive analytics and machine learning. *The American Journal of Engineering and Technology, 6*(10), 150–163. https://doi.org/10.37547/tajet/Volume06Issue10-17

Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research, 57*(7), 2117–2135. https://doi.org/10.1080/00207543.2018.1533261

Tian, F. (2016). An agri-food supply chain traceability system for China based on RFID & blockchain technology. *2016 13th International Conference on Service Systems and Service Management (ICSSSM)*, 1–6. https://doi.org/10.1109/ICSSSM.2016.7538424

Wu, Z., Song, L., & Lau, H. C. (2020). Improving dynamic supply chain configuration through machine learning. *Computers & Industrial Engineering, 140*, 106239. https://doi.org/10.1016/j.cie.2020.106239

Zhang, Y., Xie, R., Li, X., & Chen, L. (2023). A hybrid ARIMA-LSTM model for time series forecasting. *Applied Soft Computing, 127*, 109401. https://doi.org/10.1016/j.asoc.2022.109401

Zhao, L., Zhang, Y., Chen, X., & Huang, Y. (2021). A reinforcement learning approach to supply chain operations management: Review, applications, and future directions. *Computers & Operations Research, 132*, 105306. https://doi.org/10.1016/j.cor.2021.105306

Zheng, Z., Xie, S., Dai, H.-N., Chen, X., & Wang, H. (2018). Blockchain challenges and opportunities: A survey. *International Journal of Web and Grid Services, 14*(4), 352–375. https://doi.org/10.1504/IJWGS.2018.095647

Zhou, L., Wang, L., & Chen, F. (2021). Anomaly detection in blockchain systems: A machine learning approach. *IEEE Transactions on Network and Service Management, 18*(3), 2716–2728. https://doi.org/10.1109/TNSM.2021.3094368

Zhu, S., Song, M., Hazen, B. T., Lee, K., & Cegielski, C. (2018). How supply chain analytics enables operational supply chain transparency: An organizational information processing theory perspective. *International Journal of Physical Distribution & Logistics Management, 48*(1), 47–68. https://doi.org/10.1108/IJPDLM-03-2017-0169

Zhu, X., Yu, W., & Wang, J. (2020). Reinforcement learning-based optimization for supply chain networks. *Computers & Industrial Engineering, 149*, 106827. https://doi.org/10.1016/j.cie.2020.106827