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Evaluation and prioritization of artificial intelligence integrated blockchain factors in healthcare supply chain: A hybrid Decision Making Approach

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ABSTRACT

The integration of artificial intelligence and blockchain in healthcare promises a significant transformation in data management, service quality improvement, and increased patient data security. Blockchain, by offering a decentralized and transparent platform, enhances the reliability and security of information. Meanwhile, artificial intelligence, with its ability to analyse and process data, helps identify patterns and predict treatment outcomes. The aim of this study is Evaluation and prioritization of artificial intelligence integrated blockchain factors in the healthcare supply chain using F-AHP and F-DEMATEL. Following a review of previous studies, four criteria and 23 sub-criteria were identified. In the first step, these criteria were ranked using the F-AHP method. In the second step, relationships among the sub-criteria were determined through F-DEMATEL, identifying causal and effect criteria. The F-AHP results show that among the 23 sub-criteria identified from previous studies, "integration of treatment processes (C32)", "Provide fair service (C31)", "health monitoring (C12)", "security of medical data (C34)", and "clinical decision support (C21)" ranked first to fifth, respectively. The F-DEMATEL results indicate that sub-criteria are divided into causal and effect categories, with "stakeholder participation (C42)" and "technology acceptance (C44)" being the most important causal sub-criteria, while "monitoring the treatment process (C15)" and "patient-centered treatment strategies (C22)" were identified as the most important effect sub-criteria. These findings suggest that the use of AI-blockchain integration in healthcare can lead to significant improvements in managing healthcare systems.

1. Introduction

Healthcare is a vital factor for the development and improvement of every nation. It encompasses a wide, essential, and intricate system that includes processes such as telemedicine, medication

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distribution, health monitoring (such as temperature, blood pressure, heart rate, pulse rate), sanitation, and more. Effective governance of the healthcare system enhances its efficiency, reliability, and overall effectiveness [1]. The definition of supply chain management provided by the Global Supply Chain Forum is particularly significant in the realm of Healthcare Supply Chains (HcSCs). It describes supply chain management as the smooth integration of complex business processes that span from end consumers to primary suppliers, with the primary goal of creating value for stakeholders and customers. It is important to highlight that the complexities inherent in HcSCs present distinct challenges that can greatly influence their effectiveness and overall success. In this intricate environment, the ability to simultaneously manage inherent risks while optimizing performance is crucial for achieving a competitive advantage [2].

The healthcare industry, along with related sectors, encounters considerable challenges that underscore the necessity for advanced data analytics. These challenges involve reducing administrative expenses through more efficient healthcare claim processing, ensuring quality control and efficiency in manufacturing, improving demand forecasting accuracy [3], automating document categorization for compliance, enhancing supply chain management (SCM) efficiency and optimizing inventory management [4]. Advanced technologies like Artificial Intelligence (AI), Blockchain, Cloud Computing, the Internet of Things (IoT), and Machine Learning (ML) are crucial in this domain. These technologies not only accelerate the analysis and processing of vast amounts of data but also create significant improvements in operational efficiency and healthcare outcomes by enhancing transparency, security, and flexibility in healthcare systems [5].

In the field of supply chain, implementing artificial intelligence (AI) brings significant benefits. This technology can streamline the design and reconfiguration of the supply network by screening and categorizing potential stakeholders, like alternative suppliers, facilities, and technologies. Additionally, by using big data analytics, risks are assessed and clarified, which helps to increase the flexibility of the supply chain. Furthermore, AI can reduce uncertainty and demand fluctuations by processing large volumes of data from various sources [6].

Artificial intelligence can enhance efficiency in the healthcare supply chain, driving a transformative change in the industry. By synthesizing the insights of doctors, pharmacists, and nutrition specialists, AI enables comprehensive and proactive management for patients with chronic illnesses. This scientific approach aims to improve health, delay disease progression, and reduce disability rates. Utilizing machine learning, advanced medical units can analyze extensive health data to uncover complex, nonlinear relationships between the body and diseases, leading to more accurate results [7]. AI applications in healthcare span various areas, including assisting primary care physicians with note-taking, analyzing patient conversations, and managing electronic health records (EHR) [8]. This technology provides doctors with better insights into patient conditions, allowing for more effective responses to their needs [9]. Additionally, AI is applied in diagnostics, treatment protocol development, patient monitoring, drug development, personalized treatments, and predicting global disease outbreaks like COVID-19. Other uses include processing biomedical information, facilitating research , and diagnosing diseases [10].

The healthcare sector generates vast amounts of sensitive data, making reliable collection, management, and sharing essential [11]. Blockchain technology is being increasingly utilized to address these needs, particularly in healthcare, where it helps identify and prevent fraud in clinical trials and enhances data efficiency [12]. By offering unique storage solutions and ensuring high security, concerns about data manipulation can be mitigated. It is crucial for data access to be dynamic, collaborative, responsive, and trustworthy. Protecting patient confidentiality is vital for various reasons. Furthermore, blockchain enhances decentralized data protection and minimizes risks in healthcare [13]. Its applications include drug development [14], clinical trials [15], medical data management [16], security [17], drug supply chains [18], biomedical research [19], remote patient monitoring [20], and health insurance claim verification [21]. Many experts have underscored the considerable potential of this technology in the healthcare sector [22].

The integration of blockchain and artificial intelligence has garnered significant attention from universities and industries in recent years. Blockchain is valued for its decentralization, anonymity, public access, transparency, and immutability, but it requires improvements in scalability, energy consumption, and security [6]. In contrast, AI serves as a powerful tool for real-time data analysis and decision-making, yet its centralized structure and need for security and trust limit its broader applications [23]. Consequently, these two data-centric technologies can effectively complement each other to drive technological advancement [24], [25], [26].

The healthcare system can be transformed through various technologies, particularly the combination of artificial intelligence (AI) and blockchain [27]. This pairing addresses medical data privacy issues and offers promising solutions to complex healthcare challenges [8]. AI algorithms enhance diagnosis, model disease progression, and personalize treatment plans, while blockchain tackles security concerns in managing and sharing patient data. With its transparent, immutable, and decentralized data recording, blockchain provides a robust solution to data breaches in healthcare [28]. Together, the decentralized and encrypted strengths of blockchain and advanced AI analytics can revolutionize data management, pharmaceutical supply chains, clinical trials, and health insurance. These technologies empower patients by enabling greater control over their health information and ensuring secure access to medical records [29], [30]. Their full potential is realized only through effective integration [8].

The integration of AI and blockchain in healthcare is motivated by the complementary strengths these technologies offer. Studies have investigated this synergy, showing how AI supports operational efficiency and decision-making through real-time data analysis, while blockchain enhances security and transparency in health data management and pharmaceutical supply chains [24], [25], [31], [32], [33], [34], [35], [36], [37], [38].

Nevertheless, the primary factors affecting this integration are not yet well-defined, and no study has prioritized these factors specifically within the healthcare supply chain. Without a comprehensive evaluation, maximizing the potential of these technologies may be difficult. Therefore, this study seeks to assess and prioritize the essential factors for integrating AI and blockchain in healthcare supply chains, proposing strategies to improve efficiency, security, and management through a combined decision-making framework. For this purpose, two decision-making methods, Fuzzy AHP and Fuzzy DEMATEL, were applied. The fuzzy AHP approach was used to rank blockchain and AI criteria in healthcare, while the fuzzy DEMATEL method, by focusing on identifying influential relationships among criteria, provides clarity on complex interactions and mutual impacts. Additionally, this method employs fuzzy logic to address uncertainty in the data, highlighting which criteria are more pivotal in the decision-making process. The integrated outcomes of the Fuzzy AHP and Fuzzy DEMATEL approaches reveal substantial benefits.

2. Theoretical foundations

This section covers the theoretical foundations of the study. The content is organized into four parts: healthcare supply chains, artificial intelligence, blockchain, and finally, integration of artificial intelligence and blockchain.

2.1 Healthcare Supply Chain

The healthcare supply chain (HSC) is a specific type of supply chain where drugs are produced, transported, and consumed. It starts with pharmaceutical manufacturers and ends with the patient (mainly the customer) to fulfill needs through a defined delivery channel [39].

The primary objective of the healthcare supply chain is to ensure timely delivery of medications and equipment. This process involves various stakeholders, categorized into three main groups: producers (suppliers like pharmaceutical companies), buyers (such as pharmaceutical wholesalers), and provider customers (e.g., hospitals)[40], [41]. Producers supply products either directly to patients or through distributors. However, this value chain is often neither effective nor efficient for healthcare organizations at operational and strategic levels [42].

2.2 Artificial intelligence

In this section, the topic of artificial intelligence is presented in three subheadings: Concept of artificial intelligence, Characteristics of artificial intelligence and Categories of Artificial Intelligence

2.2.1 Concept of artificial intelligence

The innovation of artificial intelligence began in 1956, and it experienced its peak advancements during the years 1956-70, 1980-90, and from 2000 onwards. In 1959, the introduction of machine learning (ML) led to a surge in development during the first generation. The United States and Japan focused on artificial intelligence research during the 1980s and 1990s, which led to the rise of the second generation. Major advancements like deep learning, a massive increase in data, and computational power resulted in the third generation [43].

Defining artificial intelligence (AI) scientifically is a complex task, as it remains a debated topic within academic circles without a universally accepted definition. AI can be described as the study of intelligent systems or devices capable of interpreting their environment and making decisions to improve their chances of achieving predetermined goals [29], [30], [40].It is a broad term that covers fields focused on enhancing the intelligence of machines or agents. The "intelligence" in AI refers to abstract qualities like learning, reasoning, problem-solving, and linguistic abilities. Key goals of AI include knowledge representation, planning, object manipulation, and natural language processing. AI technology can handle complex tasks that typically require human intelligence, and its potential extends beyond human capabilities [24], [44]. In essence, AI is a multidisciplinary field that merges various domains such as computer science, logic, biology, psychology, and philosophy. AI has made significant advancements in areas like speech recognition, image processing, natural language processing, and automated theorem proving. Major AI technologies, including computer vision, Natural language processing (NLP), swarm computing, and intelligent drone systems, have proven valuable across industries like agriculture, healthcare, and the Internet of Things [45].

2.2.2 Characteristics of artificial intelligence

Some of the most important features of artificial intelligence include environmental perception, data-driven decision-making, and handling uncertainty. Environmental perception is the capability of an AI system to comprehend its external surroundings through the use of sensors and other devices. Like humans, AI can collect diverse information from the environment via auditory, visual, olfactory, and tactile inputs, allowing it to respond appropriately to external stimuli such as text, sound, gestures, and actions. These reactions can affect decisions made in both environmental and human contexts. Ideally, an AI system should have adaptive features and specialized learning abilities [23], [41], [46]. Data-driven decision-making in AI refers to its minimal reliance on manual engineering, enabling it to fully leverage the increasing amount of computational power and data available. AI is progressively shifting from representing artificial knowledge to learning from big data. Unlike traditional mathematical methods, most AI fields do not develop in the same way and are not aligned with general physics models. While AI maintains a connection to cognitive and behavioral psychology, these connections often exclude mathematical and engineering considerations. As a scientific field, AI's framework remains unfinished, and considerable uncertainty persists [47].

2.2.2 Categories of Artificial Intelligence

AI systems can be classified into the following three types:

a) Artificial Narrow Intelligence (ANI): Also called weak AI, ANI focuses on achieving a specific goal in a precise and effective way. This type of AI has many limitations, as it only mimics basic human intelligence. ANI systems are designed to carry out a single task with a clear objective in a pre-programmed manner.

b) Artificial General Intelligence (AGI): Known as strong AI, AGI replicates human intelligence fully and operates with much greater independence than ANI. It is believed that AGI has cognitive abilities equivalent to humans. It is adaptable, versatile, and can learn exceptionally well, solving problems with logic and reasoning similarly to how humans would. AGI enables machines to understand and act in specific scenarios in a way that closely resembles human behavior.

c) Artificial Superintelligence (ASI): This is a theoretical concept where machines demonstrate intelligence that surpasses even the most brilliant human minds [48].

2.3 Blockchain

The content related to blockchain is also presented in three subheadings: Concept of Blockchain, Characteristics of Blockchain and Categories of Blockchain.

2.3.1 Concept of Blockchain

The idea of blockchain was initially introduced with Bitcoin, which focuses on decentralized digital currency. The appeal of Bitcoin arises from its implementation of blockchain technology, allowing for secure and trustworthy transactions in an unreliable network without depending on a trusted intermediary [43], [49], [50], [51].

Blockchain technology comprises a sequence of blocks that hold a complete and accurate record of transactions. These blocks are interconnected through a link, forming a continuous chain. The transaction execution process on the blockchain starts when the initiating node randomly generates its private and public keys and constructs a transaction using a wallet or scripting tool, signing the transaction with its private key. This signed transaction is then disseminated to neighboring nodes through the P2P network [46], [52], [53]. The receiving node checks the validity of the transaction, and a miner then creates a new block following the consensus algorithm. Subsequently, miners distribute the new block through the P2P network to other nodes. Other miners confirm the legitimacy of the new block to determine whether to add it to their local chain or discard it. Once the new block is validated by nodes throughout the entire network, it signifies that the new transaction has been successfully processed [23].

2.3.2 Characteristics of Blockchain

Blockchain possesses numerous desirable characteristics that make it suitable for sharing reliable data. Some of the most important features of blockchain are outlined below.

Decentralization: Blockchain technology facilitates data interactions without relying on any intermediaries or third-party entities. The blockchain storage is a distributed database that holds a vast amount of related data, linking the current block to the previous one. The maintenance of the entire blockchain network's data is collaboratively managed by all nodes. Furthermore, the departure of any single node will not impact the overall system's performance, granting the blockchain network a high level of resilience [54], [55], [56].

Traceability: In blockchain networks, all transactions are public, and each node can maintain a record of all transactions. Except for the encrypted private information of the two parties involved, all data within the blockchain can be searched through public interfaces. Blockchain employs a chain block structure with timestamps for storing data, thereby adding a temporal dimension to the data. Each transaction on the block is connected to its two adjacent blocks through cryptographic methods, ensuring that users can trace the source of any transaction [57].

Transparency: The data on the blockchain is transparent to all users, which lends it credibility. Specifically, in a public blockchain, a complete version of all transactions in the network is accessible to all nodes. However, in private and consortium blockchains, access is restricted to authorized nodes only [58].

Anonymity: Since nodes in the blockchain network do not need to trust one another, there is no requirement to disclose identities among the nodes. This ensures the anonymity of each participant in the blockchain system, protecting the privacy of the nodes. Nodes can carry out transactions without knowing the identity of the other party. Both transacting nodes need only to share their addresses to communicate with each other. In the blockchain network, nodes utilize asymmetric encryption technology to establish trust among nodes in an anonymous environment [23].

Immutability: Blockchain is built upon linking all blocks using the hash value of the previous block header. Therefore, blockchain records are irreversible and undeniable. Transaction data are packaged by miner nodes and permanently stored in the blockchain to form an immutable historical ledger. By storing the hash value of the previous block in each block, the blocks are linked forward and backward, creating a chain structure. This specific chain data structure allows all blocks storing transaction data to be added in chronological order to the end of the chain. If a malicious node attempts to manipulate data, it will inevitably change the hash value of the current block and all subsequent blocks, leading to the collapse of the chain structure. Thus, the cost of data manipulation becomes prohibitively high, making changes to the blockchain nearly impossible [59].

2.3.3 Categories of Blockchain

Blockchains can be classified based on the accessibility of their data:

Public Permissioned Blockchains: These blockchains limit the ability to modify data, but they are designed to be accessible for global inspection, allowing a wide range of users to read the data. In a public blockchain, nodes can join and interact without needing authorization. Bitcoin and Ethereum are examples of such permission less blockchains, which are fully decentralized and open to all users.

Private Blockchains: These blockchains grant read and write access to a select, clearly defined group of entities. Importantly, end users of the services encoded in the blockchain do not have access to the blockchain's data.

Consortium Blockchains: In this type, all data is open to the public, and the consensus mechanism is resistant to censorship, allowing anyone to participate or leave at will. This also means that anyone can write to the blockchain. The responsibility of gatekeepers in such blockchains is enforced through economic incentives [60].

2.4 Integration of Artificial Intelligence and Blockchain

Two approaches have been used to explain the integration of artificial intelligence and blockchain: Artificial Intelligence for Blockchain and Blockchain for Artificial Intelligence.

2.4.1 Artificial Intelligence for Blockchain

Artificial intelligence, with its advanced automation and smart capabilities, can drive the natural progression and organization of blockchain data by optimizing and simulating algorithms. Moreover, AI plays a key role in preventing blockchain node forks, enhancing blockchain performance, and improving efficiency in a smart way. One of the major challenges in blockchain networks is the growing data size, as the blockchain becomes heavier with an increasing number of blocks. Here, AI's machine learning (ML) algorithms come into play, helping to refine blockchain data storage strategies [13], [61], [62], [63]. Additionally, AI can improve blockchain technology by making it more secure and energy-efficient. From a technological perspective, AI algorithms can optimize blockchain's scalability [64], and reduce energy consumption [65], [66], [67]. AI can also detect security vulnerabilities [68] in smart contract execution and consensus mechanisms, allowing for smarter decision-making [69].

2.4.2 Blockchain for Artificial Intelligence

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3. Literature Review

This section reviews the literature on the topic and consists of three parts: Artificial Intelligence in the Healthcare Supply Chain, Blockchain in the Healthcare Supply Chain and Integration of Artificial Intelligence and Blockchain in Healthcare Supply Chain.

3.1 Artificial Intelligence in the Healthcare Supply Chain

Recent research has extensively examined the use of artificial intelligence, highlighting both the challenges and potential for its broader application in healthcare. AI's contributions to healthcare span various areas, including enhancing diagnostic precision, customizing patient care, and accelerating the drug discovery process. In personalized medicine, AI processes genetic and health-related data to tailor treatments for individual patients, requiring systems that are highly efficient, interpretable, and thoroughly validated. Additionally, AI plays a pivotal role in drug development, aiding in the discovery of drugs, target identification, and the design of treatment strategies. By combining AI with imaging techniques, genomic data, and clinical information, a more holistic understanding of diseases is achieved, which can lead to more accurate diagnoses and improved treatments. In cancer care, AI models advance personalized treatments by analyzing genetic data to create individualized treatment plans, resulting in enhanced efficiency and performance [5].

In studies related to artificial intelligence, Jiang et al. [70] investigated the present status of AI applications in healthcare, specifically focusing on stroke diagnosis. Rong et al. [71] provided an overview of the latest advancements in AI applications within biomedicine. Davenport and Kalakota [72] discussed the potential of AI to automate various healthcare processes and identified the associated challenges.

Siddique et al. [73] identified several key applications of artificial intelligence and machine learning in healthcare communications, including patient health education, cancer treatment, and medical imaging. They noted that AI has the potential to significantly lower operational costs in healthcare, with this trend likely to continue expanding in the years ahead. Sunarti et al. [74] highlighted the role of AI in the healthcare sector, along with various risks and challenges related to its implementation. Gerke et al. [75] examined the ethical and legal challenges of AI in healthcare and offered recommendations for addressing these issues.

The opportunities and challenges posed by AI technologies in the healthcare sector were explored in a paper by Lee and Yoon [76] . This research analyzed the applications of AI in healthcare, highlighting that large hospitals increasingly rely on AI-based systems to assist medical personnel and deliver personalized healthcare services to patients. However, the study also pointed out that successful implementation necessitates careful planning and additional regulatory frameworks involving multiple stakeholders.

In another investigation, Manne et al. [77] addressed the opportunities and challenges of AI in healthcare. The authors conducted a comprehensive analysis of AI concepts in healthcare management and provided a literature review on AI models across various sectors, including dermatology, radiology, drug development and others.

3.2 Blockchain in the Healthcare Supply Chain

Recently, numerous studies have explored the use of blockchain technology in the healthcare field. This section discusses several recent methodologies documented in the literature concerning blockchain applications in healthcare.

Balasubramanian et al. [78] proposed a framework for assessing readiness for blockchain implementation, focusing on healthcare as a case example. The application of this framework in the healthcare sector of the United Arab Emirates illustrates the critical role of governmental readiness in facilitating blockchain projects.

Miyachi et al. [79] introduced a blockchain framework designed to safeguard the privacy of healthcare data, leveraging both on-chain and off-chain functionalities. This patient-centered framework emphasizes the importance of protecting patient information while allowing for the sharing of healthcare data. Identity management is one application that has broad relevance across various sectors, including government, education, and other civic services. In healthcare, managing patient identity is especially significant. Shoaib et al. [80] introduced a self-sufficient identity management system for healthcare that utilizes blockchain technology. When executed properly, this type of health record associated with an autonomous identity has the potential to resolve various issues tied to patient identity.

The electronic health record (EHR) system is a vital element of the healthcare industry and has been digitized across most nations. Blockchain-enabled EHR systems tackle numerous problems linked to existing centralized processing approaches. In this regard, Chelladurai et al. [81] put forth a management system for electronic health records based on blockchain technology. Hussien et al. [82] explored the disparity between the healthcare sector and blockchain technology by evaluating cutting-edge technologies. This thorough review not only covered prior methodologies but also underscored the security and privacy concerns surrounding blockchain, using telehealth and electronic health information systems as illustrative case studies. A scoping review by Abu-elezz et al. [83] examined the advantages and risks of implementing blockchain technology in the healthcare sector. The authors pointed out that ongoing challenges concerning security, privacy, scalability, and interoperability pose notable vulnerabilities for blockchain in healthcare, suggesting that the social acceptance of blockchain implementation may need to be evaluated.

3.3 Integration of Artificial Intelligence and Blockchain in Healthcare Supply Chain

The integration of blockchain and artificial intelligence has been thoroughly investigated in numerous studies [24], [25], [26], [30], [31], [32], [33], [34], [35], [69].

Xie et al. [7] examines how artificial intelligence, blockchain, and wearable technology can work together to manage chronic illnesses, introducing a new framework in smart healthcare. The research suggests that integrating these technologies can enhance current chronic disease management models by transitioning from a hospital-centric approach to a patient-focused one. The authors propose a technical framework centered on patients that incorporates artificial intelligence, blockchain, and wearable technology, analyzing how these combined technologies can improve chronic disease management. The article also addresses the limitations of this new paradigm and outlines future research directions. Anoop et al [11] introduces a framework in a study titled "Integrating Artificial Intelligence and Blockchain to Create a Reliable Ecosystem for the Healthcare Sector," which recommends a dependable data management platform for healthcare using blockchain that can work alongside artificial intelligence techniques for developing machine learning models.

Rao et al. [43] investigates the management of electronic health records through the integration of artificial intelligence and blockchain technologies. This study aims to explore the applications of both blockchain and artificial intelligence within the healthcare field. It discusses the advantages, challenges, and issues associated with merging these two technologies, along with future research avenues in healthcare. The findings offer various perspectives on the combination of blockchain technology and artificial intelligence.

Mamushina et al. [60] review cutting-edge solutions in biomedical research that integrate blockchain technology with artificial intelligence. They propose the establishment of a distributed ledger for individual patient records, allowing patients to have ownership and control over their own data. Additionally, they contend that the combination of deep learning technologies and blockchain can lead to a transparent and secure marketplace for personal data, which could help resolve issues encountered by regulators. In another study, Wehbe et al. [85] introduced a blockchain-integrated artificial intelligence model that specifies the necessary components for a computer-assisted diagnostic system based on healthcare records. To facilitate a variety of healthcare services, the authors recommended utilizing AI-enabled drones operating on a private blockchain network. Hathaliya et al. [86] proposed a biometric authentication strategy to safeguard electronic health records (EHRs). Their framework involves the collection of data from wearable devices, which is then stored in cloud databases, employing biometric verification to enhance the security of EHRs.

El Azzaoui et al. [87] focused on resolving the privacy and security challenges of the standard Electronic Health Record (EHR) system while catering to the requirements of patients, caregivers, and third parties. They implemented algorithms and smart contracts to develop a resilient public health infrastructure. Kim and Ho [88] highlighted a medical information system that integrates artificial intelligence and blockchain technology. Their research illustrates how the system's performance is verified through a blockchain framework after error reporting, ensuring data integrity by preventing fraud and inaccurate medical information through neural networks.

Zhaofeng et al. [89] introduced a blockchain-based framework specifically designed for managing data in edge computing systems. Fusco et al. [90] proposed a predictive model that merges artificial intelligence and blockchain to mitigate the risks of COVID-19 on a national scale. This predictive model can be continuously updated with clinical data from patients, producing extensive datasets that are useful for guiding national health policies and illustrating how businesses can assist the government during emergencies. In a separate study, Badré et al. [91] introduced the idea of shared decision-making in integrated healthcare services, suggesting a decentralized patient allocation system that leverages machine learning, blockchain technology, and integer programming to improve collaboration between healthcare providers and patients.

The literature review reveals that despite numerous studies on the individual applications of artificial intelligence and blockchain, as well as their integration in healthcare, there is a lack of comprehensive research evaluating and prioritizing the factors for integrating these technologies. This gap underscores the need for the current study, which aims to address it through a hybrid decision-making approach that provides new insights for effectively implementing these emerging technologies in the healthcare supply chain. For this purpose, the criteria and subcriteria related to the integration of AI and blockchain technologies have been categorized into four groups, as shown in Table 1.

Table 1
Criteria and sub criteria for AI-BC integration

Criteria		Sub criteria		Reference
C1	Digital Health	C11	Real-time data sharing	[8], [47], [92]
		C12	Health monitoring	[8], [47], [92]
		C13	Education and awareness	[6], [13], [23], [42]
		C14	Facilitate the treatment process	[5], [6], [23], [79]
		C15	Monitoring the treatment process	[2], [47], [93], [95]
		C16	Patient Engagement	[1], [5], [93], [96]
C2	Smart Health	C21	Clinical decision support	[2], [7], [13], [29], [47]
		C22	Patient-centered treatment strategy	[13], [23], [28]
		C23	Speed of clinical decision making	[5], [7], [28], [48]
		C24	Development of treatment methods	[8], [41], [28], [77]
		C25	Disease prediction with historical data	[2], [5], [60], [93]
		C26	Fraud detection	[6], [13], [28], [48], [93]
C3	Integrated Health	C31	Provide fair service	[1], [6], [29], [95], [97]
		C32	Integration of treatment processes	[1], [2], [47], [98]
		C33	Distributed treatment network	[8], [11], [60]
		C34	Security of medical data	[6], [13], [23], [43], [92]
		C35	Trackability of medical records	[11], [23], [89], [92]
C4	Accessible Health	C41	Healthcare infrastructure	[5], [7], [29], [48], [99]
		C42	Stakeholder participation	[2], [5], [23], [100]
		C43	Staff training	[8], [41], [77]
		C44	Technology Acceptance	[47], [89], [92]
		C45	Resource management	[2], [5], [93]
		C46	Affordable care facilities	[1], [5], [48], [101]

"Digital Health" refers to the use of digital technologies to enhance healthcare by enabling real-time data sharing, continuous health monitoring, and patient engagement. It supports education and awareness, facilitates the treatment process, and allows for ongoing monitoring to ensure better patient outcomes. Smart Health integrates advanced technologies like AI and data analytics to improve healthcare delivery. It supports faster clinical decisions, personalized treatments, disease prediction, and the development of new treatments while enhancing efficiency through fraud detection and process optimization.

"Smart Health" encompasses a healthcare framework that leverages advanced smart technologies to enhance various facets of clinical and patient care. This criterion focuses on improving clinical decision support and patient-centered treatment strategies, enabling personalized care that aligns closely with individual health needs. By prioritizing speed in clinical decision-making and fostering the development of innovative treatment methods, Smart Health aims to streamline care processes. Additionally, it includes predictive analytics for disease prediction using historical data and robust fraud detection mechanisms to ensure integrity and efficiency within healthcare systems.

"Integrated Health" refers to a coordinated healthcare system that ensures fair access to services by combining treatment processes across a distributed network. It focuses on secure medical data handling, traceability of medical records, and seamless collaboration to deliver comprehensive and equitable care. Accessible Health refers to the ease with which individuals can obtain necessary healthcare services, information, and resources. It emphasizes the importance of removing barriers—be they physical, financial, or informational—to ensure that everyone has the opportunity to receive quality care and support for their health needs.

"Accessible Health" refers to a healthcare framework focused on creating inclusive, equitable access to healthcare services. This criterion emphasizes the importance of robust healthcare infrastructure and active stakeholder participation to ensure that essential services are available to all. Key components include staff training to maintain high standards of care, fostering technology acceptance to improve service delivery, and efficient resource management to maximize reach and sustainability. Additionally, Accessible Health prioritizes the development of affordable care facilities, making healthcare more financially accessible and reducing barriers to quality care.

Table 2 presents the operational definitions for each sub-criteria.

Table 2
Operational definitions of sub-criteria

Code	Operational Definition
	Digital Health
C11	Real-time data sharing means monitoring an individual's health or illness information and instantly sending it to the healthcare supply chain.
C12	Health monitoring involves tracking an individual's health status through digital systems to provide timely alerts for effective management and control based on their condition.
C13	Education and awareness mean providing specific advice tailored to a person's health condition, helping to maintain their health and prevent the onset of illness.
C14	Facilitate the treatment process in the healthcare system means improving and simplifying the steps involved in treating patients, so that access to medical services, diagnosis, and treatment can happen quicker and more efficiently.
C15	The purpose of monitoring the treatment process is to collect and analyze data related to the patient's condition, medications, and treatment outcomes in order to track and control the stages of patient care, ensuring that the treatment process is carried out effectively and efficiently.
C16	Patient Engagement in the healthcare system means that patients actively get involved in their care processes and health-related decisions, allowing them to raise their questions and concerns and be part of planning their treatments.
Smart Health	
C21	Clinical decision support involves intelligent systems that assist doctors in diagnosing diseases and minimizing medical errors by analyzing medical data and recognizing patterns.
C22	Developing a patient-centered treatment strategy refers to the process of designing and implementing treatment plans that take into account the specific needs, preferences, and conditions of each patient.
C23	Clinical decision-making speed refers to how quickly doctors and treatment teams can analyze information and make effective decisions in clinical situations.
C24	The development of treatment methods includes processes like developing and discovering new drugs, improving existing medications, and also using emerging technologies such as artificial intelligence, precision medicine, and biotechnology to design and deliver more effective treatment methods.
C25	Predicting diseases using historical data refers to the process of leveraging past information and existing patterns in the data to identify the likelihood of certain diseases occurring in the future.
C26	Detecting fraud and forgery in the healthcare sector refers to the process of identifying and preventing irregularities and suspicious, illegal, and incorrect activities, such as issuing fake documents, insurance fraud, and providing unauthorized medical services.
Integrated Health	

C31	The aim of providing fair services is to create a transparent system of medical records and transactions that ensures fair access to data and healthcare services for all patients, regardless of their location or economic status.
C32	The integration of treatment processes means coordinating and synchronizing information and interactions among all stakeholders in the healthcare system, including doctors, hospitals, pharmacists, and patients.
C33	A distributed healthcare network refers to decentralized systems where medical data and patient records are stored in a distributed manner using blockchain technology. This network enables direct access to data without intermediaries.
C34	The security of medical data in terms of blockchain means protecting medical information and patient records from unauthorized access, alteration, or forgery.
C35	Trackability of medical records refers to the capability to accurately and transparently record and maintain information related to patients' medical histories.
Accessable Health	
C41	Healthcare infrastructure refers to a range of facilities and services that help people access healthcare services. This infrastructure includes hospitals, clinics, pharmacies, and digital systems that should be evenly distributed throughout the community.
C42	The involvement of stakeholders means that all parties, including patients, doctors, and healthcare providers, actively participate in the decision-making process and the design of healthcare systems.
C43	Staff training means providing healthcare workers with the necessary skills and knowledge so they can deliver effective and accessible services to everyone in the community.
C44	Technology acceptance refers to the use of blockchain and artificial intelligence to improve the processes of managing and delivering healthcare services.
C45	Resource management refers to the process of planning, organizing, and overseeing the optimal use of various resources, including medical equipment, medications, human resources, and information.
C46	Affordable care facilities in the supply chain refer to healthcare services and resources that are economically accessible and low-cost for patients.

4. Methodology

This study focuses on evaluating and ranking the factors related to artificial intelligence and blockchain in the healthcare system through a two-step process. In the first step, the fuzzy AHP method is applied to assess the factors and assign weights to each criterion. The second step involves using the fuzzy DEMATEL method to identify both the influencing and influenced criteria, aiming to uncover the relationships and interactions among them.

Although AHP is widely used, it has been criticized for not fully capturing decision-makers' perceptions and the inherent ambiguity in their judgments. Fuzzy-AHP, built on fuzzy logic, addresses the limitations of classical logic and overcomes AHP’s shortcomings. Fuzzy logic proves to be a robust tool, especially useful for solving complex problems that involve interpretation, decision-making, and reasoning [102]. Experts can express their views within a range of values, allowing them to convey their uncertainties using numerical representations [103]. As a result, this study utilizes the Fuzzy-AHP method to better account for expert uncertainty and prioritize healthcare criteria by managing the inherent uncertainty.

The DEMATEL method (Decision Making Trial and Evaluation Laboratory) was developed by Gabus and Fontella at the Geneva Research Center between 1972 and 1976 to address complex decision-making problems. Based on matrix theory and graph theory [104], DEMATEL evaluates cause-and-effect relationships between variables or criteria. This method is a practical and effective tool for visualizing intricate causal relationships by creating a clear structural model of the system. It helps identify the relationships between criteria and illustrates the influence and intensity of each variable [104], [105], [106].

The fuzzy DEMATEL method employs fuzzy linguistic variables to analyze cause-and-effect relationships between variables, aiding decision-making in uncertain environments. Experts assess the impact and importance of each variable using verbal expressions, which are then converted into fuzzy numbers, such as triangular fuzzy numbers, to eliminate ambiguity. This method has been applied in various fields, including supply chain management, energy supply, supplier selection, operations, learning management systems, healthcare, and more. In this study, triangular fuzzy numbers are used to calculate distances based on expert opinions, converting qualitative expressions into fuzzy numerical values. The steps of fuzzy AHP and fuzzy DEMATEL are given in figure 1.

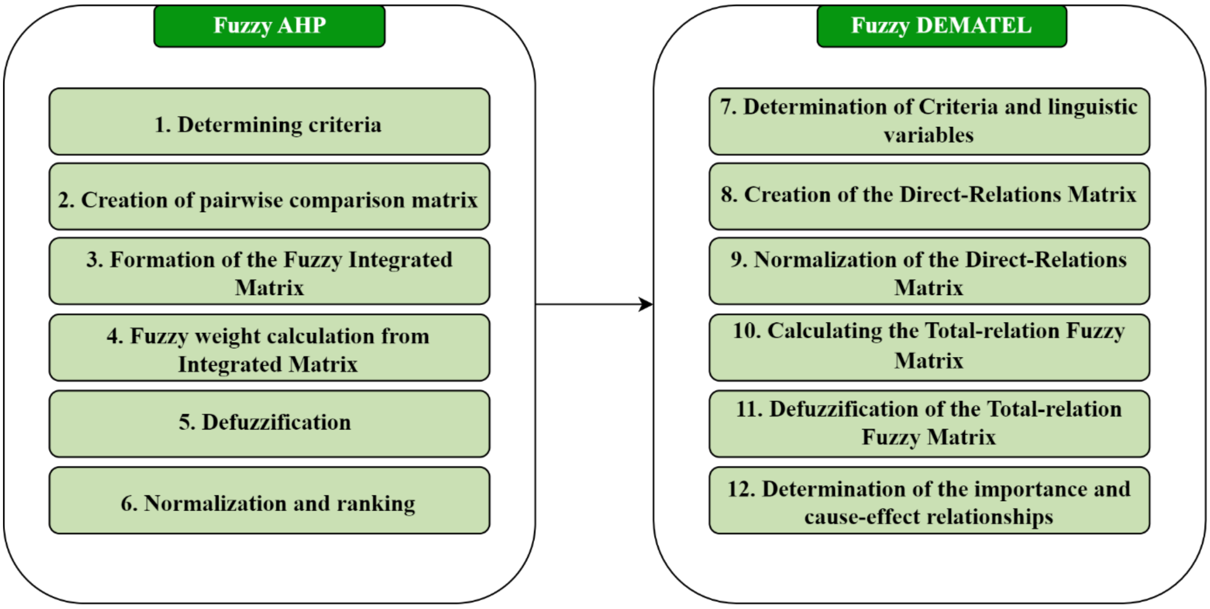

Fig. 1. Methodological structure

4.1. Steps of Fuzzy-AHP Method

Determining Criteria: Through a comprehensive review of previous research, criteria relevant to artificial intelligence and blockchain in the healthcare supply chain were identified. These criteria were refined with expert input and ultimately grouped into four categories, encompassing 23 final criteria (Table 1).

Creation of Pairwise Comparison Matrix: After determining the criteria, a pairwise comparison matrix was developed. Expert evaluations were collected based on Table 3 [102].

Table 3
Pairwise Comparison Scale [102]

Scale of Importance / Comparison Direction	Equal importance	Slight importance	Moderate importance	Strong importance	Extreme importance
The importance of rows compared to columns	1	3	5	7	9
The importance of columns compared to rows	1	0.33	0.2	0.142	0.111

Formation of the Fuzzy Integrated Matrix: Expert judgments were integrated and transformed into triangular fuzzy numbers, which represent values with three points: the minimum, most likely, and maximum estimates (Equation 1).

$$\widetilde{a_{ij}} = [a_{ij}, b_{ij}, c_{ij}] \tag{1}$$

Where

a : Minimum of experts' opinions
b : Geometric mean of experts' opinions
c : Maximum of experts' opinions

Fuzzy Weights Calculation from Integrated Matrix: Fuzzy weights were calculated by taking the geometric mean of each row in the composite matrix (Equation 2).

$$Z_i = \left[\frac{a_{i1} \times \ a_{i2} \times a_{i3} \times, \ldots}{n}\right] \tag{2}$$

Each criterion's score was normalized by dividing it by the sum of all scores, resulting in a weight between 0 and 1 (Equation 3).

$$W_i = \frac{Z_i}{(Z_1 + Z_2 + Z_3 + \cdots)} \tag{3}$$

Defuzzification: To convert fuzzy numbers into a crisp value, the arithmetic mean of the three triangular fuzzy components was computed, yielding a definitive numerical weight (Equation 4).

$$W_i = \frac{W_{ai} + W_{bi} + W_{ci}}{3} \tag{4}$$

Normalization and Ranking: To finalize the weight of each criterion, the fuzzy weights were normalized by dividing each by the total weight sum. Applying a factor of 100, the significance of each criterion was expressed as a percentage (Equation 5). Final ranking is based on the obtained weights.

$$NW_i = \frac{W_i}{\sum_{i=1}^{n} W_i} \times 100 \tag{5}$$

4.2 Steps of Fuzzy DEMATEL Method

Determination of Criteria and Linguistic variables: In the initial step of the DEMATEL technique, the criteria and sub-criteria are determined. It is worth noting that the criteria and sub-criteria were established in the first step of the AHP method. The linguistic variables are also specified based on Table 4.

Table 4
The Linguistic Terms and their Fuzzy equivalents in the research [102], [104]

Linguistic Variables/ Verbal Terms	Crisp equivalent/ Influence score	Triangular Fuzzy Numbers
Very Low Influence (VL)	0	(0.0, 0.1, 0.3)
Low Influence (L)	1	(0.1, 0.3, 0.5)
Medium Influence (M)	2	(0.3, 0.5, 0.7)
High Influence (H)	3	(0.5, 0.7, 0.9)
Very High Influence (VH)	4	(0.7, 0.9, 1.0)

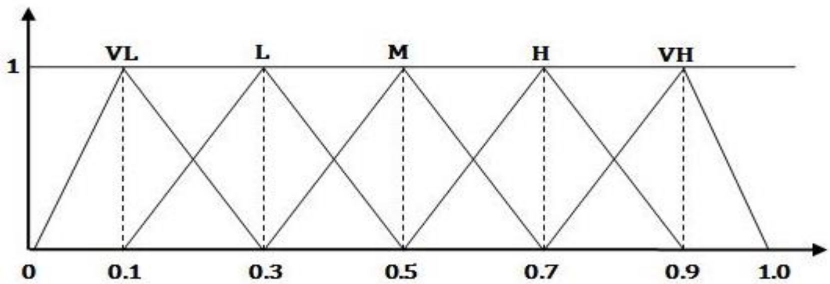

Fig. 2. Triangular fuzzy number diagram for the selected linguistic terms in Table 3

Creation of the Direct-Relations Matrix: At this step, Experts are asked to conduct pairwise comparisons of the criteria based on their influence on one another. These comparisons are recorded in a square matrix, referred to as the “Direct-Relation Matrix” where each entry is filled using qualitative (linguistic) terms. After completing this matrix, the qualitative expressions are converted into fuzzy numbers based on table 3. Finally, the average of the experts' opinions has been calculated using Equation (6).

$$\tilde{z} = \frac{\tilde{x}^1 + \tilde{x}^2 + \tilde{x}^3 + \ldots + \tilde{x}^p}{p} \tag{6}$$

Where p is the number of experts, and $\tilde{x}^1$, $\tilde{x}^2$, and $\tilde{x}^p$ are the paired scale 1 to p, respectively, and $\tilde{z}$ is the triangular Fuzzy number in the form of $\tilde{z}_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

Normalization of the Direct-Relations Matrix: The average of the experts' opinions is normalized using equations (7) and (8), allowing for standardized comparisons and the "Normalized Direct-Relation Fuzzy Matrix" is formed.

$$\tilde{a}_{ij} = \sum_{j=1}^{n} \tilde{z}_{ij} = \left(\sum_{j=1}^{n} l_{ij}, \sum_{j=1}^{n} m_{ij}, \sum_{j=1}^{n} u_{ij} \right), \quad u = \max_{1 \le i \le n} \left(\sum_{j=1}^{n} u_{ij} \right) \tag{7}$$

$$\tilde{x} = \begin{bmatrix} \tilde{x}_{11}\tilde{x}_{12}\ldots\tilde{x}_{1j} \\ \tilde{x}_{21}\tilde{x}_{22}\ldots\tilde{x}_{2j} \\ \ldots. \\ \ldots. \\ \ldots. \\ \tilde{x}_{i1}\tilde{x}_{i2}\ldots\tilde{x}_{ij} \end{bmatrix}, \tilde{x}_{ij} = \frac{\tilde{Z}_{ij}}{u} = \left(\frac{l_{ij}}{u}, \frac{m_{ij}}{u}, \frac{u_{ij}}{u}\right) \tag{8}$$

Here i denotes the row number and j the column number. For instance, $\tilde{x}_{12}$ indicates the impact degree of dimension 1 on dimension 2. The relation $\tilde{x}_{ij}$is utilized to compute the average matrix $\tilde{x}$.

Calculating the Total-Relation Fuzzy Matrix: This step involves calculating the total-relation matrix by first finding the inverse of the normalized matrix, subtracting it from the identity matrix, and then multiplying the normalized matrix by this result. To do this, it first needs to compute the total relation fuzzy matrix through relation $\tilde{T} = \lim_{n\to\infty}(x + x^2 + \ldots + x^n)$ and then obtain each Fuzzy number element that is $\tilde{t}_{ij} = (l_{ij}'', m_{ij}'', u_{ij}'')$ from equations (9) and (10).

$$\tilde{\mathrm{T}} = \begin{bmatrix} \tilde{t}_{11} \ldots \tilde{t}_{1n} \\ . \quad . \quad . \\ . \quad . \quad . \\ . \quad . \quad . \\ \tilde{t}_{n1} \ldots \tilde{t}_{nn} \end{bmatrix} \tag{9}$$

$$\begin{aligned} [l_{ij}''] &= x_l \times (I - x_l)^{-1} \\ [m_{ij}''] &= x_m \times (I - x_m)^{-1} \\ [u_{ij}''] &= x_r \times (I - x_u)^{-1} \end{aligned} \tag{10}$$

I is the unit matrix, x_l, x_m, and $x_u$are each matrix $n \times n$; Its elements form the lower, middle, and upper numbers of the fuzzy numbers of the triangular matrix x, respectively.

Defuzzification of the Total-Relation Fuzzy Matrix: The sum of each row (D_i) and column (R_i) is calculated. The crisp values are determined through equation (11).

$$B = \frac{l + u + 2m}{4}(13) \tag{11}$$

Sum of the rows and columns is calculated with the following equations.

$$\tilde{D} = (\tilde{D}_i)_{n\times1} = \left[\sum_{j=1}^{n} \tilde{T}_{ij}\right]_{n\times1} \tag{12}$$

$$\tilde{R} = (\tilde{R}_i)_{1\times n} = \left[\sum_{j=1}^{n} \tilde{T}_{ij}\right]_{1\times n} \tag{13}$$

Where $\tilde{D}$and $\tilde{R}$ are matrices $n \times 1$ and $1 \times n$, respectively. The Importance of the criteria (dimensions)$(\tilde{D_i} + \tilde{R_i})$ and the relationship between the criteria $(\tilde{D_i} - \tilde{R_i})$ are determined in the next step. If $\tilde{D_i} - \tilde{R_i} > 0$ is, the relevant criterion is "effective," and if$\tilde{D_i} - \tilde{R_i} < 0$is, the relevant criterion is "Impressive". The next step $\tilde{D_i} + \tilde{R_i}$and $\tilde{D_i} - \tilde{R_i}$from the previous step, should show the relationships between the criteria. After the defuzzification of the numbers, a Cartesian coordinate system is plotted. In this system, the longitudinal axis represents the values of $\tilde{D_i} + \tilde{R_i}$and the transverse axis of the values of $\tilde{D_i} - \tilde{R_i}$.

Determination of the importance and cause-effect relationships: The horizontal vector in the coordinate system represents the impact of a desired factor; a greater value indicates a stronger interaction with other system factors. The vertical vector reflects each factor's influence: a positive value identifies a causal variable, while a negative value denotes an effect.

5. Result

In this section, the results related to each of the methods are presented separately. For this purpose, the results of Fuzzy-AHP are presented first, followed by the results of Fuzzy-DEMATEL. Finally, the combined result of the two methods is discussed.

5.1 Fuzzy-AHP

In this study, the fuzzy AHP method was employed to prioritize blockchain and artificial intelligence criteria in the healthcare domain. The criteria were categorized into four main groups, with each criterion assigned a specific weight based on expert opinions. Subsequently, the sub-criteria for each main criterion were weighted and ranked. In the next step, the overall ranking was obtained by multiplying the weight of each criterion by the weight of its corresponding sub-criteria. In conclusion, by multiplying the weight of each sub-criterion by 100, the weighted percentage of each sub-criterion was obtained.

Table 5
Fuzzy-AHP results

Code	Criteria	weights	sub-criteria	sub-criteria	weights	Category Ranking	total weight	Total weight in percent	Total Ranking
C1	Digital Health	0.23	C11	Real-time data sharing	0.172	4	0.03956	3.956	18
			C12	Health monitoring	0.231	1	0.05313	5.313	3
			C13	Education and awareness	0.185	3	0.04255	4.255	14
			C14	Facilitate the treatment process	0.201	2	0.04623	4.623	10
			C15	Monitoring the treatment process	0.134	5	0.03082	3.082	20
			C16	Patient Engagement	0.077	6	0.01771	1.771	23
C2	Smart	0.245	C21	Clinical decision support	0.21	1	0.05145	5.145	5

	Health		C22	Patient-centered treatment strategy	0.181	3	0.044345	4.4345	13
			C23	Speed of clinical decision making	0.197	2	0.048265	4.8265	7
			C24	Development of treatment methods	0.172	4	0.04214	4.214	15
			C25	Disease prediction with historical data	0.143	5	0.035035	3.5035	19
			C26	Fraud detection	0.097	6	0.023765	2.3765	22
C3	Integrated Health	0.27	C31	Provide fair service	0.21	2	0.0567	5.67	2
			C32	Integration of treatment processes	0.25	1	0.0675	6.75	1
			C33	Distributed treatment network	0.175	4	0.04725	4.725	9
			C34	Security of medical data	0.195	3	0.05265	5.265	4
			C35	Traceability of medical records	0.17	5	0.0459	4.59	11
C4	Accessible Health	0.255	C41	Healthcare infrastructure	0.2	1	0.051	5.1	6
			C42	Stakeholder participation	0.165	4	0.042075	4.2075	16
			C43	Staff training	0.11	6	0.02805	2.805	21
			C44	Technology Acceptance	0.16	5	0.0408	4.08	17
			C45	Resource management	0.176	3	0.04488	4.488	12
			C46	Affordable care facilities	0.189	2	0.048195	4.8195	8

5.2 Fuzzy-DEMATEL

The fuzzy DEMATEL method was conducted according to its steps, including defuzzification of the matrix of relationships between variables. The relationships obtained after defuzzification are presented in Table 6. Additionally, the sum of the row and column numbers was also calculated.

Table 6
Fuzzy DEMATEL results

Code	**c11**	**c12**	**c13**	**c14**	**c15**	**c16**	**c21**	**c22**	**c23**	**c24**	**c25**	**c26**
c11	0.03	0.07	0.05	0.08	0.07	0.06	0.04	0.06	0.07	0.06	0.04	0.04
c12	0.03	0.04	0.06	0.07	0.06	0.06	0.04	0.08	0.06	0.06	0.06	0.04
c13	0.03	0.07	0.02	0.08	0.06	0.04	0.06	0.07	0.07	0.06	0.05	0.07
c14	0.03	0.03	0.02	0.03	0.06	0.03	0.03	0.04	0.03	0.04	0.03	0.03
c15	0.06	0.08	0.04	0.09	0.05	0.07	0.04	0.08	0.05	0.06	0.04	0.08
c16	0.07	0.08	0.06	0.08	0.06	0.03	0.03	0.07	0.04	0.06	0.05	0.08
c21	0.03	0.03	0.03	0.07	0.04	0.03	0.02	0.06	0.06	0.04	0.04	0.05
c22	0.07	0.08	0.07	0.10	0.09	0.07	0.06	0.05	0.08	0.07	0.07	0.08
c23	0.03	0.04	0.02	0.07	0.03	0.03	0.04	0.05	0.02	0.03	0.02	0.03

c24	0.04	0.04	0.03	0.07	0.04	0.03	0.05	0.07	0.05	0.03	0.04	0.03
c25	0.03	0.06	0.06	0.07	0.05	0.05	0.06	0.08	0.07	0.05	0.03	0.05
c26	0.04	0.05	0.03	0.06	0.07	0.04	0.04	0.05	0.04	0.04	0.04	0.03
c31	0.06	0.07	0.03	0.08	0.07	0.07	0.04	0.08	0.05	0.05	0.04	0.05
c32	0.08	0.09	0.05	0.09	0.10	0.08	0.05	0.09	0.08	0.07	0.06	0.08
c33	0.08	0.07	0.05	0.09	0.09	0.07	0.05	0.07	0.08	0.06	0.06	0.08
c34	0.04	0.06	0.04	0.05	0.06	0.04	0.03	0.05	0.04	0.04	0.03	0.06
c35	0.05	0.07	0.05	0.08	0.08	0.06	0.06	0.08	0.08	0.05	0.07	0.07
c41	0.09	0.10	0.07	0.11	0.10	0.08	0.08	0.10	0.09	0.08	0.07	0.09
c42	0.06	0.07	0.05	0.09	0.08	0.07	0.06	0.08	0.07	0.08	0.07	0.07
c43	0.06	0.08	0.05	0.09	0.08	0.07	0.06	0.08	0.08	0.07	0.07	0.07
c44	0.09	0.10	0.07	0.11	0.10	0.08	0.08	0.11	0.09	0.08	0.09	0.09
c45	0.05	0.07	0.05	0.07	0.07	0.06	0.04	0.07	0.05	0.06	0.04	0.05
c46	0.04	0.06	0.04	0.07	0.05	0.07	0.03	0.07	0.05	0.05	0.03	0.04
R	1.22	1.51	1.04	1.80	1.58	1.30	1.10	1.62	1.39	1.29	1.15	1.35

Table 6
(Continued)

Code	c31	c32	c33	c34	c35	c41	c42	c43	c44	c45	c46	D
c11	0.05	0.04	0.05	0.04	0.06	0.02	0.07	0.04	0.04	0.05	0.03	1.17
c12	0.07	0.04	0.03	0.03	0.04	0.02	0.05	0.06	0.04	0.06	0.03	1.13
c13	0.05	0.04	0.03	0.03	0.04	0.02	0.07	0.04	0.05	0.04	0.03	1.13
c14	0.06	0.05	0.03	0.03	0.04	0.02	0.05	0.05	0.03	0.03	0.02	0.81
c15	0.09	0.07	0.06	0.08	0.06	0.04	0.07	0.07	0.07	0.09	0.07	1.52
c16	0.06	0.05	0.03	0.04	0.03	0.02	0.06	0.05	0.06	0.06	0.03	1.21
c21	0.05	0.04	0.04	0.03	0.03	0.02	0.05	0.04	0.04	0.03	0.03	0.91
c22	0.09	0.08	0.07	0.08	0.04	0.03	0.06	0.04	0.05	0.07	0.06	1.56
c23	0.03	0.03	0.02	0.02	0.02	0.02	0.04	0.03	0.03	0.04	0.03	0.72
c24	0.03	0.04	0.03	0.05	0.04	0.02	0.05	0.04	0.05	0.05	0.03	0.93
c25	0.04	0.03	0.03	0.04	0.04	0.02	0.05	0.03	0.05	0.05	0.04	1.08
c26	0.07	0.04	0.04	0.06	0.03	0.02	0.06	0.04	0.05	0.06	0.03	1.05

c31	0.04	0.05	0.05	0.06	0.04	0.03	0.06	0.06	0.06	0.07	0.05	1.26
c32	0.09	0.04	0.06	0.08	0.07	0.04	0.08	0.07	0.08	0.08	0.05	1.66
c33	0.08	0.08	0.03	0.08	0.07	0.04	0.08	0.06	0.08	0.08	0.06	1.59
c34	0.05	0.04	0.04	0.03	0.05	0.02	0.05	0.05	0.05	0.06	0.03	1.01
c35	0.05	0.04	0.04	0.06	0.03	0.03	0.06	0.06	0.05	0.06	0.04	1.33
c41	0.09	0.09	0.07	0.08	0.08	0.03	0.08	0.08	0.06	0.09	0.07	1.88
c42	0.07	0.07	0.06	0.06	0.06	0.05	0.04	0.07	0.07	0.08	0.06	1.54
c43	0.08	0.06	0.06	0.06	0.06	0.04	0.07	0.04	0.07	0.08	0.06	1.52
c44	0.08	0.08	0.08	0.07	0.08	0.06	0.09	0.08	0.05	0.10	0.06	1.93
c45	0.05	0.06	0.05	0.05	0.04	0.05	0.06	0.08	0.07	0.04	0.06	1.29
c46	0.07	0.04	0.04	0.04	0.03	0.03	0.06	0.05	0.05	0.06	0.02	1.11
R	1.45	1.22	1.05	1.22	1.09	0.70	1.39	1.23	1.24	1.42	0.99	

In Table 7, the importance of sub-criteria and their degree of influence are analyzed. The value of D+R represents the importance of the sub-criteria, while the value of D−R indicates the type of relationship between them. Sub-criteria with a positive D−R value are considered influencing sub-criteria, whereas those with a negative D−R value are regarded as influenced sub-criteria.

Table 7

Importance & cause and effect relations

Code	D+ R	D− R	Cause/Effect
c11	2.389	-0.05	Effect
c12	2.638	-0.38	Effect
c13	2.173	0.088	Cause
c14	2.615	-0.99	Effect
c15	3.099	-0.06	Effect
c16	2.517	-0.09	Effect
c21	2.009	-0.19	Effect
c22	3.181	-0.07	Effect
c23	2.11	-0.66	Effect
c24	2.221	-0.36	Effect
c25	2.229	-0.07	Effect
c26	2.395	-0.3	Effect
c31	2.704	-0.19	Effect

c32	2.878	0.435	Cause
c33	2.631	0.54	Cause
c34	2.232	-0.2	Effect
c35	2.422	0.247	Cause
c41	2.584	1.181	Cause
c42	2.935	0.152	Cause
c43	2.757	0.292	Cause
c44	3.168	0.684	Cause
c45	2.711	-0.12	Effect
c46	2.091	0.121	Cause

In Figure 3, the importance and cause-effect relationships of the various sub-criteria are illustrated. The horizontal axis represents the level of importance of the sub-criteria, while the vertical axis indicates the causal relationships between them. Based on this classification, the sub-criteria located above the horizontal axis are identified as causal sub-criteria, whereas those below the horizontal axis are recognized as effect sub-criteria. The higher a sub-criteria is positioned above the horizontal axis, the stronger its causal role, while the lower a sub-criteria is placed, the greater its role as an effect (higher degree of influence). The value of D + R on the horizontal axis reflects the degree of interaction between the sub-criteria and others. Consequently, among the causal and effect sub-criteria, the higher the D + R value, the greater the importance and priority of that sub-criteria.

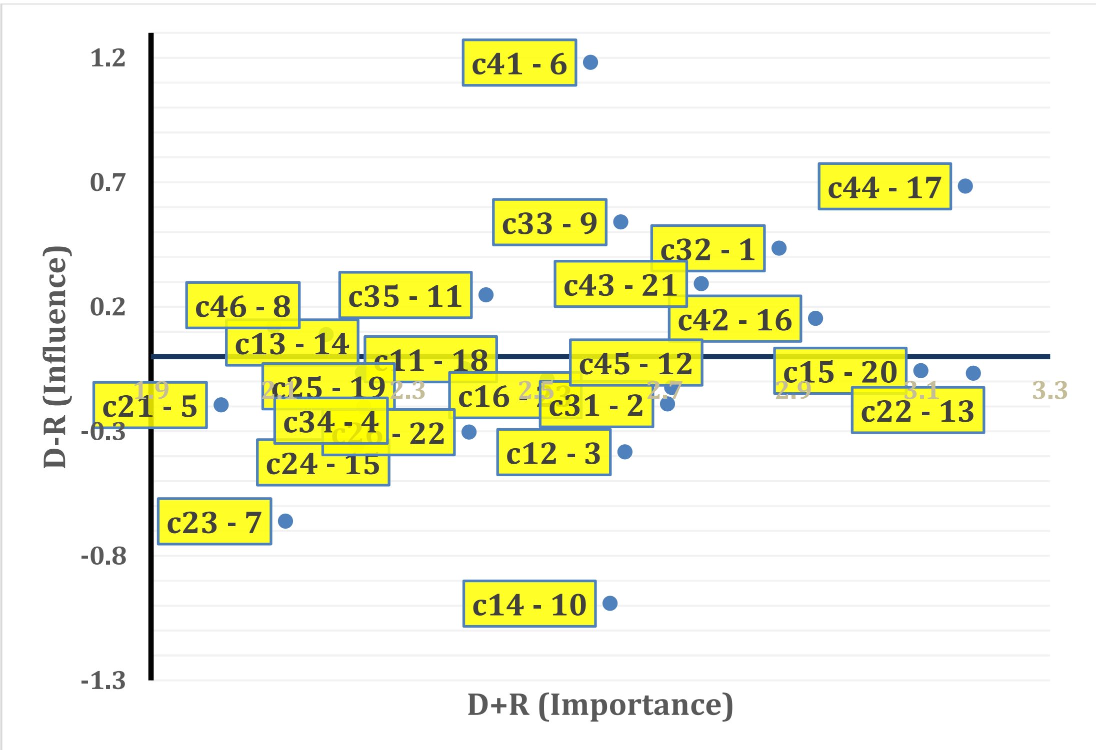

Fig. 3. Combined output of Fuzzy-AHP and Fuzzy-DEMATEL

6. Discussion and conclusion

In this research, based on a review of previous studies, 23 sub-criteria were identified across 4 main categories for evaluating and prioritizing factors in the integration of artificial intelligence and blockchain in the healthcare industry. The four main criteria are Digital Health (C1), Smart Health (C2), Integrated Health (C3), and Accessible Health (C4). To identify and prioritize key factors in AI and blockchain integration in healthcare, two decision-making approaches were utilized: first, Fuzzy AHP, and second, Fuzzy DEMATEL. The combined results of Fuzzy AHP and Fuzzy DEMATEL methods demonstrate significant advantages. In the first step, Fuzzy AHP was employed to structure complex issues and weight various factors. This method prioritized criteria and sub-criteria using fuzzy logic to manage uncertainties and human judgment ambiguities related to data.

Based on the results of the fuzzy AHP method, Integrated Health (C3), Accessible Health (C4), Smart Health (C2), and Digital Health (C1) ranked first to fourth, respectively. Initially, the sub-criteria of each main criteria were ranked individually. In the Digital Health category (C1), the Health Monitoring (C12) ranked first, while in the Smart Health category (C2), the Clinical Decision Support (C21) held the top position. In the Integrated Health category (C3), the Integration of treatment process (C32) ranked first, and in the Accessible Health category (C4), the Healthcare Infrastructure (C41) held the top spot. Subsequently, all sub-criteria were ranked collectively. Integration of treatment process (C32), Provide fair Service (C31), Health Monitoring (C12), Security of medical Data (C34), and Clinical Decision Support (C21) ranked first through fifth, respectively.

The fuzzy DEMATEL method, by focusing on identifying influential relationships between criteria, helps to clarify the complex interactions and mutual influence among various criteria. This method also incorporates fuzzy logic to account for uncertainty in the data and determines which criteria play a more significant role in the decision-making process. The results obtained from the fuzzy DEMATEL method reveal two types of criteria: causal criteria and effect criteria. Causal criteria are those that influence other criteria. These criteria play a more active role in the system and are typically recognized as driving and influential factors, including: healthcare infrastructure (C41), stakeholder participation (C42), staff training (C43), technology acceptance (C44), affordable care facilities (C46), integration of treatment process (C32), distributed treatment network (C33), traceability of medical records (C35), and education and awareness (C13).

Effect criteria are those influenced by other criteria. These criteria primarily function as outcomes, reacting to changes in cause criteria and are shaped by them. Examples include: real-time data sharing (C11), health monitoring (C12), facilitate the treatment process (C14), monitoring the treatment process (C15), patient engagement (C16), clinical decision support (C21), patient-centered treatment strategy (C22), speed of clinical decision making (C23), development of treatment method (C24), disease prediction with historical data (C25), fraud detection (C26), provide fair service (C31), security of medical data (C34), and resource management (C45).

In the output of the fuzzy DEMATEL method, the horizontal axis (D + R) represents the total interactions of each criterion. The higher the D + R value for a criterion, the more significant it is and the greater its interaction with other criteria. If a criterion is of the causal type, it means it influences a greater number of criteria and can create widespread effects in the system, such as stakeholder participation (C42) and technology acceptance (C44). To improve stakeholder participation (C42) in the healthcare system, comprehensive educational and awareness programs should be designed for stakeholders, including patients, doctors, nurses, and managers. These programs should explain the benefits of using modern technologies, such as artificial intelligence and blockchain, in simple language and with practical examples to enhance understanding and motivation for collaboration.

Conducting interactive sessions and hands-on workshops, along with collecting feedback from stakeholders, can ensure that they not only become familiar with technological changes but also play an active role in decision-making and implementation processes. Additionally, creating organizational structures that facilitate continuous consultation and engagement with stakeholders will help strengthen these interactions and increase trust in the system.

To enhance technology acceptance (C44) in healthcare systems, efforts must be directed toward aligning technologies with the actual needs of users. This includes designing simple and user-friendly interfaces, providing continuous training for end-users, and offering strong technical support to alleviate concerns about the complexities of technology. Additionally, demonstrating the benefits of technology in improving service quality, increasing accuracy in diagnosis and treatment, and reducing operational costs can strengthen acceptance among staff and patients. Creating financial and motivational incentives for employees and management teams who effectively integrate technology into their workflows can accelerate adoption and facilitate change.

If the criterion is an effect-based one, it indicates that this criterion is influenced by multiple other factors and plays a significant role within the system. Its response to changes in other criteria can have extensive consequences, such as monitoring the treatment process (C15) and patient-centered treatment strategies (C22). To enhance the monitoring the treatment process (C15) in healthcare systems, one effective approach is the use of advanced monitoring technologies, such as AI-based systems. These technologies can collect and analyze patients' vital data in real time and present it to the medical team, enabling more accurate monitoring of treatment progress and increasing the likelihood of preventing issues before they occur. Additionally, the creation of integration of treatment process (C32), which facilitate communication between doctors, nurses, and patients, can enable the efficient transfer of patient status information, ensuring continuous treatment monitoring. When developing patient-centered treatment strategies (C22), the priority should be the personalization of healthcare services. By utilizing big data and advanced AI algorithms, treatments tailored to the specific needs and conditions of each patient can be designed. Doing digital health monitoring (C12) that store and analyze comprehensive and accurate patient information can help the medical team provide customized, evidence-based treatments. Furthermore, educating and actively engaging patients (C16) in the treatment process through health education programs and digital tools plays a crucial role in improving treatment outcomes and implementing patient-centered strategies.

Author Contributions

Conceptualization, N.S., E.G., S.M., A.M., and S.K.; methodology, S.M., and A.M.; software, S.M., and S.K.; validation, N.S., and S.K.; formal analysis, N.S., and E.G.; investigation, S.K.; resources, N.S., and E.G.; writing—original draft preparation, N.S., and A.M.; writing—review and editing, A.M., and S.K.; supervision and project administration, S.K. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] 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. Scopus. https://doi.org/10.1108/JHOM-03-2024-0076
[2] 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
[3] Kantasa-ard, A., Nouiri, M., Bekrar, A., Ait El Cadi, A., & Sallez, Y. (2021). Machine learning for demand forecasting in the physical internet: A case study of agricultural products in Thailand. International Journal of Production Research, 59(24), 7491–7515.https://doi.org/10.1080/00207543.2020.1844332
[4] Deng, C., & Liu, Y. (2021). A Deep Learning-Based Inventory Management and Demand Prediction Optimization Method for Anomaly Detection. Wireless Communications and Mobile Computing, 2021(1), 9969357. https://doi.org/10.1155/2021/9969357
[5] Omidian, H. (2024). Synergizing blockchain and artificial intelligence to enhance healthcare. Drug Discovery Today, 29(9). Scopus. https://doi.org/10.1016/j.drudis.2024.104111
[6] Dar, A. A., Reegu, F. A., Ahmed, S., & Hussain, G. (2024). Blockchain Technology and Artificial Intelligence based Integrated Framework for Sustainable Supply Chain Management System. 1392–1397. Scopus. https://doi.org/10.23919/INDIACom61295.2024.10498149
[7] Xie, Y., Lu, L., Gao, F., He, S.-J., Zhao, H.-J., Fang, Y., Yang, J.-M., An, Y., Ye, Z.-W., & Dong, Z. (2021). Integration of Artificial Intelligence, Blockchain, and Wearable Technology for Chronic Disease Management: A New Paradigm in Smart Healthcare. Current Medical Science, 41(6), 1123–1133. Scopus. https://doi.org/10.1007/s11596-021-2485-0
[8] Kumar, R., & Tripathi, R. (2021). Towards design and implementation of security and privacy framework for Internet of Medical Things (IoMT) by leveraging blockchain and IPFS technology. Journal of Supercomputing, 77(8), 7916–7955. Scopus. https://doi.org/10.1007/s11227-020-03570-x
[9] Rayan, R. A., & Tsagkaris, C. (2021). Blockchain-based IoT for personalized pharmaceuticals. In Internet of medical things (pp. 51–62). CRC Press. https://www.taylorfrancis.com/chapters/edit/10.1201/9780429296864-4/blockchain-based-iot-personalized-pharmaceuticals-rehab-rayan-christos-tsagkaris
[10] Bansal, G., Chamola, V., Narang, P., Kumar, S., & Raman, S. (2020). Deep3DScan: Deep residual network and morphological descriptor based framework for lung cancer classification and 3D segmentation. IET Image Processing, 14(7), 1316–1326. Scopus. https://doi.org/10.1049/iet-ipr.2019.1164
[11] Anoop, V. S., & Asharaf, S. (2022). Integrating artificial intelligence and blockchain for enabling a trusted ecosystem for healthcare sector. In Intelligent Healthcare: Infrastructure, Algorithms and Management (pp. 281–295). Springer. https://doi.org/10.1007/978-981-16-8150-9_13

[12] Choi, A., & Shin, H. (2018). Longitudinal healthcare data management platform of healthcare IoT devices for personalized services. Journal of Universal Computer Science, 24(9), 1153–1169. Scopus. https://doi.org/10.3217/jucs-024-09-1153

[13]Alshehri, M. (2023). Blockchain-assisted cyber security in medical things using artificial intelligence. Electronic Research Archive, 31(2), 708–728. Scopus. https://doi.org/10.3934/era.2023035

[14]Sadiku, M. N., Eze, K. G., & Musa, S. M. (2018). Block chain technology in healthcare. Int. J. Adv. Sci. Res. Eng, 4(5), 154–159. https://doi.org/10.31695/IJASRE.2018.32723

[15]Mackey, T. K., & Nayyar, G. (2017). A review of existing and emerging digital technologies to combat the global trade in fake medicines. Expert Opinion on Drug Safety, 16(5), 587–602. Scopus. https://doi.org/10.1080/14740338.2017.1313227

[16]Benchoufi, M., & Ravaud, P. (2017). Blockchain technology for improving clinical research quality. Trials, 18(1). Scopus. https://doi.org/10.1186/s13063-017-2035-z

[17]Zhang, J., Xue, N., & Huang, X. (2016). A Secure System for Pervasive Social Network-Based Healthcare. IEEE Access, 4, 9239–9250. Scopus. https://doi.org/10.1109/ACCESS.2016.2645904

[18]Dey, T., Jaiswal, S., Sunderkrishnan, S., & Katre, N. (2018). HealthSense: A medical use case of Internet of Things and blockchain. 486–491. Scopus. https://doi.org/10.1109/ISS1.2017.8389459

[19]Zhou, Y., Zou, T., Liu, C., Yu, H., Chen, L., & Su, J. (2021). Blood supply chain operation considering lifetime and transshipment under uncertain environment. Applied Soft Computing, 106. Scopus. https://doi.org/10.1016/j.asoc.2021.107364

[20]Engelhardt, M. A. (2017). Hitching healthcare to the chain: An introduction to blockchain technology in the healthcare sector. Technology Innovation Management Review, 7(10). https://doi.org/10.22215/timreview/1111

[21]Secinaro, S., Dal Mas, F., Brescia, V., & Calandra, D. (2021). Blockchain in the accounting, auditing and accountability fields: A bibliometric and coding analysis. Accounting, Auditing and Accountability Journal, 35(9), 168–203. Scopus. https://doi.org/10.1108/AAAJ-10-2020-4987

[22]Kshetri, N. (2017). Blockchain's roles in strengthening cybersecurity and protecting privacy. Telecommunications Policy, 41(10), 1027–1038. Scopus. https://doi.org/10.1016/j.telpol.2017.09.003

[23]Zuo, Y., Guo, J., Gao, N., Zhu, Y., Jin, S., & Li, X. (2023). A Survey of Blockchain and Artificial Intelligence for 6G Wireless Communications. IEEE Communications Surveys and Tutorials, 25(4), 2494–2528. Scopus. https://doi.org/10.1109/COMST.2023.3315374

[24]Pandl, K. D., Thiebes, S., Schmidt-Kraepelin, M., & Sunyaev, A. (2020). On the Convergence of Artificial Intelligence and Distributed Ledger Technology: A Scoping Review and Future Research Agenda. IEEE Access, 8, 57075–57095. Scopus. https://doi.org/10.1109/ACCESS.2020.2981447

[25]Dinh, T. N., & Thai, M. T. (2018). AI and Blockchain: A Disruptive Integration. Computer, 51(9), 48–53. Scopus. https://doi.org/10.1109/MC.2018.3620971

[26]Singh, S. K., Rathore, S., & Park, J. H. (2020). BlockIoTIntelligence: A Blockchain-enabled Intelligent IoT Architecture with Artificial Intelligence. Future Generation Computer Systems, 110, 721–743. Scopus. https://doi.org/10.1016/j.future.2019.09.002

[27]Pablo, R.-G. J., Roberto, D.-P., Victor, S.-U., Isabel, G.-R., Paul, C., & Elizabeth, O.-R. (2021). Big data in the healthcare system: A synergy with artificial intelligence and blockchain technology. Journal of Integrative Bioinformatics, 19(1). Scopus. https://doi.org/10.1515/jib-2020-0035

[28]Sathyasri, B., Mary, G. A. A., Saravanan, K. A., & Kalipindi, M. (2024). Digital Transformation in Healthcare: An Engineering Perspective on Metaverse, Game Theory, Artificial Intelligence, and

Blockchain. In Healthcare Services in the Metaverse: Game Theory, AI, IoT, and Blockchain (pp. 26–50). Scopus. https://doi.org/10.1201/9781003449256-2

[29]Sai, S., Chamola, V., Choo, K.-K. R., Sikdar, B., & Rodrigues, J. J. P. C. (2023). Confluence of Blockchain and Artificial Intelligence Technologies for Secure and Scalable Healthcare Solutions: A Review. IEEE Internet of Things Journal, 10(7), 5873–5897. Scopus. https://doi.org/10.1109/JIOT.2022.3232793

[30]Haseli, G., Sheikh, R., & Sana, S. S. (2020). Base-criterion on multi-criteria decision-making method and its applications. International Journal of Management Science and Engineering Management, 15(2), 79–88. https://doi.org/10.1080/17509653.2019.1633964

[31]Salah, K., Rehman, M. H. U., Nizamuddin, N., & Al-Fuqaha, A. (2019). Blockchain for AI: Review and open research challenges. IEEE Access, 7, 10127–10149. Scopus. https://doi.org/10.1109/ACCESS.2018.2890507

[32]Shafay, M., Ahmad, R. W., Salah, K., Yaqoob, I., Jayaraman, R., & Omar, M. (2023). Blockchain for deep learning: Review and open challenges. Cluster Computing, 26(1), 197–221. Scopus. https://doi.org/10.1007/s10586-022-03582-7

[33]Wang, R., Luo, M., Wen, Y., Wang, L., Raymond Choo, K.-K., & He, D. (2021). The Applications of Blockchain in Artificial Intelligence. Security and Communication Networks, 2021. Scopus. https://doi.org/10.1155/2021/6126247

[34]Xing, B., & Marwala, T. (2018). The synergy of blockchain and artificial intelligence. Available at SSRN 3225357. https://dx.doi.org/10.2139/ssrn.3225357

[35]Hussain, A. A., & Al-Turjman, F. (2021). Artificial intelligence and blockchain: A review. Transactions on Emerging Telecommunications Technologies, 32(9), e4268. https://doi.org/10.1002/ett.4268

[36]Yang, Q., Zhao, Y., Huang, H., Xiong, Z., Kang, J., & Zheng, Z. (2022). Fusing blockchain and AI with metaverse: A survey. IEEE Open Journal of the Computer Society, 3, 122–136. https://doi.ieeecomputersociety.org/10.1109/OJCS.2022.3188249

[37]Dargie, W., Farrokhi, S., & Poellabauer, C. (2024). Identification of Persons Based on Electrocardiogram and Motion Data. TechRxiv. https://doi.org/10.36227/techrxiv.172254268.83468031/v1

[38]Rajabipoor Meybodi, A., Mohammadi, M., & Arjmandi, H. (2022). A qualitative approach to the ethical challenges of Iranian nurses during the COVID-19 pandemic. Journal of Preventive and Complementary Medicine, 1(3), 156–162. https://doi.org/10.22034/ncm.2022.336675.1035

[39]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 Healthcare Marketing, 13(4), 405–435. https://doi.org/10.1108/IJPHM-05-2018-0028

[40]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

[41]Nazarian-Jashnabadi, J., Haseli, G., & Tomaskova, H. (2024). Digital transformation for the sustainable development 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

[42]Khorasani, S. T., Cross, J., & Maghazei, O. (2020). Lean supply chain management in healthcare: A systematic review and meta-study. International Journal of Lean Six Sigma, 11(1), 1–34. https://doi.org/10.1108/IJLSS-07-2018-0069

[43]Rao, K. P. N., & Manvi, S. (2023). Survey on Electronic Health Record Management Using Amalgamation of Artificial Intelligence and Blockchain Technologies. Acta Informatica Pragensia, 12(1), 179–199. Scopus. https://doi.org/10.18267/j.aip.194

[44]Agarwal, Y., Jain, M., Sinha, S., & Dhir, S. (2020). Delivering high-tech, AI-based health care at Apollo Hospitals. Global Business and Organizational Excellence, 39(2), 20–30. https://doi.org/10.1002/joe.21981

[45]Baron, R. J. (2021). Using Artificial Intelligence to Make Use of Electronic Health Records Less Painful—Fighting Fire with Fire. JAMA Network Open, 4(7). Scopus. https://doi.org/10.1001/jamanetworkopen.2021.18298

[46]Haseli, G., Nazarian-Jashnabadi, J., Shirazi, B., Hajiaghaei-Keshteli, M., & Moslem, S. (2024). Sustainable strategies based on the social responsibility of the beverage industry companies for the circular supply chain. Engineering Applications of Artificial Intelligence, 133, 108253. https://doi.org/10.1016/j.engappai.2024.108253

[47]Kumar, K., Kumar, V., Sharma, M. K., Khan, A. A., & Idrisi, M. J. (2024). A Systematic Review of Blockchain Technology Assisted with Artificial Intelligence Technology for Networks and Communication Systems. Journal of Computer Networks and Communications, 2024. Scopus. https://doi.org/10.1155/2024/9979371

[48]Shae, Z., & Tsai, J. J. P. (2017). On the Design of a Blockchain Platform for Clinical Trial and Precision Medicine. 1972–1980. Scopus. https://doi.org/10.1109/ICDCS.2017.61

[49]Haseli, G., & Sheikh, R. (2022). Base criterion method (BCM). In Multiple criteria decision making: Techniques, Analysis and Applications (pp. 17–38). Springer. https://doi.org/10.1007/978-981-16-7414-3_2

[50]Haseli, G., Ranjbarzadeh, R., Hajiaghaei-Keshteli, M., Ghoushchi, S. J., Hasani, A., Deveci, M., & Ding, W. (2023). HECON: Weight assessment of the product loyalty criteria considering the customer decision's halo effect using the convolutional neural networks. Information Sciences, 623, 184–205. https://doi.org/10.1016/j.ins.2022.12.027

[51]Haseli, G., Torkayesh, A. E., Hajiaghaei-Keshteli, M., & Venghaus, S. (2023). Sustainable resilient recycling partner selection for urban waste management: Consolidating perspectives of decision-makers and experts. Applied Soft Computing, 137, 110120. https://doi.org/10.1016/j.asoc.2023.110120

[52]Nazarian-Jashnabadi, J., Bonab, S. R., Haseli, G., Tomaskova, H., & Hajiaghaei-Keshteli, M. (2023). A dynamic expert system to increase patient satisfaction with an integrated approach of system dynamics, ISM, and ANP methods. Expert Systems with Applications, 234, 121010. https://doi.org/10.1016/j.eswa.2023.121010

[53]Amiri Sardari, Z., Abdoli Mohamadabadi, T., Nazarian-Jashnabadi, J., Tesoriere, G., & Campisi, T. (2024). Smart Experience and Green Health Tourism: The Moderating Role of Content Marketing. Sustainability, 16(11), 4546. https://doi.org/10.3390/su16114546

[54]Shen, M., Tang, X., Zhu, L., Du, X., & Guizani, M. (2019). Privacy-preserving support vector machine training over blockchain-based encrypted IoT data in smart cities. IEEE Internet of Things Journal, 6(5), 7702–7712. https://doi.org/10.1109/JIOT.2019.2901840

[55]Jashnabadi, J. N., Pooya, A., & Bagheri, R. (2023). Provide a model for budget policy in university-community communication programs with a system dynamics approach (case study: Ferdowsi University of Mashhad). J. Ind. Manag. Perspect, 13(1), 9–39. https://doi.org/10.48308/jimp.13.1.9

[56]Kazemi, A., Kazemi, Z., Heshmat, H., Nazarian-Jashnabadi, J., & Tomášková, H. (2024). Ranking factors affecting sustainable competitive advantage from the business intelligence perspective: Using content analysis and F-TOPSIS. Journal of Soft Computing and Decision Analytics, 2(1), 39–53. http://dx.doi.org/10.31181/jscda21202430

[57]Sandner, P., Gross, J., & Richter, R. (2020). Convergence of blockchain, IoT, and AI. Frontiers in Blockchain, 3, 522600. https://doi.org/10.3389/fbloc.2020.522600

[58]Saxena, S., Bhushan, B., & Ahad, M. A. (2021). Blockchain based solutions to secure IoT: Background, integration trends and a way forward. Journal of Network and Computer Applications, 181, 103050. https://doi.org/10.1016/j.jnca.2021.103050

[59]Liu, Y., Yu, F. R., Li, X., Ji, H., & Leung, V. C. (2020). Blockchain and machine learning for communications and networking systems. IEEE Communications Surveys & Tutorials, 22(2), 1392–1431. https://doi.org/10.1109/COMST.2020.2975911

[60]Mamoshina, P., Ojomoko, L., Yanovich, Y., Ostrovski, A., Botezatu, A., Prikhodko, P., Izumchenko, E., Aliper, A., Romantsov, K., Zhebrak, A., Ogu, I. O., & Zhavoronkov, A. (2018). Converging blockchain and next-generation artificial intelligence technologies to decentralize and accelerate biomedical research and healthcare. Oncotarget, 9(5), 5665–5690. Scopus. https://doi.org/10.18632/oncotarget.22345

[61]Rezazadeh, J., Bagheri, R., Karimi, S., Nazarian-Jashnabadi, J., & Nezhad, M. Z. (2023). Examining the impact of product innovation and pricing capability on the international performance of exporting companies with the mediating role of competitive advantage for analysis and decision making. Journal of Operations Intelligence, 1(1), 30–43. https://doi.org/10.31181/jopi1120232

[62]Gharedaghi Kloucheh, S., Khoubanfar, H., Moghaddam Matin, M., & Behnam Rassouli, F. (2021). Investigating effects of galbanic acid on the viability of LoVo colon carcinoma cells. 21st International and 9th National Congress in Biology.

[63]Azad, M., Hosseini, F., Hassanzade, H., Gharedaghi, S., Mahdipour, E., Rassouli, F. B., & Jamialahmadi, K. (2024). Galbanic acid suppresses melanoma cell migration and invasion by reducing MMP activity and downregulating N-cadherin and fibronectin. Naunyn-Schmiedeberg's Archives of Pharmacology, 1–10. https://doi.org/10.1007/s00210-024-02981-4

[64]Qiu, C., Ren, X., Cao, Y., & Mai, T. (2021). Deep Reinforcement Learning Empowered Adaptivity for Future Blockchain Networks. IEEE Open Journal of the Computer Society, 2, 99–105. Scopus. https://doi.org/10.1109/OJCS.2020.3010987

[65]Chenli, C., Li, B., Shi, Y., & Jung, T. (2019). Energy-recycling Blockchain with Proof-of-Deep-Learning. 19–23. Scopus. https://doi.org/10.1109/BLOC.2019.8751419

[66]Hashemi, R., Farahi, M., Bagheri, R., Iranshahi, M., Torabinejad, S., Gharedaghi, S., & Soleymanifard, S. (2021). In vitro study of Radiosensitivity Effects of Galbanic Acid on ovarian tumor cells (OVCAR-3 cell line). Natural Product Communications, 16(10), 1934578X211046068. https://doi.org/10.1177/1934578X211046068

[67]Hosseini, F., Ahmadi, A., Hassanzade, H., Gharedaghi, S., Rassouli, F. B., & Jamialahmadi, K. (2024). Inhibition of melanoma cell migration and invasion by natural coumarin auraptene through regulating EMT markers and reducing MMP-2 and MMP-9 activity. European Journal of Pharmacology, 971, 176517. https://doi.org/10.1016/j.ejphar.2024.176517

[68]Liang, W., Xiao, L., Zhang, K., Tang, M., He, D., & Li, K.-C. (2022). Data Fusion Approach for Collaborative Anomaly Intrusion Detection in Blockchain-Based Systems. IEEE Internet of Things Journal, 9(16), 14741–14751. Scopus. https://doi.org/10.1109/JIOT.2021.3053842

[69] Mohammadi, S., & Rabieinejad, E. (2020). Prediction forks in the blockchain using machine learning. Proc. 3rd Int. Conf. Mech. Elect. Comput. Eng, 1–8.

[70] Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y., Dong, Q., Shen, H., & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. Stroke and Vascular Neurology, 2(4), 230–243. Scopus. https://doi.org/10.1136/svn-2017-000101

[71] Rong, G., Mendez, A., Bou Assi, E., Zhao, B., & Sawan, M. (2020). Artificial Intelligence in Healthcare: Review and Prediction Case Studies. Engineering, 6(3), 291–301. Scopus. https://doi.org/10.1016/j.eng.2019.08.015

[72] Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future Healthcare Journal, 6(2), 94–98. https://doi.org/10.7861/futurehosp.6-2-94

[73] Siddique, S., & Chow, J. C. (2021). Machine learning in healthcare communication. Encyclopedia, 1(1), 220–239. https://doi.org/10.3390/encyclopedia1010021

[74] Sunarti, S., Rahman, F. F., Naufal, M., Risky, M., Febriyanto, K., & Masnina, R. (2021). Artificial intelligence in healthcare: Opportunities and risk for future. Gaceta Sanitaria, 35, S67–S70. https://doi.org/10.1016/j.gaceta.2020.12.019

[75] Gerke, S., Minssen, T., & Cohen, G. (2020). Ethical and legal challenges of artificial intelligence-driven healthcare. In Artificial intelligence in healthcare (pp. 295–336). Elsevier. https://doi.org/10.1016/B978-0-12-818438-7.00012-5

[76] Lee, D., & Yoon, S. N. (2021). Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges. International Journal of Environmental Research and Public Health, 18(1), 271. https://doi.org/10.3390/ijerph18010271

[77] Manne, R., & Kantheti, S. C. (2021). Application of artificial intelligence in healthcare: Chances and challenges. Current Journal of Applied Science and Technology, 40(6), 78–89. https://ssrn.com/abstract=4393347

[78] Balasubramanian, S., Shukla, V., Sethi, J. S., Islam, N., & Saloum, R. (2021). A readiness assessment framework for Blockchain adoption: A healthcare case study. Technological Forecasting and Social Change, 165, 120536. https://doi.org/10.1016/j.techfore.2020.120536

[79] Miyachi, K., & Mackey, T. K. (2021). hOCBS: A privacy-preserving blockchain framework for healthcare data leveraging an on-chain and off-chain system design. Information Processing & Management, 58(3), 102535. https://doi.org/10.1016/j.ipm.2021.102535

[80] Shuaib, M., Alam, S., Alam, M. S., & Nasir, M. S. (2023). Self-sovereign identity for healthcare using blockchain. Materials Today: Proceedings, 81, 203–207. https://doi.org/10.1016/j.matpr.2021.03.083

[81] Chelladurai, U., & Pandian, S. (2022). A novel blockchain based electronic health record automation system for healthcare. Journal of Ambient Intelligence and Humanized Computing, 13(1), 693–703. https://doi.org/10.1007/s12652-021-03163-3

[82] Hussien, H. M., Yasin, S. M., Udzir, N. I., Ninggal, M. I. H., & Salman, S. (2021). Blockchain technology in the healthcare industry: Trends and opportunities. Journal of Industrial Information Integration, 22, 100217. https://doi.org/10.1016/j.jii.2021.100217

[83] Abu-Elezz, I., Hassan, A., Nazeemudeen, A., Househ, M., & Abd-Alrazaq, A. (2020). The benefits and threats of blockchain technology in healthcare: A scoping review. International Journal of Medical Informatics, 142, 104246. https://doi.org/10.1016/j.ijmedinf.2020.104246

[84]EskandariNasab, M., Raeisi, Z., Lashaki, R. A., & Najafi, H. (2024). A GRU–CNN model for auditory attention detection using microstate and recurrence quantification analysis. Scientific Reports, 14(1), 8861. https://doi.org/10.1038/s41598-024-58886-y

[85]Wehbe, Y., Al Zaabi, M., & Svetinovic, D. (2018). Blockchain AI framework for healthcare records management: Constrained goal model. 2018 26th Telecommunications Forum (TELFOR), 420–425. https://doi.org/10.1109/TELFOR.2018.8611900

[86]Hathaliya, J. J., Tanwar, S., Tyagi, S., & Kumar, N. (2019). Securing electronics healthcare records in healthcare 4.0: A biometric-based approach. Computers & Electrical Engineering, 76, 398–410. https://doi.org/10.1016/j.compeleceng.2019.04.017

[87]El Azzaoui, A., Singh, S. K., Pan, Y., & Park, J. H. (2020). Block5GIntell: Blockchain for AI-enabled 5G networks. IEEE Access, 8, 145918–145935. https://doi.org/10.1109/ACCESS.2020.3014356

[88]Kim, S.-K., & Huh, J.-H. (2020). Artificial neural network blockchain techniques for healthcare system: Focusing on the personal health records. Electronics, 9(5), 763. https://doi.org/10.3390/electronics9050763

[89]Zhaofeng, M., Xiaochang, W., Jain, D. K., Khan, H., Hongmin, G., & Zhen, W. (2019). A blockchain-based trusted data management scheme in edge computing. IEEE Transactions on Industrial Informatics, 16(3), 2013–2021. https://doi.org/10.1109/TII.2019.2933482

[90]Fusco, A., Dicuonzo, G., Dell'Atti, V., & Tatullo, M. (2020). Blockchain in healthcare: Insights on COVID-19. International Journal of Environmental Research and Public Health, 17(19), 7167. https://doi.org/10.3390/ijerph17197167

[91]Badré, A., Mohebbi, S., & Soltanisehat, L. (2020). Secure decentralized decisions to enhance coordination in consolidated hospital systems. IISE Transactions on Healthcare Systems Engineering, 10(2), 99–112. https://doi.org/10.1080/24725579.2019.1680582

[92]Gupta, R., Kumari, A., & Tanwar, S. (2021). Fusion of blockchain and artificial intelligence for secure drone networking underlying 5G communications. Transactions on Emerging Telecommunications Technologies, 32(1). Scopus. https://doi.org/10.1002/ett.4176

[93]Supriya, M., & Chattu, V. K. (2021). A review of artificial intelligence, big data, and blockchain technology applications in medicine and global health. Big Data and Cognitive Computing, 5(3). Scopus. https://doi.org/10.3390/bdcc5030041

[94]Farrokhi, S., Dargie, W., & Poellabauer, C. (2024). Human Activity Recognition Based on Wireless Electrocardiogram and Inertial Sensors. IEEE Sensors Journal. https://doi.org/10.1109/JSEN.2023.3348661

[95]Sepahi, T., Shahbazi, M., & Shafiei Roudposhti, M. (2020). Drug distribution system in Iran: A multi method study of defects and solutions. Depiction of Health, 11(4), 324–343. https://doi.org/10.34172/doh.2020.41

[96]Moghadam Manesh, M., & Zhao, W. (2022). Failure of the Health Transformation Plan in Iran: How much has the Fee-for-Service payment system been to blame?. The 2022 System Dynamics Conference, Frankfurt, Germany. https://proceedings.systemdynamics.org/2022/abstracts/1339.html

[97]Mahdavimanshadi, M., Anaraki, M. G., Mowlai, M., & Ahmadirad, Z. (2024). A Multistage Stochastic Optimization Model for Resilient Pharmaceutical Supply Chain in COVID-19 Pandemic Based on Patient Group Priority. 2024 Systems and Information Engineering Design Symposium (SIEDS), 382–387. https://doi.org/10.1109/SIEDS61124.2024.10534683

[98] Sadeghi, S., & Niu, C. (2024). Augmenting Human Decision-Making in K-12 Education: The Role of Artificial Intelligence in Assisting the Recruitment and Retention of Teachers of Color for Enhanced Diversity and Inclusivity. Leadership and Policy in Schools, 1–21. https://doi.org/10.1080/15700763.2024.2358303

[99] Farahani, S. D., Abadeh, A., Alizadeh, A., & Helforoush, Z. (2024). Artificial intelligence-based prediction of heat transfer enhancement in ferrofluid flow under a rotating magnetic field: Experimental study. Case Studies in Thermal Engineering, 58, 104442. https://doi.org/10.1016/j.csite.2024.104442

[100] Dokhanian, S., Sodagartojgi, A., Tehranian, K., Ahmadirad, Z., Moghaddam, P. K., & Mohsenibeigzadeh, M. (2024). Exploring the impact of supply chain integration and agility on commodity supply chain performance. World Journal of Advanced Research and Reviews, 22(1), 441–450. https://doi.org/10.30574/wjarr.2024.22.1.1119

[101] Ahmadirad, Z. (2024). Evaluating the influence of AI on market values in finance: Distinguishing between authentic growth and speculative hype. International Journal of Advanced Research in Humanities and Law, 1(2), 50–57. https://doi.org/10.63053/ijrel.11

[102] Nezhad, M. Z., Nazarian-Jashnabadi, J., Rezazadeh, J., Mehraeen, M., & Bagheri, R. (2023). Assessing dimensions influencing IoT implementation readiness in industries: A fuzzy DEMATEL and fuzzy AHP analysis. Journal of Soft Computing and Decision Analytics, 1(1), 102–123. https://doi.org/10.31181/jscda11202312

[103] Gupta, S., Modibbo, U. M., & Ali, I. (2024). Fuzzy AHP Approach for Multi-Criteria Stress Analysis During COVID-19: A Case Study. Decision Making Advances, 2(1), 238–266. https://doi.org/10.31181/dma21202448

[104] Fu, X.-M., Wang, N., Jiang, S.-S., Yang, F., Li, J.-M., & Wang, C.-Y. (2019). A research on influencing factors on the international cooperative exploitation for deep-sea bioresources based on the ternary fuzzy DEMATEL method. Ocean & Coastal Management, 172, 55–63. http://dx.doi.org/10.1016/j.ocecoaman.2019.01.019

[105] Jeng, D. J.-F. (2015). Generating a causal model of supply chain collaboration using the fuzzy DEMATEL technique. Computers & Industrial Engineering, 87, 283–295. https://doi.org/10.1016/j.cie.2015.05.007

[106] Nazarian-Jashnabadi, J., Ronaghi, M., Alimohammadlu, M., & Ebrahimi, A. (2023). The framework of factors affecting the maturity of business intelligence. Business Intelligence Management Studies, 12(46), 1–39. https://doi.org/10.22054/ims.2023.74305.2346