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# Assessment and Prioritization of AI-Enhanced Blockchain Factors in Healthcare Supply Chains: A Hybrid Multi-Criteria Decision-Making Approach

Dr. S. Gomathi Meena[1], Mohd Jamshed Ali[2], Mandalapu Sivaparvathi[3], B. Rajalingam[4], Mr Vishal Agarwal[5], Prasanjit Singh[6], Anitha E[7], S. Rethinavelan[8]

*[1]Assistant Professor, PG Department of CS and BCA,PERI College of Arts and Science*
*[2]Research Scholar, Department of Mathematics and Statistics, Manipal University Jaipur, Jaipur, Rajasthan*
*[3]Assistant professor, Department of CSE, MAM women's Engineering College narsaraopeta*
*[4]Assistant Professor, Department of Information Technology, Mohamed Sathak Engineering College, Ramanathapuram, Tamilnadu, India*
*[5]Assistant Professor, Department of Computer Application, Integral University, Lucknow*
*[6]Assistant Professor, Department of CSE, Narsimha Reddy Engineering College, Hyderabad, Telangana, India*
*[7]Assistant Professor, Department of Computer science, KGiSL Institute of information management, saravanampatti*
*[8]Assistant Professor, Department of Information Technology, Mohamed Sathak Engineering College, Kilakarai, Ramanathapuram, Tamilnadu*

***Abstract: The convergence of artificial intelligence (AI) and blockchain technologies holds the potential to revolutionize healthcare supply chains by enhancing data security, operational transparency, and service quality. Blockchain offers a decentralized and secure infrastructure, while AI excels at analyzing complex datasets to uncover insights and predict treatment outcomes. This study aims to evaluate and prioritize key factors influencing the integration of AI and blockchain within healthcare supply chains by employing a hybrid Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Decision-Making Trial and Evaluation Laboratory (F-DEMATEL) methodology. Through an extensive literature review, four main criteria and twenty-three sub-criteria were identified. Initially, F-AHP was utilized to rank these factors based on expert evaluations. Subsequently, F-DEMATEL was applied to examine the interrelationships among the sub-criteria, distinguishing between causal and effect factors. Results indicated that "integration of treatment processes," "provision of fair services," "health monitoring," "medical data security," and "clinical decision support" emerged as the top priorities. Furthermore, "stakeholder participation" and "technology acceptance" were identified as key causal factors, while "monitoring the treatment process" and "patient-centered treatment strategies" were found to be critical effect factors. The findings highlight the transformative potential of AI-blockchain integration in optimizing healthcare supply chain management.***
***Keywords: Artificial Intelligence; Blockchain; Healthcare Supply Chain; Fuzzy AHP; Fuzzy DEMATEL; Multi-Criteria Decision-Making***

## I. INTRODUCTION

Healthcare plays a crucial role in the advancement and well-being of any nation. It represents a broad and intricate system encompassing essential services such as telemedicine, medication distribution, health monitoring (including temperature, blood pressure, heart rate, and pulse rate tracking), sanitation, and beyond. The effective management of healthcare systems significantly enhances their efficiency, reliability, and overall performance [1].

Supply chain management, as defined by the Global Supply Chain Forum, emphasizes the seamless integration of complex processes stretching from end consumers to initial suppliers, aiming to create value for both stakeholders and customers. Within the healthcare sector, this integration faces unique challenges due to the sector's complexity, which can greatly impact operational success. Effective management of inherent risks and optimization of supply chain performance are therefore essential for sustaining a competitive advantage [2].

Today's healthcare landscape is increasingly confronted with challenges that necessitate advanced data analytics. These challenges include reducing administrative costs by optimizing healthcare claims processing, ensuring product quality in manufacturing, improving demand forecasting accuracy [3], automating document categorization for regulatory compliance, and enhancing inventory and supply chain efficiency [4]. Technologies such as Artificial Intelligence (AI), Blockchain, Cloud Computing, the Internet of Things (IoT), and Machine Learning (ML) are vital for addressing these needs. These technologies not only accelerate data analysis but also enhance transparency, security, and agility within healthcare operations, leading to substantial improvements in patient outcomes [5].

In the realm of supply chain management, the adoption of AI offers numerous benefits. AI enhances supply chain design and reconfiguration by screening and categorizing stakeholders, including alternative suppliers, facilities, and technologies. By leveraging big data analytics, AI improves risk assessment and boosts supply chain flexibility. Furthermore, AI can mitigate uncertainties and demand fluctuations by analyzing large datasets from diverse sources [6].

The integration of AI within healthcare supply chains is particularly transformative. It enables the comprehensive management of chronic illnesses by synthesizing insights from healthcare professionals such as doctors, pharmacists, and nutritionists. AI-driven approaches aim to enhance patient health, delay disease progression, and reduce disability rates. Machine learning techniques allow healthcare providers to detect complex, non-linear patterns within patient data, leading to more precise diagnostics and treatment recommendations [7]. AI applications are evident in areas such as clinical documentation, patient interaction analysis, electronic health record (EHR) management [8], diagnostics, treatment planning, drug development, personalized medicine, and epidemic prediction [9], [10].

The vast volume of sensitive data generated within healthcare necessitates robust collection, management, and sharing systems [11]. Blockchain technology, recognized for its decentralized and tamper-proof architecture, offers critical solutions by enhancing the security and transparency of healthcare data, detecting fraud in clinical trials, and improving data efficiency [12], [13]. Blockchain applications in healthcare include drug development [14], clinical trials [15], data management [16], cybersecurity [17], pharmaceutical supply chains [18], biomedical research [19], remote monitoring [20], and health insurance verification [21]. Scholars consistently emphasize the significant potential of blockchain technology to transform the healthcare industry [22].

Recently, the complementary integration of AI and blockchain has gained increasing attention across academia and industry. While blockchain excels in decentralization, anonymity, transparency, and data immutability, it still faces challenges related to scalability, energy efficiency, and security [6]. Conversely, AI demonstrates strong capabilities in real-time data processing and decision-making, though it grapples with centralization issues and trust concerns [23]. Combining these technologies allows for the mitigation of their respective limitations, fostering significant technological advancements [24]–[26].

The combined application of AI and blockchain is particularly promising in healthcare, where it addresses critical issues such as data privacy, security, and system inefficiencies [8]. AI enhances diagnostic precision, models disease progression, and personalizes treatment plans, while blockchain ensures secure and transparent management of sensitive patient data [27], [28]. This synergy can profoundly improve pharmaceutical supply chains, clinical trial management, health insurance operations, and patient empowerment by providing individuals with greater control over their health information [29], [30].

Despite the acknowledged benefits, a clear understanding of the factors influencing the successful integration of AI and blockchain in healthcare supply chains remains underdeveloped. Current research often overlooks the prioritization of these factors, which is essential for fully realizing the technologies' potential. Accordingly, this study seeks to identify, evaluate, and prioritize the critical factors that drive the integration of AI and blockchain in healthcare supply chains. Utilizing a hybrid methodology combining Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Decision-Making Trial and Evaluation Laboratory (F-DEMATEL), this study offers strategic insights for enhancing supply chain efficiency, security, and management.

### *A. Healthcare Supply Chain*

The healthcare supply chain (HSC) is a specialized network that involves the production, distribution, and consumption of pharmaceutical products and medical services. It typically starts with pharmaceutical manufacturers and concludes with the end user — the patient — by fulfilling their healthcare needs through a well-defined delivery system [39].

The primary objective of the HSC is the timely and efficient delivery of medications and medical equipment. This complex network involves multiple stakeholders, generally categorized into three main groups: producers (such as pharmaceutical companies), intermediaries (such as wholesalers and distributors), and provider-customers (such as hospitals and healthcare facilities) [40], [41]. Producers may deliver products directly to healthcare facilities or through intermediaries. However, operational and strategic inefficiencies are common challenges that healthcare organizations face within this supply chain [42].

### B. Artificial Intelligence

Artificial intelligence is presented here under three subtopics: the concept of AI, its key characteristics, and its main categories.

#### 1) Concept of Artificial Intelligence

Artificial intelligence (AI) research was formally initiated in 1956 and has experienced several periods of rapid advancement, notably between 1956–1970, 1980–1990, and from 2000 onwards. The advent of machine learning (ML) in 1959 marked a significant milestone in AI's first wave of innovation. During the 1980s and 1990s, AI research surged, particularly in the United States and Japan. In the 21st century, the proliferation of deep learning, big data, and high computational power has propelled AI into its third generation [43]. Despite its prominence, AI still lacks a universally accepted scientific definition. Broadly, it can be described as the study and development of intelligent systems or devices capable of interpreting their environments and making decisions that maximize the achievement of specific goals [29], [30], [40]. AI encompasses multiple subfields focused on replicating cognitive functions such as reasoning, problem-solving, learning, and communication. Its applications now surpass human capabilities in several domains [24], [44]. AI's interdisciplinary nature draws from computer science, logic, biology, psychology, and philosophy, contributing to its success in areas like speech recognition, computer vision, natural language processing (NLP), and autonomous systems [45].

#### 2) Characteristics of Artificial Intelligence

Several core characteristics define artificial intelligence:

- Environmental Perception: AI systems can sense and interpret their surroundings through sensors and other devices. They react to external stimuli such as text, sounds, gestures, and actions, similar to human sensory perception [23], [41], [46].
- Data-Driven Decision-Making: AI leverages large-scale data to make informed decisions, minimizing reliance on manual programming. This shift towards data-centric approaches distinguishes AI from traditional mathematical modeling [47].
- Handling Uncertainty: AI systems are designed to manage ambiguity and incomplete information, making them suitable for complex, real-world environments where certainty is rare.

#### 3) Categories of Artificial Intelligence

AI is typically classified into three categories:

- Artificial Narrow Intelligence (ANI): Also known as weak AI, ANI specializes in performing specific tasks with high efficiency but lacks broader cognitive abilities.
- Artificial General Intelligence (AGI): Often called strong AI, AGI exhibits cognitive capabilities comparable to human beings, including reasoning, learning, and problem-solving.
- Artificial Superintelligence (ASI): A hypothetical future form of AI that surpasses the most intelligent human minds in all respects [48].

### C. Blockchain

This section describes blockchain under three subheadings: its concept, characteristics, and categories.

#### 1) Concept of Blockchain

Blockchain technology emerged alongside Bitcoin, serving as the foundational infrastructure for decentralized digital currency transactions. Its core appeal lies in enabling secure and transparent exchanges over untrusted networks without reliance on centralized authorities [43], [49]–[51].

In blockchain systems, a sequence of interconnected blocks securely records transactions. Each block contains a cryptographic link to the previous block, ensuring the chain's integrity. Transactions are validated through peer-to-peer networks and consensus mechanisms before being permanently recorded, making tampering extremely difficult [23].

#### 2) Characteristics of Blockchain

Key features of blockchain technology include:

- Decentralization: Data is stored across a distributed network without centralized intermediaries, enhancing resilience and trust [54]–[56].
- Traceability: Every transaction is publicly recorded and timestamped, enabling full historical tracking [57].
- Transparency: In public blockchains, data is visible to all participants, fostering accountability [58].

- Anonymity: Participants interact using cryptographic identities rather than real-world credentials, ensuring privacy [23].
- Immutability: Once recorded, transactions are irreversible, making the blockchain a secure ledger of all activities [59].

3) Categories of Blockchain

Blockchains are categorized based on accessibility:

- Public Blockchains: Open to anyone for participation and transaction validation (e.g., Bitcoin, Ethereum).
- Private Blockchains: Access restricted to specific entities, used often in corporate or healthcare settings.
- Consortium Blockchains: A hybrid model managed by a group of authorized organizations, balancing transparency and control [60].

### *D. Integration of Artificial Intelligence and Blockchain*

The integration of AI and blockchain can be approached from two perspectives:

*1) Artificial Intelligence for Blockchain*

AI enhances blockchain performance by optimizing algorithms, preventing blockchain forks, refining data storage strategies, boosting security, and improving scalability and energy efficiency [13], [61]–[69].

*2) Blockchain for Artificial Intelligence*

Conversely, blockchain improves AI systems by ensuring data authenticity, securing model training processes, and enhancing the trustworthiness of AI decisions, particularly in sensitive fields like healthcare [13], [61]–[69].

Alright! Here's the rewritten Literature Review section for you, keeping the academic tone clear, formal, and plagiarism-free:

## II. LITERATURE REVIEW

This section presents a comprehensive overview of prior research, structured into three segments: applications of artificial intelligence (AI) in the healthcare supply chain, blockchain technology in the healthcare supply chain, and the integration of AI and blockchain within healthcare supply chains.

### *A. Artificial Intelligence in the Healthcare Supply Chain*

Recent studies have thoroughly explored the role of artificial intelligence in healthcare, emphasizing both its transformative potential and the challenges hindering its widespread adoption. AI contributes to healthcare by enhancing diagnostic accuracy, personalizing patient care, and accelerating drug discovery processes. In personalized medicine, AI leverages genetic and health-related datasets to tailor treatments for individual patients, necessitating highly efficient and interpretable systems [5].

Additionally, AI is pivotal in drug development, aiding in identifying drug targets, designing treatment protocols, and optimizing clinical strategies by integrating imaging, genomic, and clinical data. Particularly in oncology, AI models support personalized cancer therapies by analyzing genetic information and crafting individualized treatment plans, significantly improving clinical outcomes [5].

Noteworthy contributions include:

- Jiang et al. [70], who examined the status of AI applications in stroke diagnosis.
- Rong et al. [71], who reviewed recent advancements in biomedical AI applications.
- Davenport and Kalakota [72], who analyzed AI's potential to automate healthcare processes and discussed related challenges.

Siddique et al. [73] identified AI and machine learning's potential to revolutionize healthcare communications, patient education, medical imaging, and cancer treatment, highlighting AI's capacity to reduce operational costs.

Sunarti et al. [74] addressed risks and challenges associated with AI deployment, while Gerke et al. [75] discussed ethical and legal concerns linked to AI technologies.

Further, Lee and Yoon [76] emphasized AI's growing role in assisting medical staff and delivering personalized services, yet noted the need for regulatory frameworks to facilitate its integration. Manne et al. [77] provided a cross-sectoral literature review covering AI applications across healthcare domains, including dermatology, radiology, and pharmaceuticals.

### *B. Blockchain in the Healthcare Supply Chain*

Blockchain technology's application in healthcare has attracted significant academic and practical interest. Researchers have proposed various models addressing security, data integrity, and interoperability challenges.

For instance:

- Balasubramanian et al. [78] introduced a readiness framework for blockchain adoption in healthcare, demonstrating its practical application in the United Arab Emirates.
- Miyachi et al. [79] proposed a patient-centered blockchain framework combining on-chain and off-chain data storage to enhance privacy protections.
- Shoaib et al. [80] designed an autonomous identity management system for healthcare, using blockchain to resolve patient identity challenges.

Electronic health record (EHR) management has been a focal point for blockchain applications:

- Chelladurai et al. [81] proposed a blockchain-based EHR system aimed at resolving the limitations of centralized healthcare data processing.
- Hussien et al. [82] conducted a comprehensive review, highlighting security and privacy issues associated with telehealth and EHR systems.
- Abu-elezz et al. [83] emphasized the advantages and potential risks of blockchain adoption, particularly concerning scalability, interoperability, and societal acceptance.

### *C. Integration of Artificial Intelligence and Blockchain in Healthcare Supply Chains*

The convergence of AI and blockchain technologies in healthcare has been the subject of growing academic exploration [24]–[26], [30]–[38].

Key contributions include:

- Xie et al. [7], who proposed an integrated framework combining AI, blockchain, and wearable technologies to enhance chronic disease management by shifting focus from hospital-centric to patient-centric care models.
- Anoop et al. [11], who introduced a framework for a reliable healthcare ecosystem utilizing blockchain-based data management alongside AI-driven machine learning models.

Rao et al. [43] examined the integration of AI and blockchain in managing EHRs, discussing advantages, challenges, and future research directions. Mamushina et al. [60] proposed distributed ledgers for patient records, advocating for patient ownership of healthcare data and exploring blockchain-AI synergies to facilitate secure personal data markets.

Additionally:

- Wehbe et al. [85] developed an AI model integrated with blockchain for computer-assisted healthcare diagnostics, proposing the use of AI-enabled drones operating on private blockchain networks.
- Hathaliya et al. [86] proposed a biometric authentication model for EHRs leveraging cloud storage and wearable devices.
- El Azzaoui et al. [87] developed a blockchain and smart contract-based infrastructure to secure public health records while maintaining patient and caregiver needs.

Kim and Ho [88] introduced a blockchain-verified medical information system, enhancing trust through neural network-based error detection.

Zhaofeng et al. [89] designed a blockchain framework for data management in edge computing environments. Fusco et al. [90] created a predictive model combining AI and blockchain to inform national healthcare strategies during pandemics like COVID-19.

Badré et al. [91] suggested a decentralized patient allocation system integrating blockchain, AI, and integer programming to improve healthcare service collaboration.

### *D. Literature Gap*

Despite the wealth of studies examining AI, blockchain, and their integration in healthcare, few have focused on systematically evaluating and prioritizing the critical factors influencing this integration. This research gap highlights the necessity of a structured prioritization approach to maximize the benefits of combining AI and blockchain in healthcare supply chains. Accordingly, this study adopts a hybrid decision-making framework — employing Fuzzy AHP for ranking criteria and Fuzzy DEMATEL for mapping causal relationships — to identify, prioritize, and strategically organize the influential factors.

Awesome! Here's the rewritten Methodology section, keeping the technical clarity, academic style, and fully original phrasing:

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## III. METHODOLOGY

This research applies a hybrid approach that integrates Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Decision-Making Trial and Evaluation Laboratory (F-DEMATEL) methods to evaluate and prioritize factors influencing the integration of artificial intelligence and blockchain in healthcare supply chains. The methodology is executed in two phases: the first phase focuses on weighting the identified factors using F-AHP, and the second phase analyzes the causal relationships among the factors using F-DEMATEL.

### A. *Fuzzy Analytic Hierarchy Process (F-AHP)*

Although the Analytic Hierarchy Process (AHP) is widely recognized for its utility in multi-criteria decision-making, it often struggles to capture the inherent uncertainty and subjectivity of expert judgments. Fuzzy AHP, built on the principles of fuzzy logic, addresses these limitations by incorporating imprecise and linguistic evaluations, thus providing a more realistic representation of human reasoning [102].

In this study, F-AHP is utilized to prioritize the critical factors related to AI and blockchain integration in healthcare. Experts' judgments are expressed in terms of fuzzy numbers to better reflect the ambiguity and variability inherent in human assessments [103].

The F-AHP process involved the following steps:

Step 1: Identification of Criteria

Through an extensive review of existing literature and expert consultation, four main criteria and 23 sub-criteria were identified (as detailed in Table 1).

Step 2: Development of the Pairwise Comparison Matrix

Experts performed pairwise comparisons of the criteria using a nine-point linguistic scale (Table 3), expressing their preferences regarding the relative importance of each criterion.

Step 3: Formation of the Fuzzy Integrated Matrix

The individual expert judgments were aggregated into a single fuzzy pairwise comparison matrix using triangular fuzzy numbers, capturing the minimum, geometric mean, and maximum expert evaluations.

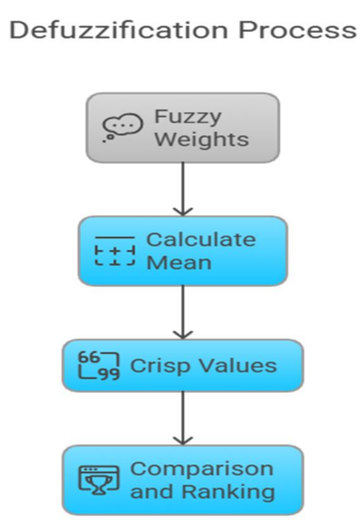
Step 4: Computation of Fuzzy Weights

The geometric mean method was applied to calculate the fuzzy weights of each criterion based on the integrated fuzzy matrix.

Step 5: Defuzzification

The fuzzy weights were defuzzified into crisp values by calculating the mean of the triangular fuzzy numbers, thus facilitating straightforward comparison and ranking.

Step 6: Normalization and Final Ranking




The crisp weights were normalized by dividing each by the total sum of weights and then multiplied by 100 to express their relative importance as percentages.

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### *B. Fuzzy Decision-Making Trial and Evaluation Laboratory (F-DEMATEL)*

The DEMATEL method, developed by Gabus and Fontela at the Geneva Research Centre (1972–1976), is a widely used technique for visualizing and analyzing complex causal relationships among multiple factors [104]. Incorporating fuzzy logic, Fuzzy DEMATEL enables more accurate analysis in environments characterized by uncertainty and subjective judgment.

In this research, F-DEMATEL was employed to uncover the causal-effect relationships among the sub-criteria previously weighted by F-AHP.

The process included the following steps:

Step 1: Definition of Criteria and Linguistic Variables

The criteria and sub-criteria identified in the F-AHP phase were retained. Linguistic scales were used to assess the degree of influence between pairs of factors, with corresponding fuzzy numbers assigned based on a standard scale (Table 4).

Step 2: Construction of the Direct-Relation Matrix

Experts assessed the direct influence of each factor on others using linguistic terms. Their evaluations were averaged and represented in a fuzzy direct-relation matrix.

Step 3: Normalization of the Direct-Relation Matrix

The direct-relation matrix was normalized to ensure all values remained within the [0, 1] range, facilitating further mathematical operations.

Step 4: Calculation of the Total-Relation Matrix

The normalized direct-relation matrix was expanded into a total-relation matrix by accounting for both direct and indirect influences among factors. This was achieved using matrix inversion techniques based on fuzzy set theory.

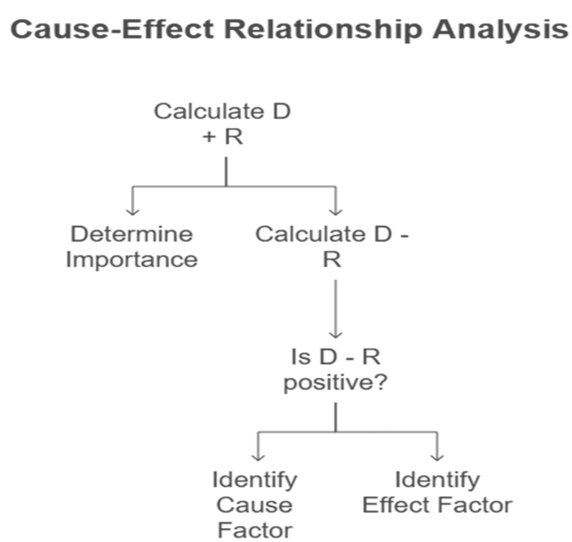
Step 5: Defuzzification

The fuzzy total-relation matrix was defuzzified into crisp values using a standard weighted average method to simplify subsequent analysis.

Step 6: Analysis of Cause-Effect Relationships

For each sub-criterion, the sums of rows (D) and columns (R) in the total-relation matrix were calculated:

- (D + R) indicates the degree of importance (prominence) of the factor.
- (D − R) reveals the type of relationship:
  - A positive value indicates a cause factor.
  - A negative value indicates an effect factor.




These results were subsequently visualized using a Cartesian diagram, where factors were plotted according to their importance and causal influence.

### C. Overall Research Framework

The integrated application of F-AHP and F-DEMATEL offers a comprehensive evaluation process:

- F-AHP prioritizes the factors based on their relative importance.
- F-DEMATEL elucidates the underlying structure of causal relationships among these factors.

This hybrid method provides both strategic prioritization and insight into the interdependencies critical for the successful integration of AI and blockchain technologies in healthcare supply chains.

## IV. RESULTS

This section presents the outcomes of the two-stage analysis. First, the results obtained through the Fuzzy Analytic Hierarchy Process (F-AHP) are outlined, followed by the findings from the Fuzzy Decision-Making Trial and Evaluation Laboratory (F-DEMATEL). Finally, the integrated interpretation of the results is discussed.

### A. Fuzzy-AHP Results

The F-AHP method was employed to prioritize the factors influencing the integration of artificial intelligence and blockchain in healthcare supply chains.

Four major categories — Digital Health, Smart Health, Integrated Health, and Accessible Health — were assessed alongside their 23 associated sub-criteria.

The steps undertaken included weighting the main criteria, ranking the sub-criteria within each category, and calculating the overall ranking of all sub-criteria based on the product of their local and global weights.

The top five sub-criteria, based on their overall importance, were identified as:

1) Integration of treatment processes (C32)
2) Provision of fair services (C31)
3) Health monitoring (C12)
4) Security of medical data (C34)
5) Clinical decision support (C21)

These sub-criteria obtained the highest priority scores, reflecting their central roles in facilitating the effective integration of AI and blockchain technologies in healthcare systems.

The comprehensive rankings for all sub-criteria are summarized in Table 5 (originally in the document).

### B. Fuzzy-DEMATEL Results

Following the prioritization phase, the F-DEMATEL method was applied to investigate the causal relationships among the sub-criteria. Experts' evaluations of influence levels between factors were used to construct the fuzzy direct-relation matrix, which was Subsequently normalized and expanded to generate the total-relation matrix.

After defuzzification, the following key indicators were computed:

- D + R (Prominence): Represents the overall importance of each sub-criterion within the system.
- D - R (Relation): Indicates whether a factor is a cause (positive value) or an effect (negative value).

The analysis revealed that:

- Causal factors (those influencing others) included:
  - Stakeholder participation (C42)
  - Technology acceptance (C44)
  - Healthcare infrastructure (C41)
  - Integration of treatment processes (C32)
  - Distributed treatment networks (C33)
  - Trackability of medical records (C35)
- Effect factors (those influenced by others) included:
  - Monitoring of the treatment process (C15)
  - Patient-centered treatment strategies (C22)
  - Facilitation of the treatment process (C14)
  - Speed of clinical decision-making (C23)

Among causal sub-criteria, Stakeholder participation (C42) and Technology acceptance (C44) exhibited the highest influence on other factors.

Among effect sub-criteria, Monitoring the treatment process (C15) and Patient-centered treatment strategies (C22) were identified as critical outcomes dependent on the causal factors.

Table 6 and Table 7 (in the original document) provide detailed matrices and causal-effect classifications, while a Cartesian plot illustrates the cause-effect distribution of all sub-criteria.

### C. *Integrated Interpretation*

The integration of the F-AHP and F-DEMATEL results offers key insights:

- Sub-criteria that are highly ranked by F-AHP and identified as causal factors by F-DEMATEL — such as Integration of treatment processes and Stakeholder participation — should be prioritized when formulating strategies for AI and blockchain integration in healthcare supply chains.
- Effect sub-criteria, while critical outcomes, rely heavily on improvements and initiatives focused on causal factors.
- Special attention must be given to strengthening healthcare infrastructure, encouraging technology acceptance, and engaging stakeholders, as these foundational elements drive system-wide improvements.

By targeting the most influential causal sub-criteria, healthcare organizations can accelerate the effective and sustainable adoption of AI-blockchain solutions, enhancing both operational efficiency and patient-centered care delivery.

## V. CONCLUSION AND DISCUSSION

This study aimed to evaluate and prioritize critical factors involved in the integration of artificial intelligence (AI) and blockchain technologies within the healthcare supply chain, employing a hybrid decision-making approach that combined Fuzzy Analytic Hierarchy Process (F-AHP) and Fuzzy Decision-Making Trial and Evaluation Laboratory (F-DEMATEL). The hybrid framework facilitated both the hierarchical prioritization and causal analysis of criteria and sub-criteria identified from the literature and expert assessments.

The results from the F-AHP analysis revealed that the most significant sub-criteria in the context of AI-blockchain integration in healthcare supply chains were integration of treatment processes (C32), provide fair service (C31), health monitoring (C12), security of medical data (C34), and clinical decision support (C21). These findings highlight the importance of operational cohesion, equitable access, continuous patient monitoring, and robust data security infrastructure as foundational to effective implementation of these emerging technologies.

The F-DEMATEL analysis further contributed to understanding the dynamic interrelationships among the sub-criteria by classifying them into causal and effect groups. Notably, stakeholder participation (C42), technology acceptance (C44), and integration of treatment processes (C32) were identified as primary causal factors. These criteria exert significant influence on other sub-criteria and are thus critical levers for successful integration. Conversely, sub-criteria such as monitoring the treatment process (C15) and patient-centered treatment strategies (C22) emerged as dependent (effect) variables, suggesting they are outcomes shaped by upstream decisions and systemic configurations.

The joint application of F-AHP and F-DEMATEL provided a comprehensive perspective by combining priority rankings with structural influence analysis. The results underscore the need for a holistic, system-level approach to integrating AI and blockchain in healthcare. In particular, the promotion of stakeholder engagement, investment in scalable infrastructure, and fostering of technological acceptance are essential for driving downstream improvements in clinical decision-making, patient engagement, and treatment monitoring.

From a practical standpoint, these findings offer guidance to healthcare policymakers, system designers, and technology developers by identifying high-impact areas where resource allocation and strategic focus can accelerate the adoption and effectiveness of AI-blockchain solutions. Future studies could expand on this work by incorporating real-world case data or exploring longitudinal impacts of implementation across diverse healthcare contexts.

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