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Factors Influencing Blockchain Adoption in Digital Healthcare: A Gaussian Fuzzy Delphi Approach for Handling Uncertainty in Experts' Opinion

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Abstract: Digital Healthcare, as an emerging industry, holds great promise in revolutionizing the way Healthcare is delivered and managed. Conversely, digital Healthcare faces numerous challenges, including data security, privacy, regulatory, reliability, transparency and efficiency. The adoption of blockchain technology offers potential solutions to these challenges. However, existing models for blockchain adoption are hindered by a limited holistic view, failing to integrate both business and end-user perspectives along with the critical consideration of various factors influencing both stakeholders. To fill this gap, this study proposes a multi-perspective model for the adoption of blockchain in digital healthcare that jointly considers the business aspect and the end user aspect. After identification from literature, factors are selected based on a comprehensive survey of 15 healthcare experts by using the fuzzy Delphi approach for handling the uncertainty in the expert opinions. The analysis reveals that the most significant factors affecting blockchain adoption are Top Management Support (0.830) and Regulation Compliance (0.830).

Keywords: Blockchain adoption, Digital healthcare, Fuzzy Delphi, Uncertainty handling, Factors selection.

1. Introduction

Healthcare, encompassing preventive measures to disease treatment, provides a range of services to maintain or improve health, offered through two main avenues: primary care for community-based essential services and secondary care for specialized, often hospital-based treatments [1]. Information technology (IT) has become integral to Healthcare, receiving increasing attention worldwide. Health IT, which includes transformative systems such as Electronic Health Records (EHRs), telemedicine, Mobile Health (mHealth), and wearable health tracking devices [2], aims to enhance patient outcomes and experiences, improve healthcare quality and performance, and drive research and innovation [3], improve population and public health, maintain privacy and security of healthcare information as well as reduce costs [4]. However, these systems often struggle with issues related to data security, interoperability [5], scalability, deployment and limited connectivity challenges [6], compatibility, limitation of computing power and reliability [7], and administrative and legal obstacles [8, 9].

As part of its continuous efforts to enhance patient care and outcomes, the healthcare sector actively investigates the potential of diverse emerging technologies [10]. Among the myriad of technologies contributing to the digitalization of Healthcare, blockchain emerges as an essential solution [11]. Blockchain, a decentralized and secure data management system, offers innovative solutions to many challenges in Healthcare. By providing a secure, fast, immutable, and decentralized data storage and exchange infrastructure, blockchain addresses issues such as data security, privacy, transparency, integrity, access to medical records and consent management. It ensures data integrity while providing a transparent, auditable record of all transactions, which is particularly valuable in Healthcare, where trust is paramount [12-14]. The potential of blockchain extends beyond these applications, promising a transformative approach that could fundamentally change how healthcare data is managed and utilized. Despite its potential, the adoption of blockchain in Healthcare is not without obstacles. These challenges, which range from technical issues such as scalability and computing power [15] to regulatory concerns, limitation in skilled technical resources to environmental concerns, necessitate a quantitative understanding. This understanding could be achieved through adoption models [16, 17], providing a structured approach to understanding the factors influencing the uptake of new technologies.

Adoption models are crucial tools in technology management, helping stakeholders identify, analyze, and address the various factors that can affect the successful implementation and use of technology [18, 19]. However, constructing an accurate adoption model is a complex task, particularly when selecting the influencing factors [20, 21]. Multi-Criteria Decision Making (MCDM) models can help address this issue, with the Delphi model being a prime candidate. The Delphi model, which relies on the consensus of a panel of experts, is widely used for its ability to handle complex problems and incorporate diverse perspectives [22, 23]. However, limitations are present in traditional Delphi models, especially when dealing with the inherent uncertainty in expert opinions. Uncertainty is a common element in decision-making processes that reflects the complexity and unpredictability of real-world scenarios. It can cause significant impacts on the results of a decision-making process, leading to skewed outcomes or ineffective decisions if not properly managed [24, 25]. To address this limitation, [26] introduced the concept of fuzzy set theory, aiming to tackle the inherent uncertainty associated with human thought and behaviour regarding decision-making [24, 27]. The Fuzzy Delphi method was widely used in the literature for factor selection. This method offers a more nuanced way to encapsulate experts' opinions [28]. However, the use of triangular numbers in these models does not accurately capture the reality of fluctuating expert opinions. The Gaussian Fuzzy Delphi approach, on the other hand, is considered a more effective method for handling uncertainty. By employing Gaussian fuzzy numbers instead of triangular ones, the Gaussian Fuzzy MCDM method provides a more realistic representation of expert opinions [29]. This improvement enhances the accuracy and reliability of the model, allowing for a more precise assessment of factors and their influences.

The research aims to define the factors influencing blockchain adoption in digital Healthcare using a Gaussian Fuzzy Delphi approach. This method allows us to handle the inherent uncertainty in expert opinions, thereby providing a more accurate and reliable model for understanding the adoption of blockchain technology in the healthcare sector. As part of this–research process, we will conduct a comprehensive literature survey to understand the current state of blockchain technology in healthcare and investigate the factors influencing its adoption. Furthermore, the literature review examines existing adoption models for blockchain and underscore the need for the proposed Gaussian fuzzy Delphi approach. The research expects to pave the way for a more efficient, effective, and patient-centred healthcare system.

This article aims at answering the following questions:

1. What are the candidate factors influencing blockchain adoption in digital healthcare through literature review?
2. How Gaussian and triangular fuzzy numbers model can be used to handle uncertainty in expert opinions?
3. How will the factors be quantified and their significance determined according to fuzzy Delphi?
4. What are the implications of the study's findings for real-world blockchain adoption in healthcare?

This article is organized as follows: Section II provides a comprehensive literature review. Section III details the methodology of the research. Section IV presents the results of the experimental work. In addition, this section includes a discussion of the importance of the factors. In section V, we compare the identified factors with findings from the existing literature. Finally, section VI presents the conclusion and contribution and identifies potential areas for future research.

2. Literature survey

2.1 Digital healthcare and blockchain

Digital Healthcare is a rapidly evolving field that leverages technology to improve health and wellness. It encompasses eHealth, mHealth, and emerging areas, integrating digital and genomic revolutions with health, living and society [9, 30] . Digital health is centred on the citizen, collecting real-time data from all social activities and using complex analyses to gain knowledge from these data to intervene in the broadest possible social and economic activities. It uses digital health technologies to improve health and provide essential services. Key technologies driving digital health include the Internet of Things, Artificial

Intelligence (AI), blockchain, cloud computing, big data, and 5G communication networks. These technologies are used interactively during the application process rather than simply existing independently [2].

For the first time in October 2008, Satoshi Nakamoto introduced blockchain technology as a non-mediated and peer-to-peer electronic cash system known as Bitcoin [31]. Bitcoin is a distributed ledger technology chain of time-stamped blocks containing a given number of validated transactions. In this technology, the hash value of the previous blocks is used to join the blocks together in a cryptographic manner. Whenever a node or a user generates a transaction, a private key is employed in digital signing, after which it is broadcasted to the network. A mining/validation node takes the given transaction and is then enclosed into a block, which is broadcasted to the network. The validation of the block is done by each node in the network through the implementation of the consensus protocol. Subsequent to the validation of the block, it is then attached to the chain, and afterwards, the ledger, which has been updated is then duplicated through the permission nodes of the network [32].

Blockchain-based Healthcare is a rapidly evolving field that leverages the unique properties of blockchain technology to securely store and transfer health information. Blockchain, a digital ledger or immutable record, forms a chain of cryptographic data blocks. This unique transaction framework is used to store encrypted healthcare data in a healthcare application network based on the blockchain. This system ensures safe data transactions among users such as medical controllers, doctors, patients, and other medical entities over the network. The healthcare blockchain enhances data authentication, transparency, and legitimacy, which influence the quality of the data, the cost, and the significance of providing Healthcare within the system [33, 34].

The implementation of blockchain-based Healthcare involves Data service, data security, and data gathering comprise the system's three modules. The data collection module is used to gather patient health data, the security module sets up safeguards for the healthcare system, and the service module responds to inquiries from patients about their medical records [35]. A data analysis module, a health guidance module, a historical case module, and a patient evaluation module make up the data service module. Data from medical institutions are kept in the blockchain and compared to patient-collected medical and health data in the data analysis module for analysis. Patients' previous recovery records are kept in the history case module. While the patient evaluation module enables patients to rate medical institutions, the health guidance module enables medical institutions to provide rehabilitation guidance to patients [36, 37].

However, adopting blockchain in the health sector would involve overcoming obstacles and building a strong hardware and network infrastructure. The difficulties in adopting blockchain technology in digital healthcare are discussed in the next section.

2.2 Blockchain challenges in digital healthcare

The adoption of blockchain technology in Healthcare is influenced by several factors and faces numerous challenges. From a technological perspective, blockchain software continuously evolves and matures as developers work tirelessly to refine its capabilities. There are challenges related to storage capacity for large amounts of data, non-standardization, lack of scalability, has the potential for information decay, throughput capacity, storage limits, and integration with existing systems. Selecting a suitable blockchain protocol, which guides the structure of the blockchain and the development of applications, is also a critical decision. Organizational factors also play a significant role in blockchain adoption. Cultural and trust concerns can hinder the adoption of blockchain technology. Encouraging organizations to participate in a shared network and addressing interoperability issues are crucial. The cost of operating blockchain and finding the return on investment can also pose challenges. The environment in which the technology is being adopted is another factor. The social adoption of technology can be hesitant, and there is a lack of successful examples of blockchain-based projects. Uncertainty around adopting the technology and participating in a shared network, as well as a knowledge gap, can deter adoption. Legal and financial considerations also influence blockchain adoption in Healthcare. The distributed storage nature of the blockchain has implications that need to be addressed. There is a lack of regulation that addresses the unique properties of blockchain data exchange. Issues related to the ownership of records, granting access, and emerging cybersecurity concerns must be addressed before patients can entrust data to a public blockchain. Finally, the users' intention to use the technology is a crucial factor [38-42]. For blockchain technology to work effectively, many barriers - technological, governance, organizational, and even societal - will have to fall. Blockchain approaches must be responsive to the unique healthcare needs from the diverse perspectives of consumers, patients, providers, and regulators [38]. Despite these challenges, blockchain technology has the potential to create new foundations for our economic and social systems [43]. These challenges underline the critical need for a comprehensive adoption model when approaching innovative technologies such as blockchain in healthcare. Such a model should identify and quantify the multifaceted barriers to adoption, while also proposing actionable strategies to overcome them. Hence, there is a need for a comprehensive understanding and investigation of the factors influencing and the obstacles in front of blockchain adoption. The next three subsections present the existing literature on blockchain adoption. The first subsection focuses on adoption models for technology acceptance, while the second subsection explores MCDM-based adoption models. The third subsection presents the factors that were selected based on the literature review.

2.3 Adoption models for technology acceptance

In the context of dynamic technological advancements, the significance of user acceptance and confidence stands as a critical determinant of successful adoption and deployment. The degree of user involvement during systems development has emerged as a pivotal influencer of technology acceptance, necessitating the formulation of comprehensive models and theories in this realm. These conceptual frameworks have been widely applied across a diverse spectrum of domains, encompassing domains such as voting, dieting, education, and computer usage, facilitating a nuanced understanding of user behavior and fostering the ability to predict patterns of acceptance. Consequently, these models play an instrumental role in guiding the evaluation and implementation of technology in various contexts [44].

Several studies have contributed to our understanding of the factors influencing blockchain adoption. In a study by [45] the researchers utilized the United Theory of Acceptance and Use of Technology (UTAUT) to probe the uptake of blockchain technology among students. Through statistical analysis using SPSS, the study discerned that anticipation, effort expectancy, social influence, facilitation conditions, personal innovativeness, and a perception of security risk have significant effects on the acceptance and use of blockchain technology. This study delineates the psychological and social aspects that contribute to the adoption of new technologies such as blockchain among younger demographics. Parallelly, research conducted on 124 elderly care institutions in China utilized the Diffusion of Innovations (DOI) and Technology-Organization-Environment (TOE) frameworks to understand the institutional factors affecting blockchain adoption [46]. The study employed SmartPLS 3.0 for data analysis. The findings reveal that the relative advantage of blockchain technology, corporate social responsibility, top management support, and organizational readiness positively influence blockchain adoption intention in elderly care institutions. Interestingly, factors often considered crucial for technological adoption, such as complexity, government support, and competitive pressure, were found to have insignificant effects in this context. These studies jointly contribute to the multifaceted understanding of blockchain adoption, highlighting the necessity to consider individual, social, and organizational factors in the technology adoption process.

The adoption models such as Technology Acceptance Model (TAM), the United Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovations (DOI), and Technology-Organization-Environment (TOE) were criticized primarily due to their oversimplification, often reducing constructs to some factors which does not necessarily reflect the actual use of technology. Furthermore, these models focus heavily on individual adopters, adopting a narrow perspective that assumes a direct causal influence of intention on behavior. Moreover, they fail to fully consider the complexity of socio-technical systems, which comprise technological, organizational, and social components [47].

The traditional models for studying technology adoption, offer valuable insights but face significant limitations in addressing the complexities of blockchain adoption in digital healthcare. TAM, while simplifying the adoption process to constructs like perceived ease of use and usefulness, falls short in capturing the multifaceted nature of technology adoption in complex socio-technical systems, particularly those found in healthcare [48]. UTAUT, focusing on user acceptance, oversimplifies system use and neglects broader influences such as organizational factors critical in health technology adoption [49]. DOI, emphasizing the spread of innovations through social systems, also overlooks the interdependent nature of technological, organizational, and social components in healthcare adoption scenarios [50, 51]. The TOE framework, though widely used, has seen limited theoretical development since its inception. Its generic nature

Table 1. Overview of various MCDM models in the literature for blockchain adoption in different industries

Author	Model	Industry	Factor selection model	Uncertainty handling	Smoothness
[54]	Bayesian-BWM	Oil And Gas Industry	×	×	×
[55]	HDM	Healthcare	×	×	×
[56]	DEMATEL	Healthcare	×	×	×
[57]	BWM and VIKORSort	Drug Supply Chain	×	×	×
[58]	Technology-Organization-Environment (TOE) and ANP.	Logistics Industry	×	×	×
[59]	Interpretive Structural Modelling (ISM) and DEMATEL	Agriculture Supply Chain	×	×	×
[60]	AHP	Maritime Industry	×	×	×
[61]	Fuzzy AHP and Fuzzy TOPSIS	Various Industries	×	√	×
[62]	Total Interpretive Structural Modelling (TISM) and Fuzzy DEMATEL	Food Security	×	√	×
[63]	TAM and Fuzzy Delphi	Financial	×	√	×
[64]	Fuzzy AHP	Renewable Energy	×	√	√
[65]	BWM Delphi MARCOS	Blood Supply Chain	√	×	×
[24]	Fuzzy Delphi and BWM	Economy	√	√	×
[25]	Fuzzy Delphi and Grey-DEMATEL	supply chains	√	√	×
[66]	Fuzzy Delphi and Best-Worst method (BWM)	humanitarian supply chain	√	√	×
This research	Fuzzy Delphi	Healthcare	√	√	√

allows for flexible variation of factors and measures, reducing the perceived need for theoretical modification [52, 53]. This critique is particularly relevant in the context of blockchain adoption in healthcare, where the TOE framework's generality and lack of specificity may not adequately capture the unique challenges and complexities of integrating blockchain technologies, such as regulatory concerns, data security, and interoperability. Thus, a more nuanced approach is needed to study blockchain adoption in healthcare, one that fully encompasses its complexities.

2.4 MCDM based adoption models

On the other hand, the Multi-Criteria Decision Making (MCDM) approach could be more suitable in certain situations. MCDM is a mathematical method designed to handle complex decision-making problems that involve conflicting and multiple criteria. It can be a more precise tool for evaluating multiple alternatives against several criteria in technology adoption decisions. For instance, it can allow us to account for a wider range of factors, both qualitative and quantitative, in assessing the technology's desirability. Moreover, MCDM can incorporate the weightings of these factors as determined by expert opinion, allowing for a more nuanced analysis that respects the complexities and interdependencies inherent in technology adoption.

The literature survey, presented in Table 1, offers a comprehensive summary of diverse studies that have employed MCDM models for blockchain adoption

across various industries. Interestingly, the survey revealed that certain studies utilized multiple MCDM

models and integrated other types of adoption models as well. Each study is evaluated based on three distinct criteria. The first criterion, factor selection, refers to the process of determining the factors that contribute to successful blockchain adoption. The table highlights that several studies have incorporated this critical aspect into their models using Delphi. The second criterion, uncertainty handling, is denoted by the use of fuzzy numbers to quantify expert opinions. This approach is seen in a subset of the studies, indicating a degree of variability in how uncertainty is accounted for in these models. The final criterion, referred to as smoothness, is determined by the use of a more complex and realistic fuzzy number model, rather than the simpler triangular fuzzy number often employed. This distinction provides insight into the sophistication of the fuzzy number models used in each study. Based on the table, it is evident that while many studies use some form of factor selection and uncertainty handling, fewer employ more advanced, smooth fuzzy number models. Furthermore, the research incorporates all three aspects: factor selection, uncertainty handling, and the smoothness of the fuzzy number model. This suggests that it offers a more comprehensive and nuanced understanding of blockchain adoption across industries.

2.5 Main criteria for blockchain adoption in healthcare

The main criteria or factors were selected based on reviewing the recent studies about blockchain adoption in various industries and healthcare adotion and investigating their selected criteria. We present them in Table 2, users' intention to use represents the user aspect factors, while the rest of the main criteria represent the business aspect. Each of them collects under it more than sub-criteria. Furthermore, they cover the majority of possible influencing factors in blockchain adoption in digital Healthcare.

2.5.1. Technology

It indicates the technological development of blockchain-based digital Healthcare. Under this criterion, various sub-criteria exist; we present an overview of them in Table 3.

2.5.2. Intra-organizational

It indicates the criteria that are associated with inside the organization involved in implementing blockchain-based digital Healthcare. Under this criterion, various sub-criteria exist; we present an overview of them in Table 4.

2.5.3. Interorganizational

It indicates the factors related to the organization from a business perspective. Under this criterion, various sub-criteria exist; we present an overview of them in Table 5.

Table 2. The various criteria used for evaluating blockchain adoption in different industries

Main Criteria	Sector	References
Technology	Healthcare, supply chains, General, Drug supply, Oil and Gas	[25, 54, 56, 57, 64, 67-69]
Organizational (Intra organizational, and Interorganizational)	Healthcare, Supply Chains, General, Drug supply, Oil and Gas	[25, 54, 56, 57, 67-69]
Environment	Healthcare, Drug supply, General	[56, 57, 64, 68, 70]
Legal	Healthcare, supply chains, General, IOT, and Real Estate	[25, 67, 71-73]
Finance	Healthcare, supply chains, General, Drug supply	[25, 56, 57, 64, 67]
Users’ Intention to Use	Healthcare, Supply Chain, Logistics, Energy Management, Manufacturing, and General	[45, 74-80]

Table 3. Overview of sub-criteria that belong to the technology factor

Sub-Criteria (Sub-Factors)	Definition	References
Infrastructure Availability	The capability of integrating blockchain with the existing infrastructure.	[67, 68]
Compatibility	It is the capacity for equipment, systems, applications, or products from several suppliers compatibility refers to the system's capacity to integrate and interact seamlessly with other systems, including its ability to share resources and exchange data, a concept known as interoperability. This enhances the efficiency of integrated systems and reduces barriers to blockchain adoption	[67, 81, 82]
Security and privacy	It measures Healthcare's ability to protect its patients' privacy and secure their data.	[67, 81, 83]
Latency	It indicates the delay that occurs in performing a certain operation in a digital health system and how much the system is adaptable to handle it.	[71, 84]
Reliability	Reliability refers to meeting robustness and correctness. The former indicates the correct operation of technology in normal conditions, and the latter indicates the proper operation of technology in abnormal conditions.	[85, 86]
Scalability	Refers to how much the technology is capable of operating on large scales, such as serving a high number of patients in different regions with different pressure and demand. It is associated with decentralized architecture where the bottleneck is handled.	[87, 88]
Limitation of Computing Power	It refers to the limited resources of devices' computing power, which prevents the execution of the blockchain operation.	[89, 90]

Table 4. Overview of sub-criteria that belong to Intra-organizational factor

Sub-Criteria (Sub-Factors)	Definition	References
Top Management Support	This factor assesses the level of senior management engagement, support, and approval for the blockchain initiative.	[67, 91, 92]
Training and Skills	It measures the level of alleviating the technical skills of the development team involved in blockchain implementation through training and courses.	[68, 93, 94]
Health IT Strategy	It measures the level of alignment of the blockchain project with the strategic vision of healthcare IT.	[68, 81, 95]
Management Stability	It refers to the status of management in terms of changing rate of administrative positions and leadership holders.	[56, 85, 92]
Appropriate Team Leadership	The suitability of leadership with the position they hold and the matching with the creative aspect that is needed in terms of changing for the better.	[92, 96]
Technology Readiness	The availability of technological infrastructure and IT human resources is needed to implement the technology.	[69, 97]
Hierarchical Structure	The hierarchical structure might cause the issue of bureaucracy and reduce the flexibility of changes.	[98, 99]

2.5.4. Environment

It refers to the set of sub-criteria related to the environment usage and interaction. We present an overview of them in Table 6.

2.5.5. Legal

It indicates the legal aspect and the relation with the law for blockchain adoption in digital Healthcare. Under this criterion, various sub-criteria exist; we present an overview of them in Table 7.

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Table 5. Overview of sub-criteria that belong to interorganizational factor

Sub-Criteria (Sub-Factors)	Definition	References
Business Parties' Unwillingness	It represents the seriousness of business parties in transferring their infrastructure to blockchain-based. It has more than one dimension, such as ideology, culture, fear of change …etc.	[65, 100]
Business Collaboration and Coordination	It indicates the willingness of other business parties to collaborate and coordinate with the healthcare organization that is working on enabling blockchain for its system.	[54, 101]
Feasible Business Model	This metric indicates the feasibility of accomplishing a blockchain-based platform for Healthcare in terms of profitability and applicability.	[65, 87, 102]

Table 6. Overview of sub-criteria that belong to environment factor

Sub-Criteria (Sub-Factors)	Definition	References
Paperwork Reduction	It represents the new technology's contribution to reducing paperwork usage. This factor is essential in adopting blockchain due to the digitization and data sharing that is accomplished by blockchain.	[56, 103]
Co2 Emission	It represents the significance of CO2 emission generated from blockchain computing in preventing its adoption.	[24, 104, 105]
Resource Wastage	It represents the significance of energy consumption needed for operating blockchain in preventing the adoption, considering that energy resources are limited and the priority of blockchain adoption is not at the top when compared with the basic needs of energy for a human being.	[98, 106]

Table 7. Overview of sub-criteria that belong to legal factor

Sub-Criteria (Sub-Factors)	Definition	References
Legal framework	It measures the available policy and regulation, the easiness of local legislation, and the clarity and maturity of the rules.	[88, 107, 108]
Regulation compliance	It represents the legalization efforts consumed by the healthcare organization in guiding the implementation with fulfilling the legal obligation.	[67, 109, 110]

Table 8. Overview of sub-criteria that belong to finance factor

Sub-Criteria (Sub-Factors)	Definition	References
Budget Availability	It represents the needed or allocated budget that can cover all types of costs, namely, management claims and operation costs and maintenance costs.	[67, 68, 111]
Financial Risk	This factor measures the ability of healthcare organizations to measure the risk involved in the blockchain project due to the ambiguity and uncertainty considering the low number of similar projects.	[67, 81, 111]
Long Term Cost Saving	It measures the benefit of long-term cost savings obtained from the successful implementation of the blockchain project.	[67, 68, 81]
Training cost	It represents the allocated budget for training the resources to upgrade their skills to be capable of proceeding in the development and implementation.	[56, 57, 92]

2.5.6. Finance

It indicates the financial aspect of technology development and integration. Under this criterion, various sub-criteria exist; we present an overview of them in Table 8.

Table 9. Overview of sub-criteria that belong to finance factor

Sub-Criteria (Sub-Factors)	Definition	References
Performance Expectancy	Performance Expectancy refers to the degree to which an individual thinks that utilizing a certain method or system would improve his or her ability to perform at work.	[76-78]
Effort Expectancy	Effort Expectancy refers to the degree of simplicity involved with using the system.	[76-78]
Social Influence	Social influence refers to the degree to which an individual perceives that others believe he or she should use the new system	[78, 80, 112]
Trust	It indicates the behaviour of tolerating uncertainty in favour of good expectations of the other party’s intention or will.	[78, 79, 112]
Attitudes	the feelings and beliefs about the benefits, quality, and effort associated with using the technology.	[76, 77, 113]
Cost	The perceived cost is defined as the degree to which a user perceived that it is expensive to utilize a specific technology or system to perform a specific task.	[76, 114]
Self-efficacy	A determination of a person's technological ability for carrying out a specific task or employment.	[115-117]
Privacy	The right to govern the acquisition, use, and dissemination of personally identifiable health data is characterized as an individual's right to privacy.	[118-120]

2.5.7. User’s Intention to Use

It indicates the factors that measure the behavior of users toward blockchain usage. Under this criterion, various sub-criteria exist; we present an overview of them in Table 9.

3. Methodology

This section outlines the research methodology designed to assess blockchain adoption, focusing on the Gaussian Fuzzy Delphi technique, which accommodates uncertainties and complexities, and systematically identifies factors influencing adoption. We then describe the consistency validation method that ensures the reliability of the research findings, and discuss the selection and data collection process involving expert panels. Finally, we explore the quantification of influential factors and delve into specific focus areas, including technological, intra-organizational, interorganizational, environmental, legal, financial aspects, and user's intention to use, to provide a comprehensive view of blockchain technology implementation. The symbols and notations used in the methodology are presented in Table 10.

3.1 Methodology design

The methodology is for conducting a survey-based study and decision-making process that leverages quantitative methods, with a particular emphasis on addressing uncertainty in expert opinion through the Fuzzy Delphi Method and enhancing validity through consistency tests. As it is depicted in Figure 1, the methodology commences by identifying potential factors and sub-factors, forming a tentative index system that will guide the study. From these elements, a questionnaire is meticulously developed, with precise prerequisites delineated for the respondents to ensure the relevance and reliability of the acquired data. Before the actual distribution of the questionnaire, a pre-survey validation is executed. This step entails pilot testing the survey with a small group combined of five experts, assessing its effectiveness and reliability, and making any necessary adjustments based on the feedback received. The real survey is then administered to the designated respondents, and the data collected. Post data collection, the Fuzzy Delphi Method is deployed to select the most relevant sub-factors from the collected data. Fuzzy Delphi method is a robust tool for handling the uncertainties and imprecision inherent in the experts' opinions. This method, which uses an iterative process to arrive at a consensus among the expert panel, is designed to refine the

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Table 10. Symbols and notations used in the methodology

Notation	Meaning
α	Significance level used in statistical tests, and in the context of fuzzy numbers, it represents the confidence interval for the bounds of the fuzzy number.
μA	Mean of a fuzzy number A representing the central point of the fuzzy set.
σA	Variance of fuzzy number A, influencing the spread or uncertainty in the fuzzy set.
x	A generic variable representing an input value to be evaluated against fuzzy number A in the Fuzzy Delphi Method.
μ^{ij}	Mean value of the fuzzy number for the i^{th} expert's judgment on the j^{th} factor.
σ^{2j}	Variance associated with the fuzzy number for the i^{th} expert's judgment on the j^{th} factor.
Z^{ij}	Fuzzy number representing the i^{th} expert's response to the j^{th} factor, defined by its mean and variance.
Z^{j}	Aggregated fuzzy number for the j^{th} factor, calculated as the average of the fuzzy numbers provided by all experts for that factor.
P^{j}	Fuzzy weight or importance of the j^{th} factor, derived from the aggregated fuzzy number Z^{j}.
pj	Defuzzification value of the j^{th} factor, used to make final decisions regarding the acceptance or rejection of factors.
γ	Threshold value used in the decision-making process to determine whether a factor's defuzzification value is sufficiently high to be accepted.
λmax	Largest eigenvalue of the judgment matrix, used to compute the consistency index (CI).
n	The order of the judgment matrix, equivalent to the number of factors or criteria evaluated.
Cl	Consistency Index, a measure derived from the eigenvalues of the judgment matrix to assess the logical consistency of the judgments.
RCl	Random Consistency Index, a reference value for comparing the consistency index, dependent on the matrix's order.
CR	Consistency Ratio, calculated as the ratio of Cl to RCI to determine the acceptability of the judgment matrix's consistency.

factors and sub-factors for the decision-making process, thereby enhancing the credibility and robustness of the study's results. A key feature of this methodology is the use of consistency tests for validation, which are executed after the fuzzy Delphi method and before the conclusion of the process.

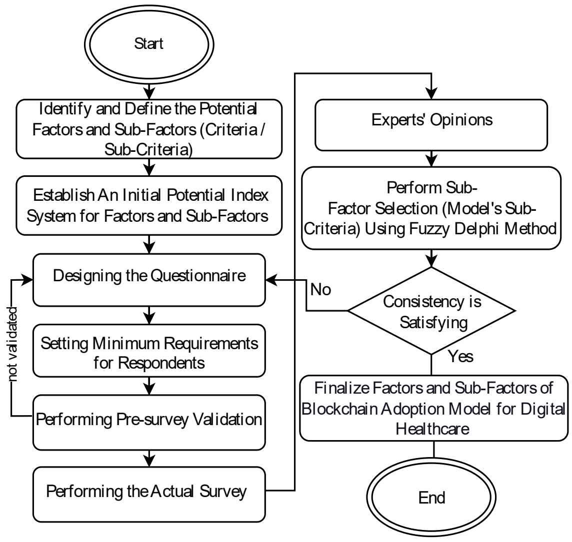

Figure. 1 Flowchart of factor selection for blockchain adoption in digital Healthcare

These tests are integral to ensuring the findings are coherent and reliable, which ultimately fortifies the study's overall validity.

3.2 Gaussian fuzzy Delphi approach

Delphi method is used to reach consensus among a panel of experts on the weights or importance of different criteria, thereby aiding in decision-making. The Fuzzy Delphi method, on the other hand, is a variant of the Delphi method that incorporates the principles of fuzzy set theory. This method is used to handle the uncertainty and subjectivity associated with the opinions of a panel of experts, especially when precise and quantitative data is lacking [121].

A fuzzy number is a type of mathematical representation rooted in fuzzy set theory, designed to deal with imprecise or ambiguous data. Instead of being a single, precise value, fuzzy numbers are represented as intervals or ranges of possible values, each associated with a degree of truth or membership, thereby allowing for partial belonging to a set. Fuzzy Delphi method is based on fuzzy set theory. If U is a universal, then fuzzy set or number of U is defined as μ_a and is given in Eq. (1) that involve the variables μ_A and α, and helps in determining the boundaries of the fuzzy number depending on whether a given value x is less than or equal to μ_A.

$$x = \begin{cases} \mu_A - \sqrt{ln\left(\frac{1}{\alpha^{\sigma_A^2}}\right)} & if x < \mu_A \\ \mu_A + \sqrt{ln\left(\frac{1}{\alpha^{\sigma_A^2}}\right)} & if\ x \geq \mu_A \end{cases} \tag{1}$$

A Gaussian number is expressed with the help of the α. In this process, the lower and upper values of the fuzzy number can be taken into consideration as presented in Eq.(2).

$$Z_{ij} = \left[\mu_{ij} - \sqrt{ln\left(\frac{1}{\alpha^{\sigma_{ij}^2}}\right)}, \mu_{ij} + \sqrt{ln\left(\frac{1}{\alpha^{\sigma_{ij}^2}}\right)}\right] \quad (2)$$

Gaussian fuzzy numbers are returned to interval arithmetic. Thus, the interval is generated for fuzzy Delphi.

Steps involved in fuzzy Delphi methods are follows

Step 1: In this step, the factors are identified and tabulated

Step2: the questionnaire containing the identified factors is given to the experts. The experts are requested to rate the factors using linguistic scale and expert input are converted into fuzzy numbers as in Eq.(3):

$$Z_{ij} = (\mu_{ij}, \sigma_{ij})$$
$$for\ i = 1,2 \ldots n\ and\ j = 1,2 \ldots m \quad (3)$$

Where:

n denotes the number of experts.

m denotes the number of factors.

Representing each Z_{ij} with Eq. (2)

And performing the averaging using the formula of addition by Eq. (4).

$$\bar{Z}_j = [\frac{1}{n}(\sum_{i=1}^{N}\mu_{ij} - \sqrt{ln\left(\frac{1}{\alpha^{\sigma_{ij}^2}}\right)}),$$
$$\frac{1}{n}(\sum_{i=1}^{N}\mu_{ij} + \sqrt{ln\left(\frac{1}{\alpha^{\sigma_{ij}^2}}\right)})] \quad (4)$$

The fuzzy weights of factors $\tilde{P}_j$ are given by $\tilde{P}_j = \bar{Z}_j$

Step3: In this last step, the defuzzification value of each factor $p_j = defuzzification(\tilde{P}_j)$ is calculated and compared with threshold γ. The factor is accepted in the case of $p_j > \gamma$ and is rejected otherwise. For defuzzification, centroid is used. Fig. 2 presents graph of Gaussian number that shown a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1.

3.3 Methodology design

Usually, because of the complexity of the evaluation problem and the subjective preferences of experts, the logical consistency of judgment thinking cannot be guaranteed. Therefore, in order to ensure that the evaluation results are basically reasonable, it is necessary to test the consistency of the judgment matrix. The calculation steps are as follows:

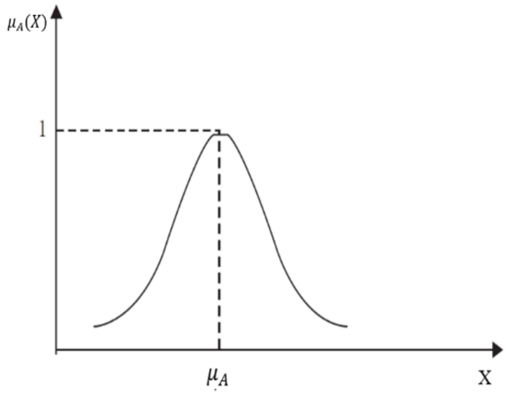

Figure. 2 Graph of Gaussian Membership Function

1. Construct a judgment matrix: A judgment matrix is a square matrix that is used to capture the pairwise comparisons between elements of a set. The elements are the factors that are used or investigated in the study. As it has been mentioned earlier, the total number of factors is 34. Hence, the size of the judgment matrix is 34×34.
2. Compute the matrix's eigenvalues: The eigenvalues of the matrix represent the extent to which each criterion or factor affects the overall evaluation. To compute the eigenvalues, we use Python.
3. Calculate the consistency index (CI): The consistency index is a measure of how consistent the judgments are, and it is computed as given in Eq. (5)

$$CI = \frac{(\lambda_{max} - n)}{n-1} \quad (5)$$

where $\lambda_{max}$is the largest eigenvalue of the matrix and n is the order of the matrix.

4. Compute the random consistency index (RCI): The random consistency index is a reference value that is used to compare with the consistency index. The RCI depends on the order of the matrix. For an order of 34 it equals 1.68 [122].
5. Calculate the consistency ratio (CR): The consistency ratio is a ratio of the consistency index to the random consistency index, and it is computed as given in Eq. (6)

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Table 11. Details of the experts background that have participated in the study

No	Certificate	Years of Experience in the Healthcare Industry	Years of Experience in a Managerial Position in the Healthcare Industry
1	PhD	10 -15 years	5 - 10 years
2	PhD	More than 20 years	5 - 10 years
3	PhD	More than 20 years	More than 10 years
4	PhD	More than 20 years	More than 10 years
5	PhD	10 -15 years	5 - 10 years
6	Master	More than 20 years	More than 10 years
7	Master	10 -15 years	More than 10 years
8	Master	10 -15 years	5 - 10 years
9	Master	10 -15 years	5 - 10 years
10	Master	10 -15 years	5 - 10 years
11	Bachelor	10 -15 years	5 - 10 years
12	Bachelor	10 -15 years	More than 10 years
13	Bachelor	10 -15 years	5 - 10 years
14	Bachelor	10 -15 years	5 - 10 years
15	Bachelor	10 -15 years	More than 10 years

Table 12. Summary of the percentages of the experts that have participated in the study.

<table>
<tr><th colspan="6">Obtained Certificate</th></tr>
<tr><th colspan="2">PhD</th><th colspan="2">Master</th><th colspan="2">Bachelor</th></tr>
<tr><td colspan="2">33.3%</td><td colspan="2">33.3%</td><td colspan="2">33.3%</td></tr>
<tr><th colspan="6">Experience in the Healthcare Industry</th></tr>
<tr><th colspan="3">10 -15 years</th><th colspan="3">More than 20 years</th></tr>
<tr><td colspan="3">73%</td><td colspan="3">27%</td></tr>
<tr><th colspan="6">Experience in a Managerial Position in the Healthcare Industry</th></tr>
<tr><th colspan="3">5 - 10 years</th><th colspan="3">More than 10 years</th></tr>
<tr><td colspan="3">70%</td><td colspan="3">30%</td></tr>
</table>

If the CR is less than or equal to 0.1, then the judgments are considered to be consistent. If the CR is greater than 0.1, then the judgments may be inconsistent [123].

3.4 Selection of expert panel and data collection process

Experts are selected carefully according to their experience or background regarding the subset of questions that are provided to them. Hence, the sampling of them is classified as purposive sampling. The expert represents individuals with an adequate background that allows them to provide their opinion on the respective matter. We select experts with a minimum of 10 years of experience in the health sector with at least a bachelor's academic degree and that have spent at least five years at the managerial level. Furthermore, we request to have a technical understanding of the digitalization of Healthcare or blockchain and its applications. pre-survey validation by peer reviewing with 5 experts which included an additional question about the clarity of the survey. Furthermore, the pre-validation about the consistency of the survey was assured using consistency ratio. The actual survey was performed on an accepted number of experts equals to 15 out of 18. The survey was conducted electronically using google survey. The details of the experts' background are presented in Table 11. In addition, we provide a summary of the different percentages in Table 12. It shows three equals parts of Bachelor, Master, and PhD holders. The percentage of experience in health with more than 20 years is 27% and the remaining are with experience between 10 and 15 years. The percentage of experience in managerial level with more than 10 years is 30% and the remaining are with experience between 5 and 10 years.

Table 13. Linguistic variables for Trian

Linguistic terms	Crisp No	Triangular Fuzzy Number (a,b,c)	Gaussian fuzzy number(μ,σ)
Very low	0	(0, 0, 0.25)	(0, 0.15)
Low	0.25	(0, 0.25, 0.5)	(0.25, 0.15)
Medium	0.5	(0.25, 0.5, 0.75)	(0.5, 0.15)
High	0.75	(0.5, 0.75, 1)	(0.75, 0.15)
Very high	1	(0.75, 1, 1)	(1, 0.15)

3.5 Factors quantification

Each factor is quantified using five fuzzy linguistic terms, namely, very low, low, medium, high, and very high. We present the triangular and Gaussian fuzzy numbers in Table 13. As it is shown, there are five linguistic variables, namely, very low, low, medium, high, and very high. The crisp values for them are 0, 0.25, 0.5, 0.75, and 1 respectively. The triangular fuzzy numbers are configured with base equals to 0.25 for very low and very high and with base equals to 0.5 for low, medium, and high. On the other side, the Gaussian number is to set to a standard deviation equals to 0.15.

Table 14. Fuzzy and defuzzified weights of the sub-factors for blockchain adoption using Triangular and Gaussian fuzzy method

Factor	Subfactor Name	Triangular			Gaussian		
		Fuzzy weight	Defuzzified weight	Select/ Reject	Fuzzy weight	Defuzzified weight	Select/ Reject
Technology	Infrastructure availability	(0,0.668,1)	0.556	Select	(0.536, 0.917)	0.726	Select
	Compatibility	(0,0.599,1)	0.533	Select	(0.456, 0.837)	0.647	Select
	Security and privacy	(0.25,0.761,1)	0.67	Select	(0.616, 0.997)	0.802	Select
	Latency	(0,0.551,1)	0.517	Select	(0.423, 0.804)	0.613	Select
	Reliability	(0.25,0.727,1)	0.659	Select	(0.583, 0.964)	0.771	Select
	Scalability	(0.25,0.797,1)	0.682	Select	(0.650, 1.000)	0.82	Select
	Computing Power	(0,0.494,1)	0.498	Reject	(0.356, 0.737)	0.547	Select
Intra-organization al	Top Management Support	(0.25,0.819,1)	0.69	Select	(0.670, 1.000)	0.83	Select
	Training and Skills	(0,0.741,1)	0.58	Select	(0.610, 0.990)	0.796	Select
	Health IT Strategy	(0,0.791,1)	0.597	Select	(0.656, 1.000)	0.823	Select
	Management Stability	(0,0.65,1)	0.55	Select	(0.516, 0.897)	0.706	Select
	Appropriate Team Leadership	(0.25,0.747,1)	0.666	Select	(0.603, 0.984)	0.79	Select
	Technology Readiness	(0,0.621,1)	0.54	Select	(0.483, 0.864)	0.673	Select
	Hierarchical Structure	(0,0,1)	0.333	Reject	(0.203, 0.584)	0.393	Reject
Interorganiza tional	Business Parties' Willingness	(0,0.822,1)	0.607	Select	(0.683, 1.000)	0.837	Select
	Business Collaboration and Coordination	(0,0.791,1)	0.597	Select	(0.656, 1.000)	0.823	Select
	Feasible Business Model	(0,0.485,1)	0.495	Reject	(0.343, 0.724)	0.533	Select
Environment	Paperwork Reduction	(0,0,1)	0.333	Reject	(0.236, 0.617)	0.427	Reject
	Co2 Emission represents	(0,0,1)	0.333	Reject	(0.110, 0.490)	0.3	Reject
	Resource Wastage	(0,0,1)	0.333	Reject	(0.170, 0.550)	0.36	Reject
legal	Legal Framework	(0,0.813,1)	0.604	Select	(0.676, 1.000)	0.834	Select
	Regulation Compliance	(0,0.806,1)	0.602	Select	(0.670, 1.000)	0.83	Select
Finance	Budget Availability	(0,0.638,1)	0.546	Select	(0.503, 0.884)	0.693	Select
	Financial Risk	(0,0.419,1)	0.473	Reject	(0.250, 0.630)	0.44	Reject
	Long Term Cost Saving	(0,0.408,1)	0.469	Reject	(0.243, 0.624)	0.433	Reject
	Training Cost	(0,0.628,1)	0.543	Select	(0.490, 0.870)	0.68	Select
Intention to use	Performance Expectancy	(0,0.785,1)	0.595	Select	(0.650, 1.000)	0.82	Select
	Effort Expectancy	(0.25,0.788,1)	0.679	Select	(0.643, 1.000)	0.817	Select
	Social Influence	(0,0.65,1)	0.55	Select	(0.516, 0.897)	0.706	Select
	Trust	(0.25,0.803,1)	0.684	Select	(0.656, 1.000)	0.823	Select
	Attitudes	(0.25,0.583,1)	0.611	Select	(0.423, 0.804)	0.613	Select
	Perceived Cost	(0,0.588,1)	0.529	Select	(0.443, 0.824)	0.633	Select
	Self-Efficacy	(0,0.755,1)	0.585	Select	(0.623, 1.000)	0.806	Select
	Privacy	(0.25,0.785,1)	0.678	Select	(0.636, 1.000)	0.813	Select

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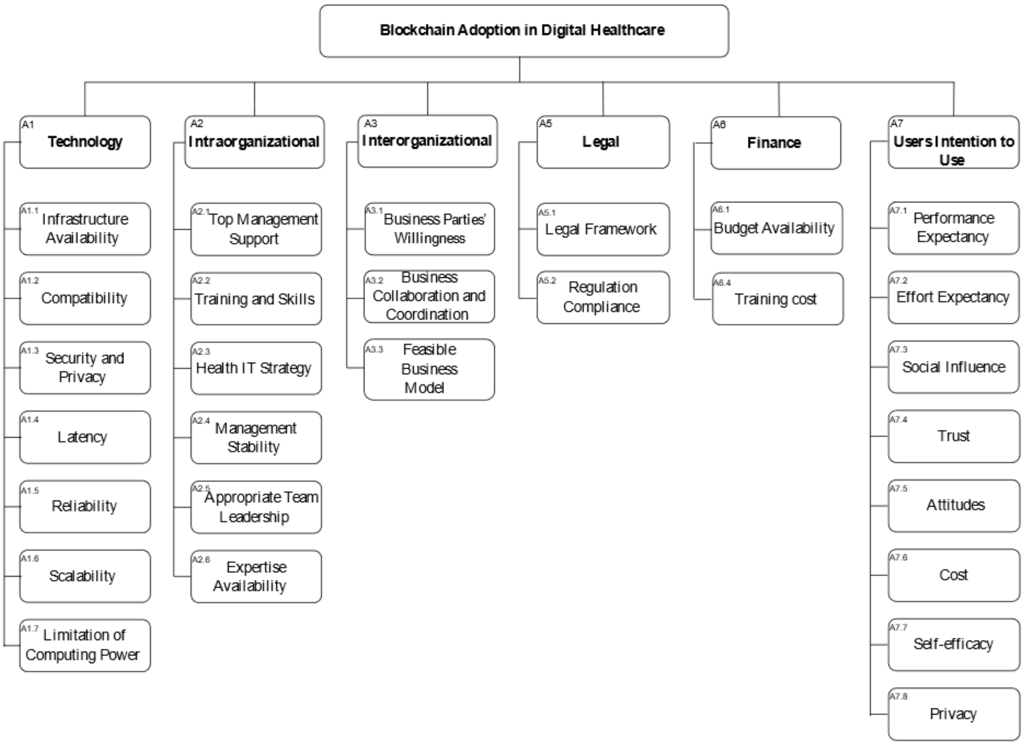

Figure. 3 Final adoption model

4. Experimental results

This section presents the experimental results based on the answers provided by the experts. We present the results of the weights of the factors based on triangular and Gaussian fuzzy sets in Table 14 and the decision of accepting or rejecting the factors based on 0.5 threshold for the defuzzified value. For Triangular fuzzy result, the defuzzified weights show the relative importance of each factor and subfactor in the adoption of blockchain in digital Healthcare. Based on the defuzzified weights, the subfactors with the highest importance are Scalability (0.6824), Top management support (0.6897), Trust (0.6845), Effort expectancy (0.6794), and privacy (0.6783). These sub-factors have the highest defuzzified weights and thus have the greatest influence on the adoption of blockchain in digital Healthcare. Based on the defuzzified weights, all subfactors are recommended for selection except for “Computing Power,” “Hierarchical Structure,” “Feasible Business Model,” “Paperwork Reduction,” “Co2 Emission represents,” “Resource Wastage,” “Financial Risk,” and “Long Term Cost Saving” which are recommended for rejection. These results provide insights into the subfactors that organizations should consider when evaluating the adoption of blockchain in digital Healthcare. The triangular method is less effective in handling uncertainty. Therefore, we applied the Gaussian method to investigate the difference between the two approaches in terms of the selected and rejected factors.

Table 15. The consistency ratio for each of the two types of the fuzzy numbers and for two set of experts, pilot set and the total set

	Pilot set (size is 5)	Total set (size is 15)
Triangular	0.049	0.079
Gaussian	0.034	0.061

For Gaussian fuzzy result, we find that the top six important sub-factors for selection, based on their defuzzified weights, are: Top Management Support (0.830), Regulation Compliance (0.830), Legal Framework (0.834), Health IT Strategy (0.823), Business Parties’ Willingness (0.837), and Business Collaboration and Coordination (0.823). On the other side, the non-recommended sub-factors for selection are: Hierarchical Structure, Paperwork Reduction, Co2 Emission represents, Resource Wastage, Financial Risk, and Long-Term Cost Saving.

Based on considering fuzzy Gaussian decision for fuzzy Delphi, we modify the proposed initial model for blockchain adoption in digital Healthcare by omitting the non-selected sub-factors. The resulted final diagram is presented in Figure 3.

In order to validate the model, we calculate the values of the consistency ratio. They are presented in Table 15 for each of the two types of the fuzzy numbers, namely, triangular and Gaussian and for two types of experts sets, namely, pilot set which includes 5 experts and total set excluding the pilot set which is combined of 14 experts. It found that the consistency ratio was for all cases lower than 0.1 which indicates a valid result.

5. Comparison of selected factors with literature findings

This analysis delves into two prominent models: the Alzahrani et al. [55] model and our model, highlighting the nuanced differences and demonstrating the superiority of our approach.

The Alzahrani model utilizes a Hierarchical Decision Making (HDM) approach from Multi-Criteria Decision Making (MCDM) techniques, focusing on structured and quantifiable factors. In contrast, our model employs the Fuzzy Delphi method, which draws on the consensus of expert opinions to estimate the importance of each factor. This method not only captures the subjective nuances of expert judgments but also iteratively refines these judgments to align with a broader expert consensus, making our model more adaptable to the complex dynamics of healthcare environments.

The comparative analysis of these two models, as illustrated through a detailed chart, categorizes factors into those recognized by both models, those unique to each, and their agreement or disagreement on the relevance of these factors. This visualization clearly shows that while both models agree on eight fundamental factors such as Regulation Compliance, Security and Privacy, and Budget Availability the weights assigned by our model often reflect a deeper understanding of their practical implications in real-world settings.

Furthermore, our model identifies 25 unique factors that the Alzahrani model does not account for, including business parties' willingness, legal framework, compatibility, latency, technology readiness and scalability. This extensive inclusion underlines our model's comprehensive approach, which considers a wider range of technology, organization, and user-related factors essential for the successful adoption of blockchain in healthcare.

Conversely, the Zahrani model includes six factors not covered by our model. Thes tend to focus on specific technical readiness and governance issues, indicating a narrower, albeit focused, perspective. However, the lack of broader technology and user-related factors in the Alzahrani model can be seen as a limitation in fully addressing the multifaceted challenges of blockchain adoption.

Figure 4 employs a color-coded system to denote agreement and disagreement on the non-selection or low prioritization of factors, with green indicating agreement and red showing disagreement. In the comparative analysis of blockchain adoption models our model and the Alzahrani model a significant alignment and a few discrepancies underscore the strategic focus of each approach within the digital healthcare sector. Both models are designed to evaluate and prioritize the myriad factors that influence the successful integration of blockchain technology in healthcare settings. The analysis reveals a substantive agreement between the two models on several factors that were either ignored or assigned low priority. This consensus indicates a mutual recognition of the lesser importance of these factors in driving blockchain adoption within the healthcare context. For instance, factors like "Talent & Knowledge Acquisition," "Stakeholder's Awareness & Acceptance," and "Blockchain Ecosystem" received minimal attention in the Alzahrani model and were not specified in our model. This overlapping non-prioritization reflects a shared perspective between the two models, reinforcing the notion that these aspects may not be as critical to the immediate operationalization of blockchain technology in healthcare.

However, a notable discrepancy lies in the treatment of "Infrastructure and Platform Integration." Contrary to the general trend of agreement, this factor presents a unique divergence in priority setting between the two models. The ALzahrani model assigns it a relatively lower priority, whereas our model implicitly integrates this factor through other closely related factors, acknowledging its critical role in ensuring the effective deployment of blockchain solutions. This suggests that our model places a higher emphasis on the foundational technological aspects necessary for blockchain technology, considering them integral to the broader strategy of blockchain adoption.

Additionally, our model has also prioritized the elimination of the environmental factor due to its low relevance and contribution values, mirroring approaches seen in other analytical frameworks like the Bali et al. [56] which has obtained low weight for Paperwork Reduction (0.769) and Green Initiative (1.746) suggesting eliminating them as well. By discarding the Environment main factor, which the Bali model also completely eliminates, our model aligns with this precedent, further justifying its exclusion based on empirical evidence and aligned expert consensus. This decision reflects a strategic choice to focus resources and attention on factors that yield the greatest impact and efficiency in blockchain adoption, specifically within the healthcare sector.

6. Conclusion and future works

In conclusion, this study has developed a comprehensive multi-perspective model for the adoption of blockchain in digital healthcare. It meticulously integrates both business and end-user perspectives, facilitating a holistic assessment of blockchain adoption. Utilizing triangular and Gaussian fuzzy models, the research effectively manages the inherent uncertainties in expert opinions regarding the adoption factors, employing these fuzzy methods to rigorously determine the importance of various sub-factors.

From the Gaussian fuzzy analysis, significant sub-factors identified include Top Management Support with a defuzzified weight of 0.830, and Health IT Strategy with a defuzzified weight of 0.823, indicating strong leadership and strategic integration are pivotal for blockchain adoption within the intra-organizational context. In the legal domain, Compliance and Legal Framework stand out with defuzzified weights of 0.830 and 0.834 respectively, emphasizing the critical role of aligning with legal standards.

Furthermore, the interorganizational factors such as Business Parties' Willingness and Business Collaboration and Coordination, both achieving high defuzzified weights of 0.837 and 0.823, respectively, underscore the necessity for strong cooperative relationships among business entities for successful blockchain integration.

The study corroborates the consistency between the Gaussian and triangular fuzzy methods, particularly in their agreement on excluding Hierarchical Structure (triangular: 0.333, Gaussian: 0.393), Paperwork Reduction (triangular: 0.333, Gaussian: 0.427), and CO2 Emission Representation (triangular: 0.333, Gaussian: 0.300) from the recommended selection due to their notably lower defuzzified weights. These results highlight these factors as less influential or potentially detrimental to the successful adoption of blockchain in digital healthcare.

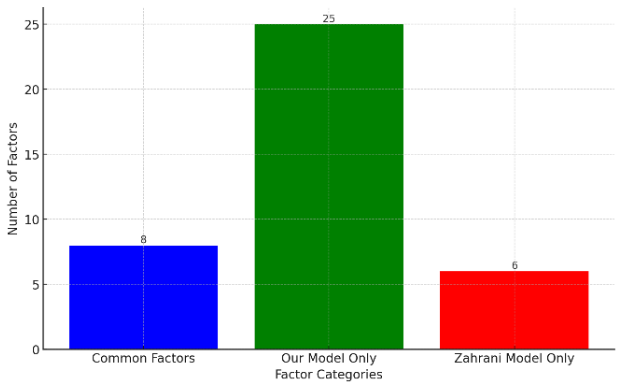

Figure. 4 Number of factors for each of common, our model only, and Zahrani only

The triangular fuzzy method uniquely points out Computing Power (triangular: 0.498, Gaussian: 0.547) and Feasible Business Model (triangular: 0.495, Gaussian: 0.533) as additional factors to be reconsidered, possibly due to their marginal influence on the adoption decision.

This research not only introduces a robust model for evaluating blockchain adoption but also offers a comparative analysis between Gaussian and triangular fuzzy methods, highlighting their strengths and limitations in real-world applications. The deployment of these fuzzy methods provides a sophisticated mechanism for capturing the subtleties in expert assessments, enhancing the decision-making process.

Looking forward, the proposed model is poised for real-world testing and validation to confirm its effectiveness and reliability in practical scenarios. Further comparative studies with other blockchain adoption frameworks can enhance the understanding and application of these results. The exploration of additional fuzzy variants, such as Type-2 fuzzy sets, could refine the handling of uncertainties. The development of a decision support system based on this comprehensive model would enable healthcare organizations and policymakers to make more informed decisions about implementing blockchain technology. Such advancements could potentially optimize healthcare delivery, ensuring both efficiency and security. Moreover, the implications of this study may extend into the realm of sustainable energy, exploring how blockchain technology could facilitate more sustainable practices within and beyond healthcare.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Both authors contributed to the conception and design of the study. Preparation, data collection, and analysis were conducted by the authors. The initial draft of the manuscript was written by Ahmed Altawri, and Dr. Rosnafisah Bt Sulaiman provided input on earlier iterations of the manuscript. Both authors have reviewed and endorsed the final version of the manuscript.

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