

AI-Driven Optimization of Healthcare Supply Chains: From Prediction to Real-Time Response

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DOI: <https://doi.org/10.51244/IJRSI.2026.1305000192>

Received: 28 April 2026; Accepted: 03 May 2026; Published: 09 June 2026

ABSTRACT

Healthcare supply chains operate at the intersection of clinical care, logistics, and public health, where efficiency is not merely a matter of cost but of life and survival. Over the past decade, increasing demand variability, globalization of pharmaceutical production, and rising complexity in healthcare delivery have exposed structural weaknesses in traditional supply chain systems. These systems have historically relied on linear forecasting methods, siloed data environments, and delayed decision-making processes, which are inadequate in addressing rapidly evolving healthcare needs. This review synthesizes existing scholarly literature on AI-driven optimization in healthcare supply chains, with particular emphasis on the continuum from predictive analytics to real-time operational intelligence. The paper further explores how AI technologies such as machine learning, deep learning, and IoT-enabled systems enhance forecasting accuracy, improve inventory management, and enable dynamic logistics optimization. Additionally, it examines the implications of these advancements for global health systems, especially in the context of pandemic preparedness and equitable access to healthcare resources. The review concludes by identifying key challenges, including data fragmentation, ethical concerns, and implementation barriers, while proposing future directions for research and practice.

Keywords: AI; Optimization; Healthcare; Supply Chain; Prediction; Real-Time Response

INTRODUCTION

Healthcare supply chains are fundamentally different from those in other industries because they directly influence patient outcomes [1, 2]. Unlike commercial supply chains, where delays may result in financial losses, inefficiencies in healthcare logistics can lead to treatment interruptions, increased morbidity, and even mortality. This unique characteristic underscores the importance of reliability, responsiveness, and resilience in healthcare supply systems. Traditionally, healthcare supply chains have been managed using deterministic and rule-based approaches [3, 4]. These systems often rely on historical averages and manual decision-making processes, which limit their ability to adapt to sudden changes in demand or supply disruptions. For instance, hospitals frequently experience stockouts of essential medicines or overstocking of low-demand items, both of which contribute to inefficiencies and increased operational costs [5-7].

The emergence of AI has introduced new possibilities for transforming these systems. By leveraging large datasets and advanced computational techniques, AI enables healthcare organizations to uncover hidden patterns, predict future trends, and optimize decision-making processes [8, 9]. The integration of AI into healthcare supply chains represents a shift toward data-driven and intelligent systems that can continuously learn and adapt. This transformation has been particularly evident during global health crises such as the COVID-19 pandemic, where traditional supply chain models struggled to cope with unprecedented demand for medical supplies [10-12]. AI-driven systems demonstrated their potential by enabling rapid forecasting, dynamic resource allocation, and real-time monitoring of supply chain activities. As a result, there is growing interest in understanding how AI can be systematically integrated into healthcare supply chains to enhance performance and resilience.

THEORETICAL FOUNDATIONS OF AI IN SUPPLY CHAINS

2.1 Artificial Intelligence and Machine Learning

Artificial Intelligence encompasses a broad range of computational techniques designed to mimic human cognitive functions such as learning, reasoning, and decision-making [13, 14]. Within this domain, machine learning plays a central role by enabling systems to learn from data without explicit programming. In the context of healthcare supply chains, machine learning algorithms analyze historical and real-time data to identify patterns and generate predictions.

Different types of machine learning models are applied depending on the nature of the problem. Supervised learning models are commonly used for demand forecasting and risk prediction, where labeled data is available [15, 16]. Unsupervised learning techniques, on the other hand, are used for clustering and anomaly detection, helping to identify unusual patterns in supply chain operations [17, 18]. Reinforcement learning, a more advanced approach, enables systems to learn optimal strategies through trial and error, making it particularly suitable for dynamic decision-making environments [19-21]. The application of these techniques allows healthcare organizations to move beyond traditional statistical models, which often fail to capture the complexity and variability inherent in healthcare systems. By incorporating multiple data sources and leveraging nonlinear relationships, AI models provide more accurate and robust insights.

2.2 Predictive Informatics in Healthcare Logistics

Predictive informatics represents the integration of data analytics, statistical modeling, and computational intelligence to forecast future events and optimize decision-making. In healthcare logistics, predictive informatics enables organizations to anticipate demand fluctuations, identify potential disruptions, and allocate resources more effectively [22, 23]. One of the key advantages of predictive informatics is its ability to incorporate diverse data sources, including electronic health records, epidemiological data, weather patterns, and socio-economic indicators [24-26]. This holistic approach provides a more comprehensive understanding of the factors influencing supply chain dynamics. For example, predictive models can analyze disease outbreak patterns to estimate future demand for specific medications or medical supplies [27, 28]. Similarly, they can assess supplier reliability and transportation risks, enabling organizations to develop contingency plans and mitigate potential disruptions. By transforming raw data into actionable insights, predictive informatics plays a critical role in enhancing the efficiency and resilience of healthcare supply chains.

2.3 Transition from Prediction to Real-Time Intelligence

While predictive analytics provides valuable insights into future trends, it is inherently limited by its reliance on historical data and assumptions about future conditions. In rapidly changing environments, such as healthcare, these assumptions may not always hold true. This limitation has led to the development of real-time intelligence systems that continuously monitor and analyze data to support immediate decision-making. Real-time intelligence is enabled by advancements in technologies such as IoT, cloud computing, and edge analytics [29, 30]. These technologies allow for the continuous collection and processing of data from various sources, including sensors, devices, and information systems. AI algorithms analyze this data in real time, identifying patterns and anomalies and triggering appropriate responses [31, 32]. The transition from prediction to real-time response represents a significant advancement in supply chain management. It enables healthcare organizations to respond dynamically to changing conditions, reducing delays and improving overall system performance. This capability is particularly important in critical situations, such as emergency response and pandemic management, where timely decision-making is essential.

PREDICTIVE ANALYTICS IN HEALTHCARE SUPPLY CHAINS

3.1 Demand Forecasting

Demand forecasting is a cornerstone of supply chain management, and its importance is magnified in healthcare settings [33-35]. Accurate demand forecasting ensures that the right products are available at the right

time and in the right quantities, minimizing both shortages and excess inventory [36]. AI-driven demand forecasting models leverage large datasets and advanced algorithms to improve prediction accuracy. Unlike traditional models, which rely on linear relationships, AI models can capture complex interactions between multiple variables. For instance, they can analyze the impact of seasonal trends, demographic changes, and disease outbreaks on demand patterns. In healthcare, demand forecasting is particularly challenging due to the unpredictable nature of patient needs [37, 38]. AI models address this challenge by continuously learning from new data and updating their predictions accordingly. This adaptive capability allows healthcare organizations to anticipate demand more accurately and respond proactively.

3.2 Risk Prediction and Supply Chain Resilience

Risk prediction is another critical application of AI in healthcare supply chains [39, 40]. Supply chains are inherently vulnerable to various risks, including supplier disruptions, transportation delays, and geopolitical factors [41, 42]. AI models can analyze historical data and external indicators to identify potential risks and assess their impact [43, 44]. By providing early warnings of potential disruptions, AI enables organizations to take preventive measures and enhance supply chain resilience. For example, predictive models can identify suppliers with a high risk of failure, allowing organizations to diversify their supplier base or establish alternative sourcing strategies [45-47]. In addition, AI can simulate different scenarios and evaluate their potential outcomes, helping decision-makers develop robust contingency plans. This capability is particularly valuable in healthcare, where disruptions can have severe consequences for patient care.

3.3 Inventory Optimization

Inventory management is a critical component of healthcare supply chains, as it directly affects the availability of essential products and the efficiency of operations [48-50]. AI-driven inventory optimization models use predictive analytics to determine optimal stock levels, balancing the need to avoid stockouts with the goal of minimizing excess inventory [51, 52]. These models consider various factors, including demand variability, lead times, and storage constraints. By optimizing inventory levels, AI reduces waste, lowers costs, and ensures the availability of critical supplies. This is especially important for perishable items, such as vaccines and biologics, which require careful handling and storage. Furthermore, AI enables continuous monitoring and adjustment of inventory levels, ensuring that they remain aligned with changing demand patterns [53, 54]. This dynamic approach to inventory management enhances the overall efficiency and responsiveness of healthcare supply chains.

REAL-TIME RESPONSE SYSTEMS

4.1 Integration of IoT and AI

The integration of IoT and AI represents a significant advancement in healthcare supply chain management. IoT devices, such as sensors and tracking systems, provide real-time data on various aspects of the supply chain, including temperature, location, and environmental conditions [55-57]. AI algorithms analyze this data to identify patterns and detect anomalies. For example, in the distribution of temperature-sensitive products, IoT sensors can monitor storage conditions and transmit data to AI systems [58, 59]. If the temperature deviates from the acceptable range, the system can trigger alerts and initiate corrective actions, preventing spoilage and ensuring product quality. This integration enhances visibility and control across the supply chain, enabling organizations to respond quickly to changing conditions and maintain the integrity of their operations.

4.2 Dynamic Routing and Logistics Optimization

Transportation and logistics are critical components of healthcare supply chains, and inefficiencies in these areas can lead to delays and increased costs [60]. AI-driven dynamic routing systems optimize transportation routes in real time, taking into account factors such as traffic conditions, weather, and delivery priorities [61-63]. These systems use advanced algorithms to analyze data and identify the most efficient routes, reducing travel time and fuel consumption. In addition, they can adjust routes dynamically in response to

changing conditions, ensuring timely delivery of critical supplies. Dynamic routing is particularly important in emergency situations, where rapid delivery of medical supplies can make a significant difference in patient outcomes [64-66]. By optimizing logistics operations, AI enhances the efficiency and reliability of healthcare supply chains.

4.3 Autonomous Decision-Making

One of the most transformative aspects of AI in healthcare supply chains is its ability to enable autonomous decision-making. AI systems can analyze data, identify patterns, and make decisions without human intervention, improving efficiency and reducing the risk of errors [67, 68]. For example, AI systems can automatically reorder supplies when inventory levels fall below a certain threshold, ensuring continuous availability [69, 70]. They can also prioritize the allocation of resources based on urgency and importance, optimizing the use of limited resources. While autonomous decision-making offers significant benefits, it also raises important considerations regarding accountability and trust. Ensuring that AI systems are transparent and explainable is essential for their successful adoption in healthcare settings.

CHALLENGES AND LIMITATIONS

The effectiveness of AI systems depends on the availability of high-quality data. In healthcare, data is often fragmented across different systems and formats, making integration challenging. Ensuring data accuracy, consistency, and interoperability is essential for the successful implementation of AI. The use of AI in healthcare raises important ethical and regulatory issues, including data privacy, security, and algorithmic bias. Addressing these concerns requires the development of robust governance frameworks and adherence to regulatory standards. The complexity of AI models, particularly deep learning systems, can make them difficult to interpret. This lack of transparency can undermine trust among stakeholders. Developing explainable AI models is therefore critical for ensuring accountability and acceptance. Implementing AI systems in healthcare supply chains requires significant investment in technology, infrastructure, and human resources. In addition, organizational resistance to change can hinder adoption. Addressing these barriers is essential for realizing the full potential of AI.

FUTURE DIRECTIONS

Digital twins enable the creation of virtual replicas of supply chains, allowing organizations to simulate different scenarios and optimize operations. This technology has the potential to enhance decision-making and improve system performance. The integration of AI with blockchain technology can enhance transparency and traceability in healthcare supply chains. Blockchain provides a secure and immutable record of transactions, ensuring the integrity of supply chain data. AI enables the development of personalized supply chains tailored to individual patient needs. This approach improves efficiency and ensures that patients receive the right products at the right time. Future healthcare supply chains will likely involve close collaboration between humans and AI systems. By combining human expertise with AI capabilities, organizations can achieve better outcomes and enhance decision-making.

CONCLUSION

AI-driven optimization represents a significant advancement in healthcare supply chain management. By enabling predictive analytics and real-time response systems, AI enhances efficiency, resilience, and sustainability. The transition from prediction to real-time intelligence allows healthcare organizations to anticipate disruptions and respond dynamically to changing conditions. However, realizing the full potential of AI requires addressing challenges related to data quality, ethics, and implementation. Continued research and collaboration among stakeholders will be essential for developing robust and scalable AI solutions. Ultimately, AI has the potential to transform healthcare supply chains, improving patient outcomes and strengthening health systems worldwide.

REFERENCES

1. Dobrzykowski D. Understanding the downstream healthcare supply chain: unpacking regulatory and industry characteristics. *Journal of Supply Chain Management*. 2019 Apr;55(2):26-46.
2. Mathur B, Gupta S, Meena ML, Dangayach GS. Healthcare supply chain management: literature review and some issues. *Journal of Advances in Management Research*. 2018 Jul 25;15(3):265-87.
3. Govindan K, Mina H, Alavi B. A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (COVID-19). *Transportation research part e: logistics and transportation review*. 2020 Jun 1;138:101967.
4. Nelson ML, Sen R. Business rules management in healthcare: A lifecycle approach. *Decision Support Systems*. 2014 Jan 1;57:387-94.
5. Bam L, McLaren ZM, Coetzee E, Von Leipzig KH. Reducing stock-outs of essential tuberculosis medicines: a system dynamics modelling approach to supply chain management. *Health Policy and Planning*. 2017 Oct 1;32(8):1127-34.
6. Karamshetty V, De Vries H, Van Wassenhove LN, Dewilde S, Minnaard W, Ongarora D, Abuga K, Yadav P. Inventory management practices in private healthcare facilities in Nairobi county. *Production and Operations Management*. 2022 Feb;31(2):828-46.
7. Saddikuti V, Prakash S, Siddharth V, Jain K, Satpathy S. A prescription for efficiency: optimizing the surgical item inventory management practices in a healthcare facility. *Journal of Advances in Management Research*. 2024 Jul 4;21(3):478-506.
8. Singh H. Artificial intelligence for predictive analytics: Gaining actionable insights for better decision-making. *International Journal of Research in Electronics and Computer Engineering*. 2019;8(1).
9. Selvarajan GP. Harnessing AI-Driven Data Mining for Predictive Insights: A Framework for Enhancing Decision-Making in Dynamic Data Environments. *International Journal of Creative Research Thoughts*. 2021 Jun;9(2):5476-86.
10. Gereffi G. What does the COVID-19 pandemic teach us about global value chains? The case of medical supplies. *Journal of International Business Policy*. 2020 Jul 15;3(3):287.
11. Mekonen ZT, Fenta TG, Nadeem SP, Cho DJ. Global health commodities supply chain in the era of COVID-19 pandemic: challenges, impacts, and prospects: a systematic review. *Journal of Multidisciplinary Healthcare*. 2024 Dec 31:1523-39.
12. Bhaskar S, Tan J, Bogers ML, Minssen T, Badaruddin H, Israeli-Korn S, Chesbrough H. At the epicenter of COVID-19—the tragic failure of the global supply chain for medical supplies. *Frontiers in public health*. 2020 Nov 24;8:562882.
13. Kumar KP, Swarubini PJ, Ganapathy N. Cognitive artificial intelligence. In *Artificial intelligence and biological sciences 2025* Mar (pp. 301-323). CRC Press.
14. Siemens G, Marmolejo-Ramos F, Gabriel F, Medeiros K, Marrone R, Joksimovic S, De Laat M. Human and artificial cognition. *Computers and Education: Artificial Intelligence*. 2022 Jan 1;3:100107.
15. Zohdi M, Rafiee M, Kayvanfar V, Salamiraad A. Demand forecasting based machine learning algorithms on customer information: an applied approach. *International Journal of Information Technology*. 2022 Jun;14(4):1937-47.
16. Carbonneau R, Laframboise K, Vahidov R. Application of machine learning techniques for supply chain demand forecasting. *European journal of operational research*. 2008 Feb 1;184(3):1140-54.
17. Usmani UA, Haponen A, Watada J. A review of unsupervised machine learning frameworks for anomaly detection in industrial applications. In *Science and information conference 2022* Jul 7 (pp. 158-189). Cham: Springer International Publishing.
18. Choi WH, Kim J. Unsupervised learning approach for anomaly detection in industrial control systems. *Applied System Innovation*. 2024 Feb 21;7(2):18.
19. Meyer G, Adomavicius G, Johnson PE, Elidrisi M, Rush WA, Sperl-Hillen JM, O'Connor PJ. A machine learning approach to improving dynamic decision making. *Information systems research*. 2014 Jun;25(2):239-63.
20. Padakandla S. A survey of reinforcement learning algorithms for dynamically varying environments. *ACM Computing Surveys (CSUR)*. 2021 Jul 13;54(6):1-25.
21. Mishra S. A reinforcement learning approach for training complex decision making models. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*. 2022 Oct 30;

- 3(3):82-92.
22. Akande SA, Enyejo JO. Leveraging predictive analytics to improve demand forecasting and inventory management in healthcare supply chains. *International Journal of Scientific Research in Science, Engineering and Technology*. 2024 Mar;11(2).
 23. Oluwole O, Emmanuel E, Ogbuagu OO, Alemede V, Adefolaju I. Pharmaceutical supply chain optimization through predictive analytics and value-based healthcare economics frameworks. *International Journal of Engineering Technology Research & Management*. 2024;8(2):88-104.
 24. Inam SA. A review of artificial intelligence for predicting climate driven infectious disease outbreaks to enhance global health resilience. *Discover Public Health*. 2025 Nov 23;22(1):738.
 25. Ekundayo F. Using machine learning to predict disease outbreaks and enhance public health surveillance. *World J Adv Res Rev*. 2024;24(3):794-811.
 26. Ogwu MC, Izah SC. Technologies for predictive modeling of tropical diseases. In *Technological Innovations for Managing Tropical Diseases 2025 Feb 20* (pp. 109-130). Cham: Springer Nature Switzerland.
 27. Adegoke BO, Odugbose T, Adeyemi C. Data analytics for predicting disease outbreaks: A review of models and tools. *International journal of life science research updates [online]*. 2024;2(2):1-9.
 28. Desai AN, Kraemer MU, Bhatia S, Cori A, Nouvellet P, Herringer M, Cohn EL, Carrion M, Brownstein JS, Madoff LC, Lassmann B. Real-time epidemic forecasting: challenges and opportunities. *Health security*. 2019 Aug 1;17(4):268-75.
 29. Modupe OT, Otitoola AA, Oladapo OJ, Abiona OO, Oyeniran OC, Adewusi AO, Komolafe AM, Obijuru A. Reviewing the transformational impact of edge computing on real-time data processing and analytics. *Computer Science & IT Research Journal*. 2024 Mar;5(3):693-702.
 30. Ficili I, Giacobbe M, Tricomi G, Puliafito A. From sensors to data intelligence: Leveraging IoT, cloud, and edge computing with AI. *Sensors*. 2025 Mar 12;25(6):1763.
 31. Gudala L, Shaik M, Venkataramanan S, Sadhu AK. Leveraging artificial intelligence for enhanced threat detection, response, and anomaly identification in resource-constrained iot networks. *Distributed Learning and Broad Applications in Scientific Research*. 2019 Jul 5;5:23-54.
 32. Ghouri A. Real Time Data Analytics with AI: Improving Security Event Monitoring and Management. *Unique Journal of Artificial Intelligence*. 2026 Jan 16;4(1):99-110.
 33. Subramanian L. Effective demand forecasting in health supply chains: emerging trend, enablers, and blockers. *Logistics*. 2021 Feb 28;5(1):12.
 34. Islam S, Habib MM. Integrating forecasting & planning management for sustainable hospital supply chains and societal advancement. *International Journal of Supply Chain Management*. 2024;12(4):34-41.
 35. Niaz M, Nwagwu U. Managing healthcare product demand effectively in the post-COVID-19 environment: Navigating demand variability and forecasting complexities. *American Journal of Economic and Management Business (AJEMB)*. 2023 Sep 26;2(8):316-30.
 36. Tadayonrad Y, Ndiaye AB. A new key performance indicator model for demand forecasting in inventory management considering supply chain reliability and seasonality. *Supply chain analytics*. 2023 Sep 1;3:100026.
 37. Niaz M, Nwagwu U. Managing healthcare product demand effectively in the post-COVID-19 environment: Navigating demand variability and forecasting complexities. *American Journal of Economic and Management Business (AJEMB)*. 2023 Sep 26;2(8):316-30.
 38. Levine R, Pickett J, Sekhri N, Yadav P. Demand forecasting for essential medical technologies. *American journal of law & medicine*. 2008 Jun;34(2-3):225-55.
 39. Khan MI, Lama R, Islam KS, Karim MR, Tamang B. AI-Driven Risk Management & Optimization in Healthcare Supply Chain: A Machine Learning Approach. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*. 2025;8(02):149-60.
 40. Kumar V, Goodarzian F, Ghasemi P, Chan FT, Gupta N. Artificial intelligence applications in healthcare supply chain networks under disaster conditions. *International Journal of Production Research*. 2025 Jan 17;63(2):395-403.
 41. Krykavskyy Y, Shandrivska O, Pawłyszyn I. A study of macroeconomic and geopolitical influences and security risks in supply chains in times of disruptions. *LogForum*. 2023;19(3).
 42. Byrapu SR. Supply chain risk management. *J. Algebr. Stat*. 2023 Jan 30;14:150-5.

43. Giudici P, Centurelli M, Turchetta S. Artificial Intelligence risk measurement. *Expert Systems with Applications*. 2024 Jan 1;235:121220.
44. Tian T, Jia S, Lin J, Huang Z, Wang KO, Tang Y. Enhancing industrial management through AI integration: A comprehensive review of risk assessment, machine learning applications, and data-driven strategies. *Economics & Management Information*. 2024 Nov 11:1-8.
45. Chowdhury AR. A systematic review of risk-based procurement strategies in retail supply chains: Sourcing flexibility and vendor disruption management. *American Journal of Advanced Technology and Engineering Solutions*. 2025 Apr 17;1(01):466-505.
46. Goldschmidt K, Kremer M, Thomas DJ, Craighead CW. Strategic sourcing under severe disruption risk: Learning failures and under-diversification bias. *Manufacturing & Service Operations Management*. 2021 Jul;23(4):761-80.
47. Yoon J, Talluri S, Yildiz H, Ho W. Models for supplier selection and risk mitigation: a holistic approach. *International journal of production research*. 2018 May 19;56(10):3636-61.
48. Leaven L, Ahmmad K, Peebles D. Inventory management applications for healthcare supply chains. *International Journal of Supply Chain Management*. 2017 Sep 30;6(3):1-7.
49. Essila JC. Strategies for reducing healthcare supply chain inventory costs. *Benchmarking: An International Journal*. 2023 Nov 22;30(8):2655-69.
50. Azizi S, Yoltay DN, Kundakcioglu OE. Inventory Management for Medical Supplies. In *Encyclopedia of Optimization 2024* May 24 (pp. 1-10). Cham: Springer Nature Switzerland.
51. Farooq A, Abbey AB, Onukwulu EC. Inventory optimization and sustainability in retail: A conceptual approach to data-driven resource management. *International Journal of Multidisciplinary Research and Growth Evaluation*. 2024 Nov;5(6):1356-63.
52. Amosu OR, Kumar P, Ogunsuji YM, Oni S, Faworaja O. AI-driven demand forecasting: Enhancing inventory management and customer satisfaction. *World Journal of Advanced Research and Reviews*. 2024 Aug 8;23(2):100-10.
53. Nweje U, Taiwo M. Leveraging Artificial Intelligence for predictive supply chain management, focus on how AI-driven tools are revolutionizing demand forecasting and inventory optimization. *International Journal of Science and Research Archive*. 2025 Jan 30;14(1):230-50.
54. Sajja GS, Addula SR, Meesala MK, Ravipati P. Optimizing inventory management through AI-driven demand forecasting for improved supply chain responsiveness and accuracy. In *AIP conference proceedings 2025* Jun 5 (Vol. 3306, No. 1, p. 050003). AIP Publishing LLC.
55. da Costa TP, Gillespie J, Cama-Moncunill X, Ward S, Condell J, Ramanathan R, Murphy F. A systematic review of real-time monitoring technologies and its potential application to reduce food loss and waste: Key elements of food supply chains and IoT technologies. *Sustainability*. 2022 Dec 29;15(1):614.
56. Bhutta MN, Ahmad M. Secure identification, traceability and real-time tracking of agricultural food supply during transportation using internet of things. *Ieee Access*. 2021 Apr 28;9:65660-75.
57. Tsang YP, Choy KL, Wu CH, Ho GT, Lam CH, Koo PS. An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks. *Industrial Management & Data Systems*. 2018 Sep 28;118(7):1432-62.
58. Pajic V, Andrejic M, Chatterjee P. Enhancing cold chain logistics: A framework for advanced temperature monitoring in transportation and storage. *Mechatron. Intell Transp. Syst*. 2024 Jan;3(1):16-30.
59. Müller WA, Ferreira SB, Botelho da Silva S. Enhancing food safety in the cold chain through internet of things and artificial intelligence. *Journal of Food Science*. 2026 Feb;91(2):e70871.
60. Ageron B, Benzidia S, Bournakis M. Healthcare logistics and supply chain—issues and future challenges. In *Supply Chain Forum: An International Journal* 2018 Jan 2 (Vol. 19, No. 1, pp. 1-3). Taylor & Francis.
61. Veluru CS. A comprehensive study on optimizing delivery routes through generative AI using real-time traffic and environmental data. *Journal of Scientific and Engineering Research*. 2023;10(10):168-75.
62. Mohsen BM. AI-driven optimization of urban logistics in smart cities: Integrating autonomous vehicles and IoT for efficient delivery systems. *Sustainability*. 2024 Dec 22;16(24):11265.
63. Hussain KM. Revolutionizing Route Optimization Systems with Artificial Intelligence for a Smarter, Sustainable Logistics Ecosystem. *International Journal of Computer Science and Mobile Computing*. 2025 Feb;14(2).

64. Créput JC, Hajjam A, Koukam A, Kuhn O. Dynamic vehicle routing problem for medical emergency management. Self organizing maps-applications and novel algorithm design. 2011 Jan 21:233-50.
65. Yazdani M, Shahriari S, Haghani M. Real-time decision support model for logistics of emergency patient transfers from hospitals via an integrated optimisation and machine learning approach. Progress in Disaster Science. 2025 Jan 1;25:100397.
66. Mills AF, Argon NT, Ziya S. Dynamic distribution of patients to medical facilities in the aftermath of a disaster. Operations Research. 2018 Jun;66(3):716-32.
67. Baurasien BK, Alareefi HS, Almutairi DB, Alanazi MM, Alhasson AH, Alshahrani AD, Almansour SA, Alshagag ZA, Alqattan KM, Alotaibi HM. Medical errors and patient safety: Strategies for reducing errors using artificial intelligence. International journal of health sciences. 2023 Jan;7(S1):3471-87.
68. Verma A, Singhal N. Integrating artificial intelligence for adaptive Decision-Making in complex system. In International Conference on Advances in Data-driven Computing and Intelligent Systems 2023 Sep 21 (pp. 95-105). Singapore: Springer Nature Singapore.
69. Bhavikatta NB. AI-Driven inventory optimization in supply chains: A comprehensive review on reducing stockouts and mitigating overstock risks. Journal of Computer Science and Technology Studies. 2025 Jun 30;7(7):01-13.
70. Devabhaktuni R. Trustworthy AI Framework for Intelligent Warehouse Automation and Predictive Inventory Management. International Journal of Artificial Intelligence and Expert Systems (IJAE). 2025 Dec 1;14(3):50-62.