Volume 2, Issue 3, pp 1-13
Article history:
Received 25 April 2025
Revised 02 July 2025
Accepted 10 July 2025
Published online 10 September 2025

Article type:
Original Research

How to cite this article:
Maleki, M. H., Nasrollahi, M., & Mohammadi, Z. (2025). Identifying and Prioritizing Drivers Affecting the Future of the Healthcare Supply Chain with a Focus on Fourth-Generation Technologies. Foresight and Health Governance, 2(3), 1-13. https://doi.org/10.61838/jfhg.21

Identifying and Prioritizing Drivers Affecting the Future of the Healthcare Supply Chain with a Focus on Fourth-Generation Technologies

Mohammad Hasan. Maleki [1], Mahdi. Nasrollahi [2*], Zahra Mohammadi [3]

1 Professor of Management, University of Qom, Qom, Iran
2 Associate Professor of Management
3 Ms.C. of Business Management, University of Qom, Qom, Iran

Corresponding author email address: m.nasrollahi@soc.ikiu.ac.ir

ABSTRACT

This study aimed to identify and prioritize the key drivers influencing the future of the healthcare supply chain, focusing on the transformative role of fourth-generation (Industry 4.0) technologies. This applied research adopted a multi-method quantitative design integrating the fuzzy Delphi technique, fuzzy hesitant analytic hierarchy process (F-HAHP), and the MARCOS method. Twenty-five potential drivers were initially extracted through a systematic literature review and expert interviews. These drivers were validated for content using Lawshe's CVR and screened via fuzzy Delphi to eliminate low-relevance items, retaining nine drivers with defuzzified scores above 0.7. Ten experts in healthcare supply chains, futures studies, and Industry 4.0 participated through judgmental sampling. Drivers were subsequently weighted using F-HAHP and prioritized using the MARCOS method based on three criteria: expert expertise, importance intensity, and certainty. The analysis revealed that the most influential future drivers include: developing intelligent decision-support systems for logistics management and medical supplies (score = 0.856), applying artificial intelligence to predict drug demand and optimize the medical equipment supply process (0.799), using big data technology to analyze drug consumption patterns and predict health crises (0.755), employing smart contracts to streamline procurement, purchasing, and payment processes in the healthcare industry (0.699), and combating fraud in distributed medicines through blockchain technology and authenticity verification (0.584). These top-ranked drivers outperformed others such as integrating IoT-enabled medical devices, expanding cloud computing, increasing automated robotic systems, and using blockchain for counterfeiting prevention. The study highlights that deploying advanced Industry 4.0 technologies—particularly AI, big data, smart contracts, and blockchain—will be critical to building resilient, transparent, and efficient healthcare supply chains. Prioritizing these drivers can guide policymakers and healthcare organizations toward strategic investments, enabling proactive crisis response, cost reduction, improved decision-making, and secure supply chain operations.

Keywords: Healthcare supply chain; Fourth-generation technologies; Industry 4.0; Fuzzy Delphi; MARCOS; Artificial intelligence; Big data; Blockchain; Smart contracts.

Introduction

Health systems constitute a complex web of organizations, individuals, and activities primarily focused on promoting, restoring, or delivering health services, ranging from high-level institutional interventions to basic caregiving by family members (World Health Organization, 2007). These systems are supported by the healthcare supply chain, which serves as the backbone for the delivery of medical products, devices, and pharmaceuticals to end users. The strength of a health system is closely tied to the effectiveness and resilience of its supply chain, which must ensure the right products reach the right place at the right time (White, 2015). Within this intricate network, the concept of digital transformation and the integration of fourth-generation (Industry 4.0) technologies have emerged as transformative forces poised to reshape the future of healthcare supply chain management (HSCM).

The healthcare supply chain differs from typical industrial supply chains because it must balance efficiency and cost-effectiveness with patient safety, service reliability, and regulatory compliance (Dixit et al., 2019). This supply chain encompasses diverse stakeholders, including manufacturers, distributors, purchasers, caregivers, and payers (Kritchanchai, 2014; Mathew et al., 2013; Noorfa Haszlinna & Potter, 2009). These actors operate in an environment marked by complexity, unpredictability, and high stakes. The COVID-19 pandemic exposed critical vulnerabilities in this network, revealing deficiencies in coordination, demand forecasting, and resource allocation (Choi, 2020; Krammer, 2021; Zanni, 2020). Disruptions in sourcing raw materials, logistical bottlenecks, and workforce shortages intensified mismatches between supply and demand, often resulting in delayed access to essential medicines and medical devices.

In response, scholars and practitioners are increasingly advocating for digital transformation and the adoption of Industry 4.0 technologies to enhance the performance, transparency, and resilience of healthcare supply chains (Avinash & Joseph, 2024; Golinelli et al., 2020). Industry 4.0 represents the convergence of cyber-physical systems, automation, and data-driven intelligence, integrating technologies such as artificial intelligence (AI), blockchain, big data analytics, the Internet of Things (IoT), robotics, and cloud computing (Alexander, 2021; George, 2024; Gorecki et al., 2021). These technologies enable real-time tracking of medical goods, predictive analytics for demand planning, and automation of logistical operations, thereby improving accuracy, speed, and cost-efficiency (Ala et al., 2024; Bag et al., 2023; Manavalan & Jayakrishna, 2019).

AI-based solutions in particular have shown promise for forecasting drug demand, optimizing procurement cycles, and improving warehouse management, which in turn reduces shortages and excess inventory (Adhikari et al., 2023; Iftikhar & Jamil, 2025). Machine learning models can analyze prescription data, patient records, and epidemiological trends to anticipate consumption patterns, while natural language processing can extract insights from unstructured medical data to inform decision-making (Omidian, 2024). These capabilities facilitate data-driven planning, enabling healthcare providers to proactively respond to shifts in demand and mitigate disruptions (Dada et al., 2025; Kumar et al., 2024). In parallel, blockchain technology offers tamper-proof data sharing, authentication of pharmaceuticals, and transparent financial transactions, addressing long-standing issues of counterfeiting, fraud, and lack of traceability (Bak et al., 2023; Jayaraman et al., 2019).

Automation technologies further complement these advances by streamlining repetitive and labor-intensive tasks. Robotic process automation (RPA) can execute routine procurement and inventory operations, while autonomous robots and drones can expedite the delivery of medical supplies, particularly in remote areas (Saiya et al., 2022). RFID and NFC technologies improve inventory visibility, reducing human error and enhancing medication safety in hospital settings (Lahtela et al., 2008). The growing use of digital twins—virtual replicas of physical systems—also enables scenario testing and optimization of supply chain processes in real time, enhancing operational resilience (Sharma et al., 2025; Smart et al., 2025).

The urgency for these transformations is underscored by the environmental volatility facing healthcare systems. The COVID-19 crisis revealed that resilience—defined as the ability to anticipate, absorb, adapt, and recover from disruptions—has become a critical performance criterion (Tortorella et al., 2024). Industry 4.0 technologies can strengthen resilience by enabling real-time monitoring, rapid reconfiguration of logistics networks, and decentralized decision-making (Chatterjee et al., 2023). However, their adoption is not without challenges: concerns over cybersecurity, data privacy, interoperability, cost, and workforce readiness often hinder implementation (Bak, 2016; Seifi et al., 2025). Addressing these challenges requires coordinated policy frameworks, investment in digital infrastructure, and capacity-building among healthcare personnel (Goel et al., 2024; Nazarian-Jashnabadi et al., 2024).

Scholars have begun to examine structured approaches to navigating this transformation. For instance, Umoren et al. (Umoren et al., 2025) developed an analytical framework linking digital transformation initiatives to performance outcomes using the Supply Chain Operations Reference (SCOR) model, highlighting how digital tools improve access, affordability, and accountability. Similarly, Maleki et al. (Maleki et al., 2024) emphasized the importance of multi-criteria decision-making models to prioritize strategic interventions within complex healthcare systems. Integrating these approaches can help decision-makers target high-impact technologies while balancing cost, feasibility, and risk.

Despite these advancements, the healthcare industry still lags behind other sectors in embracing full-scale digitalization (Golinelli et al., 2020). Unlike manufacturing or automotive industries, where Industry 4.0 has significantly reshaped operations, many healthcare systems remain reliant on fragmented, manual processes (Alexander, 2021). This gap reflects both cultural resistance to change and the sector's high stakes, where errors can directly endanger lives. Yet, as evidence mounts on the benefits of smart technologies—from improved efficiency and traceability to reduced costs and enhanced patient safety—the case for their adoption grows stronger (Avinash & Joseph, 2024; Haseli et al., 2021).

Overall, the convergence of Industry 4.0 technologies offers an unprecedented opportunity to revolutionize healthcare supply chains. By embedding AI, blockchain, IoT, and big data analytics into core operations, healthcare systems can transition from reactive, fragmented networks to proactive, intelligent ecosystems. This study therefore seeks to identify and prioritize the key drivers that will shape the future of the healthcare supply chain under the influence of fourth-generation technologies, providing a strategic roadmap to guide policy makers, industry leaders, and healthcare organizations toward more resilient, transparent, and efficient systems.

Methods and Materials

The main purpose of the present study is to identify and evaluate the drivers affecting the future of the health supply chain with a focus on fourth-generation technologies. For this reason, fuzzy Delphi, fuzzy hesitant analytic hierarchy process, and Marcos techniques were used to evaluate the drivers of the future of the health supply chain with a focus on fourth-generation technologies. All three are quantitative methods and use quantitative judgmental data for evaluation and analysis. The fuzzy Delphi method was used to sifting the drivers, and the Marcos method was used to evaluate and prioritize the drivers. The weight of the research driver evaluation indicators was also obtained with the fuzzy hesitating AHP method. Given the quantitative nature of the methods used in the study, the current study has a multiple quantitative methodology. Also, due to the benefits of the research outputs for the health sector and its supply chain, the study has an applied orientation.

To collect data, two tools were used: structured interviews and questionnaire. The research drivers were extracted from a review of researches that were related to the health supply chain, fourth-generation technologies, and futures studies. Then, to analyze the research drivers, three questionnaires were distributed among the experts: screening, paired comparison, and Marcos prioritization. The expert questionnaires were evaluated with the Fuzzy Delphi technique; the paired comparison questionnaires with the Hesitant Fuzzy AHP; and the priority measurement questionnaires with the Marcos technique.

Due to the future drivers of the health supply chain being obtained from a review of reputable articles in the fields of futures studies, fourth-generation technologies, and health supply chain, and interviews with health supply chain experts, the research questionnaires have appropriate validity. In addition, the Lawshe content validity index was used to measure the validity of the research questionnaires. The value of this index was higher than 0. 79 for all drivers, indicating the desirable validity of the research questionnaires.

The current research experts were experts in futures studies and 4th generation technologies in the health sector. The research sampling method was judgmental, and the samples were selected based on their expertise in the fields of health supply chain, 4th generation technologies, and futures studies. The sample size in this study was 10 people.

The present study was conducted in six steps. In the first step, the future drivers of the healthcare supply chain were obtained by focusing on fourth-generation technologies through a review of the literature and interviews with experts in futures studies and fourth-generation technologies. In the next step, these drivers were screened using the fuzzy Delphi method. Finally, by combining the two methods, Marcos and fuzzy hesitant AHP, the priority degree of the drivers was determined.

In the current study, the fuzzy Delphi technique was used to screen future drivers of the healthcare supply chain, focusing on fourth-generation technologies. In the fuzzy Delphi method algorithm for screening, a suitable fuzzy spectrum must first be developed to fuzzify the linguistic expressions of the experts. In this regard, common fuzzy spectra can be used. In the current study, a five-point Likert spectrum was used, which is shown in Table 1.

Table 1. Spectrum of the Fuzzy Delphi Method

Verbal variable	Fuzzy value	Triangular fuzzy number
Very low	$\tilde{1}$	(0.025 ,0 ,0)
Low	$\tilde{2}$	(0.50, 0.25 ,0)
Medium	$\tilde{3}$	(0.75 , 0.50,0.25)
High	$\tilde{4}$	(1.00 , 0.75 , 0.50)
Very high	$\tilde{5}$	(1.00 ,1.00 , 0.75)

The Marcos method is one of the new multi-criteria decision-making methods, which means evaluating and prioritizing options based on a compromise solution. In the current study, the Marcos technique was used to rank the future drivers of the health supply chain, focusing on fourth-generation technologies. The indicators for evaluating the research drivers were extracted from the global business network approach, which is a valid and classic method in futures research. The indicators for evaluating the drivers in the current study are: the expertise of experts, the importance of each driver, and the degree of certainty of each driver. The indicators for the expertise of experts and the importance of each driver are positive and increasing in nature, while the certainty index is negative and decreasing in nature. In short, the greater the expertise of experts on a driver and its importance, and the lower its certainty, the more desirable the driver is for scenario planning.

The steps of the MARCOS method are:

Step 1: Creating a decision matrix: During this phase, specialists provided their insights regarding the significance of each research driver based on the indicators, rating them on a scale from 1 to 10. The outcome of this process is the decision matrix. Ultimately, the experts' evaluations were combined through the use of the arithmetic mean

Step 2: Determining Ideal and Anti-Ideal Options: In this section, the values of ideal and anti-ideal options are determined based on the following formulas.

$$AI = \max_{i} x_{ij} \quad if\ j \in B \quad and\ \min_{i} x_{ij}\ if\ j \in C$$

$$AAI = \min_{i} x_{ij} \quad if\ j \in B \quad and\ \max_{i} x_{ij}\ if\ j \in C$$

Step 3: Normalization: In this section, the data in the combined matrix is normalized using the following formulas. Normalization is done in a linear manner, and the normalization method will be distinct for positive and negative indices.

$$n_{ij} = \frac{x_{aj}}{x_{ij}} \quad if \;\; j \in C$$

$$n_{ij} = \frac{x_{ij}}{x_{aj}} \quad if \;\; j \in B$$

Step 4: Formation of the weighted normal matrix: The weighted normal matrix is calculated by multiplying the normal matrix by the weights of the indicators. In this study, the weights of the indicators were obtained using fuzzy hierarchical hesitating analysis.

Step 5: Calculate the degree of desirability of the options (here, the drivers): In this section, the ideal and anti-ideal desirability of the options is determined based on the following relationships.

$$K_i^+ = \frac{S_i}{S_{ai}}$$

$$K_i^- = \frac{S_i}{S_{aai}}$$

Step 6: Determining the Final Performance and Ranking the Options: In this section, the desired performance of each option is determined using the following formula**.**

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}}$$

Findings and Results

The drivers influencing the future of the healthcare supply chain, with an emphasis on fourth-generation technologies, were identified through an analytical review of the literature and interviews with healthcare experts. Initially, scholarly articles related to fourth-generation technologies and futures studies published in reputable databases between 2010 and 2025 were reviewed.

The primary search keywords used in this study were: *health supply chain*, *future of supply chain*, and *fourth-generation technologies*.

The retrieved articles were first screened by title and abstract, and then evaluated using the Critical Appraisal Skills Programme (CASP) checklist. In total, 96 articles were initially extracted from reputable databases. After evaluating their quality and excluding low-quality studies, the remaining articles were selected for final review. In addition to the literature review, interviews were conducted with seven experts in healthcare supply chains, and these interviews were analyzed using thematic analysis.

Table 2. Future drivers of the healthcare supply chain with a focus on fourth-generation technologies

Research drivers	Research resources	Content Validity Index
Application of artificial intelligence in predicting drug demand and optimizing the medical equipment supply process	Dada et al. (2025)	0.85
Applying machine learning to analyze health data and improve distribution and supply processes	Omidian (2024)	0.82
Employing natural language processing technology to analyze medical data for enhanced decision-making within the supply chain	Interview	0.81
Developing intelligent decision support systems for logistics management and medical supplies	Manavalan & Jayakrishna (2019)	0.84

Creating automatic systems for diagnosing and preventing medical equipment failures using artificial intelligence	Interview	0.83
Expanding advanced sensors to monitor the status of medicines and medical devices throughout the supply chain	Interview	0.81
Improving cold chain management with the help of IoT to control the temperature of vaccines and sensitive drugs	Interview	0.82
Using RFID and NFC technologies to track and authenticate pharmaceutical products and medical equipment	Lahtela et al. (2008)	0.81
Integrating internet-connected medical devices to monitor patient health and automatically adjust drug supply	Ahsan & Siddique (2022)	0.86
Creating smart hospitals with the ability to exchange data between medical equipment and supply systems	Massaro (2021)	0.83
Using blockchain to increase transparency and prevent counterfeiting in the pharmaceutical supply chain	Bak et al. (2023)	0.87
Using smart contracts to facilitate procurement, purchasing, and payment processes in the healthcare industry	Adhikari et al. (2023)	0.88
Creating blockchain-based platforms for secure sharing of medical information between healthcare facilities and providers	Bak et al. (2023)	0.81
Combating fraud in distributed medicines through blockchain technology and recording product authenticity information	Ahsan & Siddique (2022)	0.84
Setting up immutable medical data storage systems to increase patient security and privacy	Bak et al. (2023)	0.82
Increasing use of automated robots to manage and move goods in pharmaceutical warehouses and hospitals	Saiya et al. (2022)	0.86
Expanding robotic surgeries and advanced equipment to improve precision in medical treatments	Interview	0.81
Automating pharmaceutical production and packaging processes to reduce costs and increase quality	Dada et al. (2025)	0.82
Using drones and autonomous vehicles to speed up the delivery of medicine and equipment to remote locations	Adhikari et al. (2023)	0.81
Creating laboratories equipped with smart and automated systems for faster processing of medical tests	Smart et al. (2025)	0.83
Expanding the use of cloud computing for supply chain data management and medical information processing	Ahsan & Siddique (2022)	0.85
Creating digital simulation models to predict and optimize supply processes in the health sector	Umoren et al. (2025)	0.82
Using big data technology to analyze drug consumption patterns and predict health crises	Ahsan & Siddique (2022)	0.88
Using 3D printing to produce customized medical devices and create personalized implants	Massaro (2021)	0.84
Increasing the use of augmented reality and virtual reality technologies for medical education and managing complex treatments	Sharma et al. (2025)	0.83

The 25 drivers identified from the literature review and expert interviews on fourth-generation technologies were subsequently screened using the fuzzy Delphi method. Methods such as MARCOS are highly sensitive to the inclusion of numerous factors. At this stage, 16 drivers were excluded from further analysis, and 9 drivers were retained for final prioritization. Drivers with a defuzzified score above 0.7 were considered eligible for prioritization using the MARCOS method. In this study, nine drivers surpassed this threshold. While most studies adopt a threshold value between 0.5 and 0.7, the present study used 0.7 as the cutoff point for screening and evaluating the drivers. Table 3 presents the list of drivers affecting the future of the healthcare supply chain with a focus on fourth-generation technologies, along with their defuzzified scores.

Table 3. Defuzzified Scores of Healthcare Supply Chain Drivers

Drivers	Lower Limit	Median	Upper Limit	Defuzzified Score
Application of artificial intelligence in predicting drug demand and optimizing the medical equipment supply process	0.71	0.78	0.86	0.78
Applying machine learning to analyze health data and improve distribution and supply processes	0.44	0.51	0.57	0.51
Employing natural language processing technology to analyze medical data and enhance decision-making within the supply chain	0.46	0.57	0.64	0.56
Developing intelligent decision support systems for logistics management and medical supplies	0.74	0.88	0.95	0.86
Creating automatic systems for diagnosing and preventing medical equipment failures using artificial intelligence	0.45	0.56	0.62	0.54
Expanding advanced sensors to monitor the status of medicines and medical devices throughout the supply chain	0.40	0.48	0.57	0.48
Improving cold chain management with the help of IoT to control the temperature of vaccines and sensitive drugs	0.51	0.60	0.66	0.59
Using RFID and NFC technologies to track and authenticate pharmaceutical products and medical equipment	0.46	0.55	0.63	0.55
Integrating internet-connected medical devices to monitor patient health and automatically adjust drug supply	0.74	0.83	0.94	0.84
Creating smart hospitals with the ability to exchange data between medical equipment and supply systems	0.52	0.60	0.66	0.59
Using blockchain to increase transparency and prevent counterfeiting in the pharmaceutical supply chain	0.75	0.88	0.93	0.85
Using smart contracts to facilitate procurement, purchasing, and payment processes in the healthcare industry	0.76	0.85	0.96	0.86
Creating blockchain-based platforms for secure sharing of medical information between healthcare facilities and providers	0.42	0.49	0.54	0.48

Combating fraud in distributed medicines through blockchain technology and recording product authenticity information	0.71	0.80	0.87	0.79
Setting up immutable medical data storage systems to increase patient security and privacy	0.52	0.61	0.68	0.60
Increasing the use of automated robots to manage and move goods in pharmaceutical warehouses and hospitals	0.73	0.84	0.92	0.83
Expanding robotic surgeries and advanced equipment to improve precision in medical treatments	0.41	0.49	0.54	0.48
Automating pharmaceutical production and packaging processes to reduce costs and increase quality	0.40	0.47	0.56	0.48
Using drones and autonomous vehicles to speed up the delivery of medicine and equipment to remote locations	0.45	0.52	0.60	0.52
Creating laboratories equipped with smart and automated systems for faster processing of medical tests	0.38	0.44	0.56	0.46
Expanding the use of cloud computing for supply chain data management and medical information processing	0.73	0.85	0.93	0.84
Creating digital simulation models to predict and optimize supply processes in the health sector	0.37	0.45	0.53	0.45
Using big data technology to analyze drug consumption patterns and predict health crises	0.74	0.86	0.92	0.84
Using 3D printing to produce customized medical devices and create personalized implants	0.46	0.55	0.61	0.54
Increasing the use of augmented reality and virtual reality technologies for medical education and managing complex treatments	0.43	0.50	0.58	0.50

After screening the 25 identified drivers, the nine with defuzzified scores greater than 0.7 were selected for further prioritization using the MARCOS method. This approach required collecting expert evaluations on each driver using a 10-point scale based on three indicators: expertise of experts, importance intensity, and degree of certainty.

The collected ratings were aggregated using the arithmetic mean formula to construct a combined decision matrix. The values in this matrix were normalized using the linear normalization method, and a weighted normalized matrix was obtained by multiplying the normalized values by the indicator weights. The indicator weights were derived through the fuzzy analytic hierarchy process (F-AHP).

Table 4. Weights of Driver Evaluation Indicators

Normalized Definite Weight	Definite Weight	Fuzzy Weight	Indicator
0.23	0.21	[0.09, 0.17, 0.25, 0.33]	Expertise of experts
0.21	0.19	[0.09, 0.15, 0.21, 0.28]	Importance intensity
0.56	0.50	[0.34, 0.43, 0.56, 0.64]	Degree of certainty

Table 5 presents the data from the weighted normalized matrix. The final column shows the row sum for each driver. Among the three indicators, expert expertise and importance intensity are positive and increasing indicators, while degree of certainty is considered a decreasing indicator. In other words, the lower the certainty associated with a driver, the more suitable and desirable it is for future research and foresight studies.

Table 5. Weighted Normal Matrix

Weight of Indicators	0.23	0.21	0.56	—
Research Drivers	Expertise of Experts	Importance Intensity	Degree of Certainty	Si
Application of artificial intelligence in predicting drug demand and optimizing the medical equipment supply process	0.219	0.210	0.497	0.926
Developing intelligent decision support systems for logistics management and medical supplies	0.230	0.202	0.560	0.992
Integrating internet-connected medical devices to monitor patient health and automatically adjust drug supply	0.150	0.131	0.346	0.627
Using blockchain to increase transparency and prevent counterfeiting in the pharmaceutical supply chain	0.124	0.106	0.306	0.536
Utilizing smart contracts to facilitate procurement, purchasing, and payment processes in the healthcare industry	0.198	0.194	0.418	0.810
Combating fraud in distributed medicines through blockchain technology and recording product authenticity information	0.193	0.148	0.335	0.676
Increasing the use of automated robots to manage and move goods in pharmaceutical warehouses and hospitals	0.121	0.087	0.277	0.485
Expanding the use of cloud computing for supply chain data management and medical information processing	0.127	0.095	0.301	0.523
Using big data technology to analyze drug consumption patterns and predict health crises	0.187	0.191	0.497	0.875
Ideal option	0.230	0.210	0.560	1.000
Anti-ideal option	0.121	0.087	0.277	0.485

Based on the weighted normal matrix data, the ideal and anti-ideal desirability of the drivers, the overall performance of each driver, and their priority rankings were determined. The last column represents the row sum of the weighted normal matrix values.

Table 6. Scores and Priority of Future Healthcare Supply Chain Drivers

Research Drivers	Ki+	Ki-	f(Ki+)	f(Ki-)	f(Ki)
Application of artificial intelligence in predicting drug demand and optimizing the medical equipment supply process	0.926	1.909	0.673369	0.326631	0.799
Developing intelligent decision support systems for logistics management and medical supplies	0.992	2.045	0.673362	0.326638	0.856
Integrating internet-connected medical devices to monitor patient health and automatically adjust drug supply	0.627	1.293	0.673438	0.326563	0.541
Using blockchain to increase transparency and prevent counterfeiting in the pharmaceutical supply chain	0.536	1.105	0.673370	0.326630	0.463
Utilizing smart contracts to facilitate procurement, purchasing, and payment processes in the healthcare industry	0.810	1.670	0.673387	0.326613	0.699
Combating fraud in distributed medicines through blockchain technology and recording product authenticity information	0.676	1.394	0.673430	0.326570	0.584
Increasing the use of automated robots to manage and move goods in pharmaceutical warehouses and hospitals	0.485	1.000	0.673401	0.326599	0.419
Expanding the use of cloud computing for supply chain data management and medical information processing	0.523	1.078	0.673329	0.326671	0.451
Using big data technology to analyze drug consumption patterns and predict health crises	0.875	1.804	0.673386	0.326614	0.755

According to the scores of the drivers shown in Table 6, the top-priority drivers were identified as:

- Developing intelligent decision-support systems for logistics management and medical supplies.
- Applying artificial intelligence to predict drug demand and optimize the medical equipment supply process.
- Using big data technology to analyze drug consumption patterns and predict health crises.
- Utilizing smart contracts to facilitate procurement, purchasing, and payment processes in the healthcare industry.
- Combating fraud in distributed medicines through blockchain technology and recording product authenticity information.

Discussion and Conclusion

The present study aimed to identify and prioritize the key drivers shaping the future of the healthcare supply chain with a specific focus on fourth-generation (Industry 4.0) technologies. Through a comprehensive methodological framework combining fuzzy Delphi screening, fuzzy hesitant analytic hierarchy process (F-HAHP), and MARCOS prioritization, this study systematically evaluated twenty-five initially identified drivers and ultimately ranked nine as the most critical. The findings revealed that the top-ranked drivers include: developing intelligent decision-support systems for logistics management and medical supplies, applying artificial intelligence to predict drug demand and optimize the medical equipment supply process, using big data technology to analyze drug consumption patterns and predict health crises, utilizing smart contracts to facilitate procurement and payment processes in the healthcare sector, and combating fraud in distributed drugs through blockchain-based authenticity verification mechanisms.

This prioritization aligns with a growing body of literature emphasizing the transformative role of Industry 4.0 technologies in healthcare supply chains. The prominence of intelligent decision-support systems underscores the field's shift toward data-driven and automated decision-making. Intelligent systems can integrate real-time information from suppliers, distributors, and medical centers, enabling proactive responses to supply-demand fluctuations and minimizing waste. This is consistent with the work of Avinash and Joseph, who highlighted how digital transformation enhances responsiveness, transparency, and operational efficiency in healthcare supply networks (Avinash & Joseph, 2024). Similarly, Bag et al. demonstrated that collaborative platforms leveraging big data analytics and artificial intelligence can enhance absorptive capacity and accelerate learning across supply chain stakeholders, resulting in improved decision quality and resilience (Bag et al., 2023). The high ranking of this driver reflects a paradigm shift from reactive crisis management toward anticipatory and real-time operational planning.

The second key finding—the prioritization of AI applications for demand prediction and procurement optimization—further affirms the central role of predictive analytics in resilient supply chain design. AI-based forecasting models can synthesize epidemiological trends, prescription data, and historical consumption patterns to predict future drug requirements accurately. This not only reduces shortages and excess inventory but also mitigates the bullwhip effect, which has traditionally plagued healthcare supply chains. Dada et al. argued that the absence of predictive analytics and real-time inventory oversight exacerbated shortages during the COVID-19 crisis, undermining patient care and inflating costs (Dada et al., 2025). Similarly, Kumar et al. showed that AI-driven analysis of social media data during disasters could identify emerging shortages of essential medical supplies and support rapid interventions (Kumar et al., 2024). By confirming the significance of AI-driven forecasting, the present study strengthens the evidence that predictive analytics can serve as a foundational capability for crisis-resilient healthcare logistics.

Closely tied to AI forecasting is the third top-ranked driver: leveraging big data to analyze drug consumption patterns and predict health crises. Big data technologies enable the aggregation and analysis of large-scale, heterogeneous data from pharmacies, hospitals, and distribution centers to detect anomalies, identify emerging disease clusters, and forecast demand surges. This finding resonates with the conclusions of Ahsan and Siddique, who emphasized that the convergence of big data, machine learning, and IoT forms the backbone of Healthcare 4.0 and can substantially enhance supply chain transparency, responsiveness, and safety (Ahsan & Siddique, 2022). Moreover, Nazarian-Jashnabadi et al. underscored that digital transformation anchored in data-driven intelligence is pivotal for building sustainable decision support systems and achieving strategic business intelligence goals in healthcare (Nazarian-Jashnabadi et al., 2024). The prioritization of big data technologies in this study thus reflects a clear recognition that visibility and analytics are indispensable for proactive healthcare supply chain management.

The inclusion of smart contracts as a high-priority driver further highlights the increasing importance of blockchain-enabled automation in healthcare logistics. Smart contracts can execute procurement and payment transactions automatically once predefined conditions are met, thereby reducing delays, administrative costs, and human error. They also enhance transactional transparency and accountability between suppliers, hospitals, and insurers. These benefits have been echoed by Jayaraman et al., who showed that blockchain and IoT can collectively improve supply chain traceability, reduce intermediation, and enhance trust among stakeholders (Jayaraman et al., 2019). Bak et al. also highlighted how blockchain can safeguard data integrity and ensure secure transactions even under severe supply chain disruptions, as observed during the COVID-19 pandemic (Bak et al., 2023). The prioritization of smart contracts in the current study reflects the growing recognition that process automation and trustless verification can resolve many inefficiencies that have historically undermined healthcare supply chain performance.

Finally, the prioritization of blockchain-based mechanisms for combating drug distribution fraud and verifying product authenticity emphasizes the sector's urgent need to address counterfeiting risks. Counterfeit drugs not only jeopardize patient safety but also erode trust in healthcare systems. Blockchain's immutable ledger can trace pharmaceuticals across their lifecycle, enabling real-time authentication and tamper-proof record-keeping. Iftikhar and Jamil argued that combining blockchain with AI could create end-to-end visibility and trust, ensuring that only authentic products reach end users (Iftikhar & Jamil, 2025). This aligns with findings from Golinelli et al., who noted that the accelerated adoption of digital technologies during the COVID-19 pandemic significantly improved traceability and reduced counterfeit risks in supply chains (Golinelli et al., 2020). Thus, the high ranking of this driver indicates that ensuring drug authenticity is increasingly viewed as a strategic imperative for safeguarding both patients and institutions.

Interestingly, several other drivers—such as integrating IoT-connected medical devices, increasing automated robotic systems in warehouses, and expanding cloud computing for data management—received lower prioritization despite their known benefits. This suggests that while these technologies enhance operational efficiency, stakeholders perceive data-centric and trust-enhancing technologies like AI, big data, smart contracts, and blockchain as having a more transformative and immediate impact on healthcare supply chain resilience. This perception aligns with broader Industry 4.0 literature, which emphasizes data intelligence, interoperability, and trust as the foundational pillars of digital supply chains (Alexander, 2021; George, 2024; Gorecki et al., 2021). The current study's focus on strategic rather than operational drivers reflects a maturing understanding of digital transformation, where enabling technologies are viewed not merely as tools for cost reduction but as catalysts for systemic resilience and innovation (Chatterjee et al., 2023; Umoren et al., 2025).

Moreover, the findings reinforce earlier claims that resilience depends not only on technological adoption but also on organizational capabilities. Tortorella et al. showed that resilience abilities mediate the effect of Industry 4.0 technologies on healthcare supply chain performance, especially under pandemic-induced disruptions (Tortorella et al., 2024). Similarly, Haseli et al. emphasized the importance of structured decision frameworks—such as the best-worst method—to manage trade-offs among competing priorities and ensure coherent implementation of technological innovations (Haseli et al., 2021). The present study, by employing fuzzy Delphi, F-HAHP, and MARCOS, aligns with this perspective by offering a structured, multi-criteria framework to prioritize strategic drivers and guide resource allocation. This methodological alignment with existing decision science literature further validates the study's approach and enhances its practical relevance.

Another important implication is the potential synergy between these prioritized drivers. AI-driven demand forecasting and big data analytics can feed predictive insights into intelligent decision-support systems, while blockchain-based smart contracts can automate the procurement decisions generated by these systems. Simultaneously, blockchain authentication ensures that only verified drugs enter the supply chain, creating a closed-loop, secure, and responsive network. Omidian highlighted that integrating AI and blockchain can produce powerful synergies that enhance accuracy, efficiency, and trust across healthcare operations (Omidian, 2024). This synergy-oriented perspective suggests that these technologies should not be adopted in isolation but rather implemented as interconnected components of a holistic digital ecosystem, a view also supported by Seifi et al. (Seifi et al., 2025).

In essence, the study advances the discourse on digital transformation in healthcare by offering an empirically grounded prioritization of high-impact technological drivers. While earlier studies often focused on individual technologies or qualitative analyses of digital transformation barriers (Bak, 2016; Golinelli et al., 2020), this study employs a rigorous, multi-criteria quantitative framework to identify which drivers hold the greatest potential for reshaping the future of healthcare supply chains. This makes a novel contribution to the literature and provides a strategic roadmap for healthcare decision-makers seeking to invest in digital capabilities that yield the highest returns in resilience, efficiency, and trust.

Despite its contributions, this study is subject to several limitations. First, the study relied on expert judgment from a relatively small sample of ten participants selected through judgmental sampling. While these experts possessed deep knowledge in healthcare supply chains, Industry 4.0 technologies, and futures studies, their perspectives may not fully capture the diversity of viewpoints across different healthcare contexts, regions, or organizational types. Second, the methodological framework—while robust—relies on subjective weighting and scoring of criteria, which introduces inherent biases. The fuzzy Delphi, F-HAHP, and MARCOS methods can reduce but not eliminate the subjectivity embedded in expert-based evaluations. Third, the study focused exclusively on technological drivers, without explicitly accounting for regulatory, cultural, or economic factors that may influence technology adoption in healthcare. Such contextual factors could significantly mediate the feasibility and impact of the identified drivers. Lastly, the prioritization reflects current perceptions of technological importance, which may shift rapidly as new technologies emerge and healthcare systems evolve.

Future studies could address these limitations by expanding the sample size to include a broader and more diverse group of stakeholders, such as policymakers, healthcare administrators, clinicians, and technology providers from different countries and healthcare systems. Comparative studies across developed and developing economies could illuminate how contextual factors shape the prioritization and implementation of Industry 4.0 technologies. Moreover, longitudinal research could examine how the perceived importance of these drivers evolves over time as technologies mature and adoption progresses. Incorporating additional variables—such as regulatory readiness, financial feasibility, and cultural acceptance—into multi-criteria models could also provide a more holistic understanding of digital transformation pathways. Finally, empirical case studies tracking real-world implementations of AI, big data, blockchain, and smart contracts in healthcare supply chains could validate and refine the prioritization framework proposed in this study.

Practically, healthcare organizations should use the prioritized drivers identified in this study as a strategic guide for their digital transformation roadmaps. Investments should focus on building foundational data infrastructure to support AI and big data analytics, while simultaneously developing governance frameworks for blockchain-based smart contracts and authentication systems. Policymakers should foster public-private collaborations to pilot these technologies, establish interoperability and cybersecurity standards, and allocate funding for digital upskilling of the healthcare workforce. Supply chain leaders should adopt an ecosystem perspective, integrating these technologies as interdependent components rather than isolated tools, and gradually transition from manual, fragmented operations to intelligent, automated, and trust-embedded systems. This strategic alignment will help healthcare systems move toward more resilient, transparent, and patient-centric supply chains capable of withstanding future disruptions.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

References

Adhikari, A., Joshi, R., & Basu, S. (2023). Collaboration and coordination strategies for a multi-level AI-enabled healthcare supply chain under disaster. *International Journal of Production Research*, *63*(2), 497-523. https://doi.org/10.1080/00207543.2023.2252933

Ahsan, M. M., & Siddique, Z. (2022). Industry 4.0 in Healthcare: A systematic review. *International Journal of Information Management Data Insights*, *2*(1), 100079. https://doi.org/10.1016/j.jjimei.2022.100079

Ala, A., Goli, A., Mirjalili, S., & Simic, V. (2024). A fuzzy multi-objective optimization model for sustainable healthcare supply chain network design. *Applied Soft Computing*, *150*, 111012. https://doi.org/10.1016/j.asoc.2023.111012

Alexander, R. (2021). The Fourth Industrial Revolution in South African Manufacturing and Connectivity: Case Studies of Automotive and Mining Equipment Manufacturing, along with Transportation and ICT Infrastructure and Services. *SARChI Industrial Development Working Paper Series*, 1-80. https://www.uj.ac.za/wp-content/uploads/2021/10/sarchi-wp-2022-8c-alexander-september.pdf

Avinash, B., & Joseph, G. (2024). Reimagining healthcare supply chains: A systematic review on digital transformation with specific focus on efficiency, transparency and responsiveness. *Journal of Health Organization and Management*. https://doi.org/10.1108/JHOM-03-2024-0076

Bag, S., Dhamija, P., Kumar Singh, R., Rahman, M. S., & Sreedharan, V. R. (2023). Big data analytics and artificial intelligence technologies based collaborative platform empowering absorptive capacity in health care supply chain: An empirical study. *Journal of Business Research*, *154*, 113315. https://doi.org/10.1016/j.jbusres.2022.113315

Bak, O. (2016). An Application of the BPCM Model in an e-business Driven Transformation Agenda: Assessing Resource Implications for a European Automotive Multinational Corporation (MNC). *Information Technology &People*, *29*(2), 334-353. https://doi.org/10.1108/ITP-12-2013-0212

Bak, O., Braganza, A., & Chen, W. (2023). Exploring blockchain implementation challenges in the context of healthcare supply chain (HCSC). *International Journal of Production Research*, *63*(2), 687-702. https://doi.org/10.1080/00207543.2023.2286491

Chatterjee, S., Chaudhuri, R., Gupta, S., Kumar Mangla, S., & Kamble, S. (2023). Examining the influence of industry 4.0 in healthcare supply chain performance: Moderating role of environmental dynamism. *Journal of Cleaner Production*, *427*, 139195. https://doi.org/10.1016/j.jclepro.2023.139195

Choi, T.-M. (2020). Innovative "Bring-Service-Near-Your-Home" operations under Corona-Virus (COVID-19/SARS-CoV-2) outbreak: Can logistics become the Messiah. *Transportation Research Part E: Logistics and Transportation Review*, *140*, 101961. https://doi.org/10.1016/j.tre.2020.101961

Dada, S. A., Azai, J. S., Umoren, J., Utomi, E., & Akonor, B. G. (2025). Strengthening US healthcare Supply Chain Resilience Through Data-Driven Strategies to Ensure Consistent Access to Essential Medicines. *Strengthening US healthcare Supply Chain Resilience Through Data-Driven Strategies to Ensure Consistent Access to Essential Medicines*, *164*(1), 10. https://doi.org/10.47119/IJRP1001641120257438

Dixit, A., Routroy, S., & Dubey, S. K. (2019). A systematic literature review of healthcare supply chain and implications of future research. *International Journal of Pharmaceutical and HealthcareMarketing*, *13*(4), 405-435. https://doi.org/10.1108/IJPHM-05-2018-0028

George, A. S. (2024). The Fourth Industrial Revolution: A Primer on Industry 4.0 and its Transformative Impact. (Vol. 2, pp. 16-40).

Goel, A., Singh, A., Taneja, U., & Jain, S. (2024). Consumer adoption of digital health services: A systematic literature review and research agenda. *International Journal of Consumer Studies*, *48*(4), e13070. https://doi.org/10.1111/ijcs.13070

Golinelli, D., Boetto, E., Carullo, G., Nuzzolese, A. G., Landini, M. P., & Fantini, M. P. (2020). Adoption of Digital Technologies in Health Care During the COVID-19 Pandemic: Systematic Review of Early Scientific Literature. *Journal of medical Internet research*, *22*(11). https://doi.org/10.2196/22280

Gorecki, S., Possik, J., Zacharewicz, G., Ducq, Y., & Perry, N. (2021). Business Models for Distributed-Simulation Orchestration and Risk Management. *Information*, *12*(2), 71. https://doi.org/10.3390/info12020071

Haseli, G., Sheikh, R., Wang, J., Tomaskova, H., & Tirkolaee, E. B. (2021). A novel approach for group decision making based on the best-worst method (G-bwm): Application to supply chain management. *Mathematics*, *9*(16), 1881. https://doi.org/10.3390/math9161881

Iftikhar, H., & Jamil, D. S. (2025). Leveraging AI and Blockchain Technologies for Optimizing Healthcare Supply Chain Management.

Jayaraman, R., Salah, k., & King, N. (2019). Improving opportunities in healthcare supply chain processes via the Internet of Things and blockchain technology. *Int. J. Healthcare Inf. Syst. Informat.*, *14*(2), 49-65. https://doi.org/10.4018/IJHISI.2019040104

Krammer, S. M. (2021). Navigating the New Normal: "Which firms have adapted better to the COVID-19 disruption?". *Technovation*, *110*, 102368. https://doi.org/10.1016/j.technovation.2021.102368

Kritchanchai, D. (2014). A framework for healthcare supply chain improvement in Thailand. *Oper Supply Chain Management: Int J*, *5*(2), 103-113. https://doi.org/10.31387/oscm0120080

Kumar, V. V., Sahoo, A., Balasubramanian, S. K., & Gholston, S. (2024). Mitigating healthcare supply chain challenges under disaster conditions: a holistic AI-based analysis of social media data. *International Journal of Production Research*, *63*(2), 779-797. https://doi.org/10.1080/00207543.2024.2316884

Lahtela, A., Hassinen, M., & Jylha, V. (2008). *RFID and NFC in healthcare: Safety of hospitals medication care* Tampere, Finland.

Maleki, M. H., Zadeh, E. J., & Ferdowsi, A. (2024). Prioritizing the challenges of compensation methods for doctors and nurses in Iranian public hospitals. *Depiction of Health*, *15*(1), 99-113. https://doi.org/10.34172/doh.2024.08

Manavalan, E., & Jayakrishna, K. (2019). A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. *Computers & Industrial Engineering*, *127*, 925-953. https://doi.org/10.1016/j.cie.2018.11.030

Mathew, J., John, J., & Kumar, S. (2013, May). *New trends in healthcare supply chain* Denver. https://www.semanticscholar.org/paper/New-Trends-in-Healthcare-Supply-chain-Mathew-John/b5c1803e7c5ea48550af03a1c479c555b2381bb7

Nazarian-Jashnabadi, J., Haseli, G., & Tomaskova, H. (2024). Digital transformation for the sustainabledevelopment of business intelligence goals. In *Decision Support Systems for Sustainable Computing* (pp. 169-186). Elsevier. https://doi.org/10.1016/B978-0-443-23597-9.00008-1

Noorfa Haszlinna, M., & Potter, A. (2009). "Healthcare supply chain management in Malaysia: a case study". *SupplyChain Management: An International Journal*, *14*(3), 234-243. https://doi.org/10.1108/13598540910954575

Omidian, H. (2024). Synergizing blockchain and artificial intelligence to enhance healthcare. *Drug Discovery Today*, *29*(9). https://doi.org/10.1016/j.drudis.2024.104111

Saiya, H., Doshi, S., Seth, J., Badgujar, V., & Kalme, G. (2022). Automation of Supply Chain Management for Healthcare. In *Progresses in Artificial Intelligence & Robotics: Algorithms & Applications. ICDLAIR 2021* (Vol. 441). Springer. https://doi.org/10.1007/978-3-030-98531-8_4

Seifi, N., Ghoodjani, E., Majd, S. S., Maleki, A., & Khamoushi, S. (2025). Evaluation and prioritization of artificial intelligence integrated block chain factors in healthcare supply chain: A hybrid Decision Making Approach. *Computer and Decision Making: An International Journal*, *2*, 374-405. https://doi.org/10.59543/comdem.v2i.11029

Sharma, A. K., Srivastava, M. K., & Sharma, R. (2025). Barriers and Challenges for Digital Twin Adoption in Healthcare Supply Chain and Operations Management. *Global Business Review*, *0*(0). https://doi.org/10.1177/09721509251314795

Smart, D., Schreier, J., & Singh, I. R. (2025). Inappropriate laboratory testing: significant waste quantified by a large-scale year-long study of Medicare and commercial payer reimbursement. *Archives of Pathology & Laboratory Medicine*, *149*(3), 253-261. https://doi.org/10.5858/arpa.2023-0486-OA

Tortorella, G. L., Prashar, A., Antony, J., Fogliatto, F. s., Gonzalez, v., & Godinho Filho, M. (2024). Industry 4.0 adoption for healthcare supply chain performance during COVID-19 pandemic in Brazil and India: the mediating role of resilience abilities development. *Oper Manag Res*, *17*, 389-405. https://doi.org/10.1007/s12063-023-00366-z

Umoren, J., Ajayi-Kaffi, O., & Kaiser, F. (2025). An analytical framework for digital transformation in healthcare product supply chains. *International Journal of Science and Research Archive*, *14*(1), 1920-1930. https://doi.org/10.30574/ijsra.2025.14.1.0190

White, F. (2015). Primary health care and public health: foundations ofuniversal health systems. *Med Principles Pract*, *24*(2), 103-116. https://doi.org/10.1159/000370197

World Health Organization. (2007). Everybody's business-strengthening health systems to improve health outcomes: WHO's framework for action. https://apps.who.int/iris/bitstream/handle/10665/43918/9789241596077_eng.pdf
Zanni, T. (2020). Technology supply chain disruption. *KPMG*. https://doi.org/10.1080/09537287.2020.1768450