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Electronic Health Record using Blockchain with Data Security Approach

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Abstract: Electronic Health Records (EHRs) have revolutionized the healthcare landscape by enabling the digitized storage and management of patient information. This work explores the critical role of EHRs in facilitating healthcare research and driving evidence based on medical practices. The integration of blockchain technology presents a promising data security approach for EHRs. Blockchain technology is considered a vital component in informational technology. It has an important place in the digital age we live in and has made a great impact on people's lives. Additionally, blockchain technology is expected to improve existing IT infrastructure in many areas in the coming years. Recent technological developments have led to significant advances in healthcare. When sharing private health information, Information security is unfavorable to integrating and communicating with electronic health records (EHR). In this, choosing the best model of blockchain for security and reliability. Electronic health records in healthcare need a precise method to analyze the effect of different models of blockchain on their work. This study uses empirical studies to evaluate the effect of blockchain gives new ideas and methods for further workers. This work study collected responses from many experts in the field of medical management to evaluate the effect of different models of blockchain. In addition to many ideas of these experts, a decision-making model is used in the study to eliminate confusion arising from external studies and organize information regarding the content of the chosen blockchain model. Fuzzy analytical network analysis (F-ANP) is applied to calculate the weight of model, and the same method as fuzzy preference sequence (TOPSIS) medical ideal is used to evaluate the results of other methods. problem-solving. Additionally, the results from this empirical research will serve as a tool for selecting the most appropriate blockchain model to maintain the absence of EHR breaches.

Keywords: Blockchain, Cryptographic security, Data security, Healthcare, Integration.

I. Introduction

Today, some countries are facing a growing number of health problems, even as access to junior doctors or doctors makes it difficult for patients. Considering the word "blockchain", it becomes clear that this technology is not only important but also important in the age of the World Wide Web [1]. In general terms, blockchain is a database that stores or distributes information regarding all transactions or electronic products made and exchanged between participants. Blockchain contains a clear record and proof of every transaction made [2], [3]. Trading can be done as a transaction management system using blockchain technology. Thus, blockchain can reduce costs and increase efficiency [4].

Today's innovations based on blockchain technology have reformed each field, like as energy [5], civil [6], e-business [7], bank sector [8], government [9], medical facilities [10], health sector [11], education [12], agriculture [13] and many other businesses. Gartner, a well-known research and marketing company, predicts that the value of investment decisions in blockchain technology will reach US$ 3.1 trillion by 2030 [14]. Fig. 1 below shows Gartner's forecast for blockchain capital growth. The transformative potential of blockchain technology is rapidly being recognized by leading companies, and the technology is seen as a game-changer in many business applications, including the medical industry. Since the business using blockchain technology is huge, many works has been done in it. According to HPAA Magazine's report, there were so many data breaches affecting more than 500 documents in the healthcare industry between 2009 and 2019. These breaches resulted in 230,954,151 records in the medical industry being destroyed, stolen, leaked, or released without permission. This equates to more than 69.78% of the American population. In 2019, the number of leaked medical records was 1.4 cases per day. The health sector has begun to show interest in blockchain applications [15-20].

Blockchain is a new technology currently generating great interest in healthcare. However, 40% of healthcare executives rank blockchain as one of their top priorities 5. Additionally, global adoption of blockchain technology in healthcare is expected to reach $5.75 billion by 2025, according to research. The work states that blockchain could conserve up to $10-140 billion in annual costs till 2025, including loss of data, IT expenditures, operational expenditures, service fees, and advertising, as well as fraudulent and fraudulent products. Medical industry [21]. Acceptance of EMRs (electronic medical records) is now viewed as a key step in improving health information, efficiency, user experience, products, and associated costs. Kemkar *et al.* EMR programs are estimated to save billions of dollars annually [22]. Communicating health information will give us more information; for example, we agree on a better understanding of the behavior of healthy and diseased groups [23] and optimization of doctors' messages to provide better treatment [24]. However, due to its functionality and design, it is still exposed to various security and privacy risks [25], [27]. The biggest challenge in advanced medical information is how to acquire, manage, and interpret patient medical information without violating privacy [26].

Blockchain technology holds the potential to integrate medical and pharmaceutical data from various sources, facilitating the creation of new medical information that can be securely shared among healthcare professionals to enhance patient care. Nonetheless, the adoption of blockchain in the healthcare industry faces substantial barriers [29], [30], which necessitate in-depth examination. The assessment of the impact of various blockchain models on the security of medical data online is a complex and essential task. Understanding how blockchain technology influences the healthcare sector is critical for the formulation of effective healthcare policies. In our research study, we employed multidimensional decision-making (MCDM) techniques to model the effects of different blockchain models on healthcare applications. Numerous MCDM methods are available for addressing such issues [31]. In our investigation, we utilized the Analytic Hierarchy Process (AHP) and the Anomalous Network (ANP) technique [32]. AHP is tailored for hierarchical models, while ANP is designed for network models. Although AHP-TOPSIS is commonly used for similar assessments, we chose ANP as an alternative MCDM method [33]. Several researchers have made similar choices and presented their findings using fuzzy ANP-TOPSIS in various decision-making scenarios. Remarkably, our study is distinctive in that it examines the impact of blockchain technology on the security of medical data in web-based electronic systems using fuzzy decision-making techniques, an area that has received limited prior investigation.

II. Literature Survey

Blockchain technology's transformative potential spans across multiple sectors, as highlighted by various studies. In the energy sector, Andoni *et al.* [5] and Teufel *et al.* [6] emphasize how blockchain can revolutionize the industry by enhancing transparency and efficiency. Blockchain's decentralized nature makes it ideal for optimizing resource allocation and improving sustainability, enabling peer-to-peer energy trading and reducing the need for centralized intermediaries. This increased transparency can also help in tracking and verifying the source of energy, which is essential for renewable energy certificates and ensuring the authenticity of clean energy sources. In the healthcare domain, as explored by Zhang and Boulos [10] and P. P. Ray *et al.* [11], blockchain is positioned as a technology capable of addressing critical challenges. It offers enhanced data security and interoperability, which are paramount in healthcare systems. The immutable nature of blockchain provides a robust foundation for securely managing and sharing sensitive medical data across multiple stakeholders. By creating secure, decentralized ecosystems for patient data management, healthcare can become more patient-centric and interoperable, facilitating better care delivery and reducing administrative overhead. Similarly, in the education sector, Alammary *et al.* [12] underscore the transformative potential of blockchain technology. Blockchain can enhance authentication, certification, and student data management within educational institutions. This can lead to more secure and verifiable records, making credential verification a more streamlined and reliable process, while also safeguarding student data privacy. Blockchain is not confined to these sectors alone; it has found application in agriculture, as exemplified by Xiong *et al.* [13]. In agriculture, blockchain technology can streamline supply chain management and enhance data transparency. By providing a secure and immutable ledger of transactions, it can reduce fraud, improve traceability, and enhance trust between different stakeholders in the agricultural supply chain. In the financial sector, Li *et al.* [7] demonstrate how blockchain is transforming logistics finance execution. It allows for more efficient capital allocation, especially in the context of e-commerce retail. By automating and streamlining financial processes, blockchain can reduce delays and improve capital utilization, making financial operations more efficient and transparent. Moreover, Kumar *et al.* [11] delve into the broader potential of blockchain in healthcare, emphasizing its role in fostering patient-driven interoperability and making healthcare systems more patient-centric. This shift is crucial for improving the patient experience and ensuring that health data is accessible and secure. Lastly, Kaur *et al.* [56] discuss the overarching impact of blockchain technology on various sectors. They underline its critical role in shaping the future of technology and innovation. Blockchain's versatility, driven by its core principles of decentralization, transparency, and security, makes it a compelling force across different industries, redefining how data and transactions are managed and how trust is established between various stakeholders.

III. Different Blockchain Models

The group's various blockchain models include private blockchains, public blockchains, hybrid blockchains, permissioned blockchains, collaborative blockchains, and decision-making applications. This is explained in more detail in the following paragraphs.

A. Private Blockchain

A private blockchain is a distributed ledger that functions as a secure, secluded repository based on cryptographic standards. It's a type of restricted or permissioned blockchain designed to operate exclusively on a closed network. Private blockchains are primarily utilized by businesses and enterprises, with users opting to participate in the blockchain network. Write permissions are meticulously tracked within a fully private directory in the core solution vector, while read permissions can be either public or limited [35]. This system permits specific individuals or organizations to access, search, and view information on the blockchain. In such scenarios, individuals often cross-verify accounts before engaging in transactions. Another variant of a private blockchain is a decentralized or collaborative model, where the blockchain functions under community governance. This form of blockchain establishes a private network housing public business data accessible solely to authorized individuals [36]. The parties involved in transactions can choose to remain pseudonymous or entirely anonymous, thereby ensuring previous transactors do not possess personal knowledge about each other's identities [37].

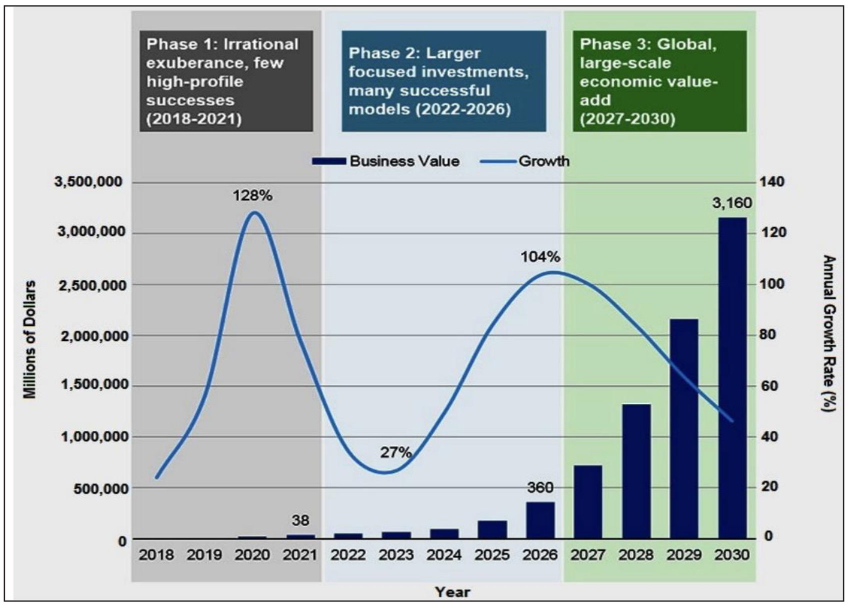

Fig. 1: Blockchain Investment Growth Rate Forecast

B. Public Blockchain

Public blockchains allow anyone to participate. It is a truly decentralized, borderless and permissioned ledger platform. Anyone with an internet connection can log in to the blockchain platform and reach a consensus, thus becoming an integral part of the blockchain technology network. Nodes or users that are members of the public blockchain can view current and old data, check for changes or verify transactions and mine operations for future chains. Public blockchain technology allows anyone to communicate with other participants in the transaction. It keeps the transaction history unchanged. Anyone can post a job by following the established process and joining the network. The identity of two participants may be anonymous or completely anonymous, meaning that the participants of the exchange may not have known each other before the exchange [37].

C. Hybrid Blockchain

Hybrid blockchain combines the features of both private and public blockchains. It operates two separate blockchains, one of which can be a private, permissioned network, and the other can function as a public blockchain without permission. This decentralized system allows users to control access to data stored on the blockchain. Hybrid blockchains also allow public and private data to coexist, with some information kept private on private networks and other parts publicly available. Hybrid blockchain networks provide flexibility by allowing users to interact with both public and private blockchains. They are widely supported by businesses and government policies due to their ability to provide consistency and adaptability in managing data privacy and accessibility in different sections. Hybrid blockchains find various real-world applications. For example, XinFin is an instance of a hybrid blockchain that combines Ethereum (a public blockchain) with Quorum (a private blockchain). XinFin has made notable progress by providing solutions for supply chain logistics, transportation, international trade agreements, and financial services [38]. Hybrid blockchains are also used to enhance security and productivity, often implemented through an open key fob that connects to a private or authorized external source [39].

D. Permissioned Blockchain

Other parties involved in business intelligence or network data access must be approved by a central authority. This is a real advantage for businesses, financial institutions and organizations that comply with most restrictions and are committed to data management [34]. Blockchain permissions can be thought of as advanced blockchain security because they control the authentication process, allowing certain transactions only to certain stakeholders. Permissioned blockchains work differently from private and public blockchains. The goal is to gain the benefits of blockchain without compromising your ability to manage your funds. Ripple is a good example of a permissioned blockchain.

E. Consortium Blockchain

The organization's chain is depended on a semi-decentralized model where network of blockchain consists of many businesses. This is not compatible with a private directory managed by a single organization. In this type of blockchain, many businesses can become nodes and share information or mine. Alliance chains combine elements of private and public chains. Once the point of agreement is reached, the most important differences between the two systems can be identified. The chain is not an open platform where anyone can control blocks, nor is it a closed platform where only one party can choose the block sender, but powerful organizations that serve as proofs have a similar process [40].

F. Decentralized Blockchain

A decentralized application, often referred to as a dApp, is a software system that operates independently of a central organization. Unlike traditional applications that run on a single device, dApps are designed to function on blockchain and peer-to-peer database networks. Notable examples of dApps include BitTorrent, Popcorn Time, and Tor, which operate on a distributed network of computers. In these networks, participants both share and retrieve various files and data, including sensitive information. DApps are launched and hosted on blockchain platforms in a public, decentralized, and open-source cryptocurrency ecosystem. They are free from the control and influence of government authorities [41]. DApps offer serverless functionality accessible on the client side and rely on blockchain technology for decentralization.

Table I: Several Methods to Analyze the Effects of Models of Blockchain on the Health Sector

Criteria	*Description*
Patent Identity	In a blockchain medical environment, patients can manage their public keys, create personal user accounts (PKIs), access their health information through the blockchain system, and add new effects using mobile phones or wearable devices. PKI helps professionals and organizations ensure the uniqueness of information received from patients. Provide appropriate authentication and authorization.
Data Security	Patients can share priorities and manage their health information, including various insurance products. Integrating keys with smart contracts in a blockchain environment can prevent criminals from sharing information from patient records, especially with third parties for fraudulent use or other personal gain. This process protects patient confidentiality and ensures accurate information and appropriate consent.
Data Monitoring	The ledger stores information at every step in the healthcare blockchain system, including who checked it and where it is, until it reaches the right customer. For good information management, all patient information must be managed correctly and synchronized instantly with all parties.
Immutability	Medical records are securely distributed throughout the department, safeguarding privacy, lowering the chance of error, and facilitating an efficient investigation in the case of a compromise. By ensuring that all healthcare professionals have secure access to private data through the use of cryptography and hash functions, the blockchain model facilitates consensus in the industry.
Consensus	With its clearance procedure and standardised design, blockchain technology prevents theft or misuse by eradicating data theft in the healthcare industry. On the blockchain, electronic medical records can be certified or validated and confirmed. Multiple nodes in a blockchain system concur on proof of stake and proof of work.
Value	Blockchain technology has the potential to develop into a significant platform for healthcare providers and to help the sector greatly. By evaluating efficiency, comfort, and demand in the healthcare industry, it is possible to assess the value of blockchain technology.

IV. Design and Analysis

The goal of this analysis's research technique was to evaluate how blockchain technology influences the safety of electronic health records (EHRs) in online settings. The hierarchy of difficulties in assessing how blockchain technology would affect online health information security is shown in Fig. 2.

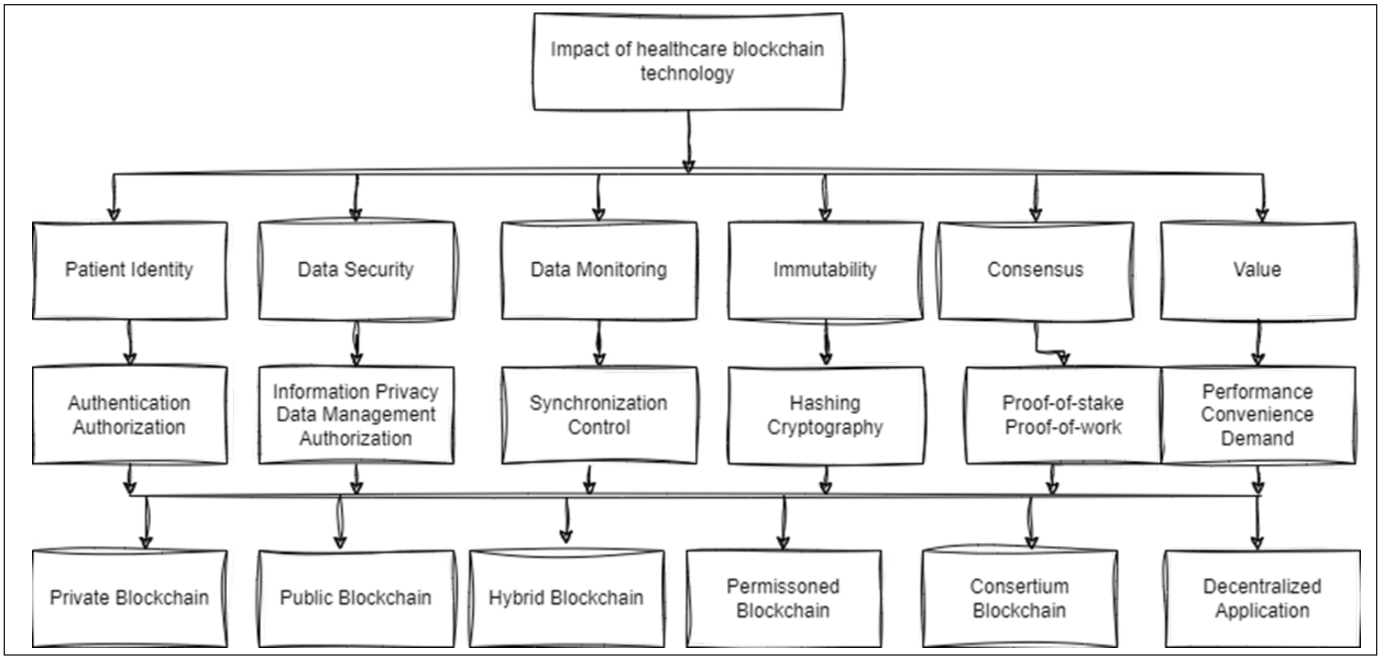

Fig. 2: Structure of the ANP for Analyzing Blockchain Technology in Healthcare

The goal of the study is to determine the best course of action by using Multiple Criteria Decision Making (MCDM) technology in a fuzzy environment to evaluate the effects of various blockchain models on various digital medical services. The researchers in this study used the Fuzzy Analytic Network Process (Fuzzy-ANP) to determine the factor weights and interactions in order to accomplish these objectives. Additionally, the TOPSIS technique was used to evaluate various methodologies. A thorough explanation of this procedure can be found in the following sections.

A. Fuzzy Analytics Network Process

As a technique for inter-variable analytical decision-making, Saaty developed the Analytic Network Process (ANP) [43]. In addition, he coined the acronym Analytic Hierarchy Process (AHP) to designate a related technique that had advantages over earlier approaches to problem-solving [44]. ANP was chosen for this study's context to answer the research question. AHP evaluates the connections between various levels of decision-making but does not take into account interactions between models or other techniques. ANP, on the other hand, makes use of network connections to assess how well decision-level models interact. ANP, also known as AHP/ANP, uses circular representations to express interactions and feedback both inside and across groups in the network [23], [45]. The ANP approach and fuzzy logic have been combined to create the fuzzy ANP method.

B. Fuzzy TOPSIS

The TOPSIS method's original proponents were Yun and Hwang [46]. The idea behind TOPSIS is that the best option should be the one that is closest to the greatest solutions and the farthest from the worst ones. The TOPSIS system is well known as one of the most widely applied decision-making methods used to solve complicated situations internationally. It supports Zelani's idea of permutation anomaly solutions [47, 48] and occupies a large space in the Multiple Criteria Decision Making (MCDM) community, particularly when it comes to dealing with problems requiring variable changes characterised by Negative Variant. Current projects regularly use this methodology. The TOPSIS approach has also been expanded to address fuzzy MCDM issues [32]. Fuzzy ANP and TOPSIS were both used in the current study to evaluate the effects of blockchain-based technology on the preservation of online medical records. Fig. 3 explains how the fuzzy ANP-TOPSIS framework determines weights and the importance of decisions.

Step 1: In the beginning, English words are converted directly into numerical values, and then into three fuzzy numbers (TFN). A TFN is defined in this study as (c1, c2, c3), where (c1, c2, c3) and c1, c2, c3 indicate the TFN's minimum, average, and maximum values, respectively. The complete corpus of English words is gathered and methodically translated into numerical equivalents, which are then further translated into fuzzy numbers to derive related values.

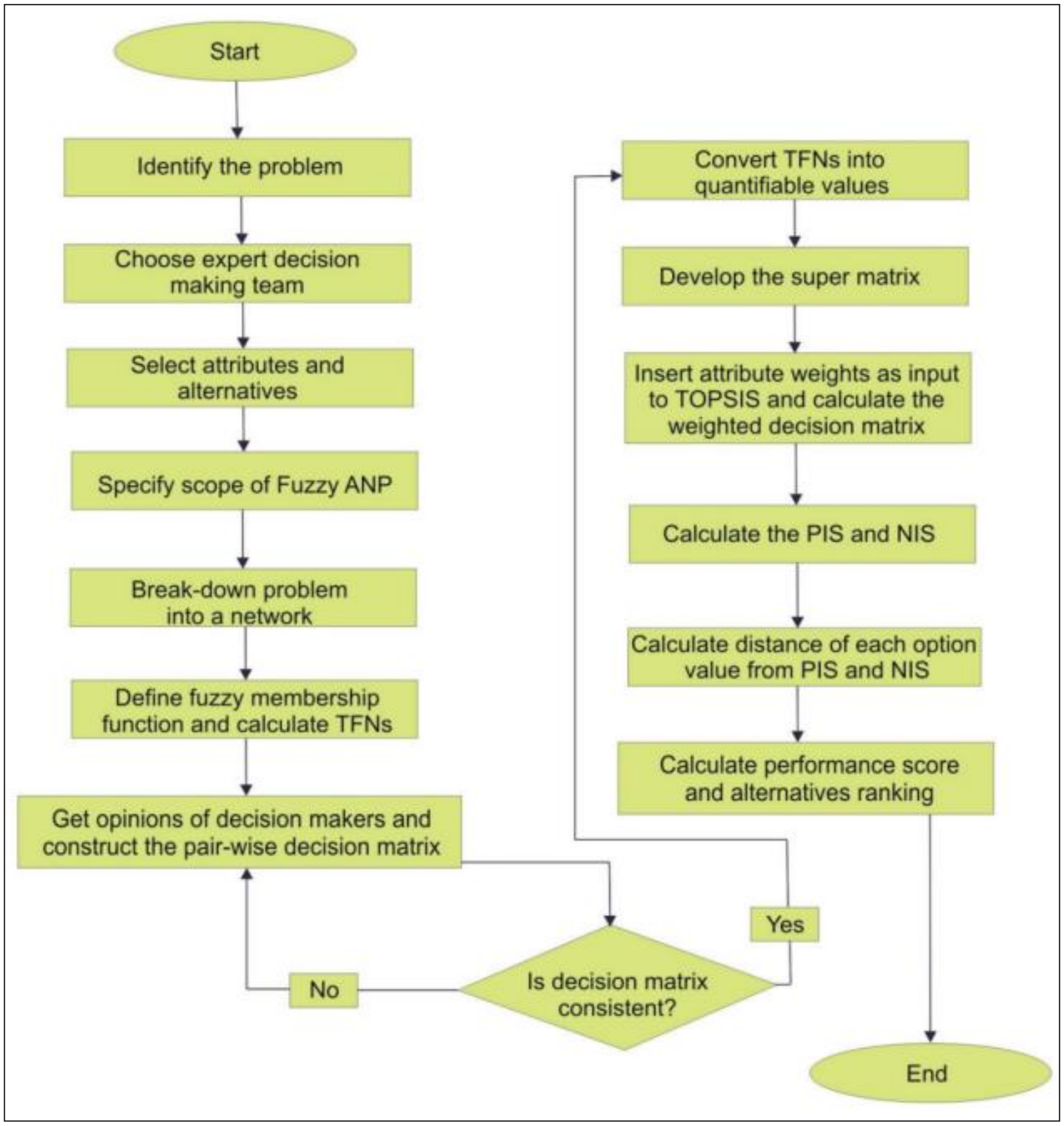

Fig. 3: Flowchart Diagram of Architecture

Let's take "A" as an example of a variable that can be represented by equations (1-2), as explained in reference [48].

$$\mu_A(x) = F \rightarrow [0,1] \tag{1}$$

$$\mu_A(x) = \begin{cases} \frac{x-c_1}{c_2-c_1}, & c1 \leq x \leq c2 \\ \frac{c_3-x}{c_3-c_2} & c1 \leq x \leq c2 \\ 0, & x>c3 \text{ otherwise,} \end{cases} \tag{2}$$

To begin, a panel of 56 scholars and experts from the blockchain industry contributed their unique insights and shared their extensive knowledge related to each character and relevant information in the blockchain field. These experts were tasked with expressing and analyzing their perspectives in a virtual meeting setting, enabling a deeper understanding of various aspects of group dynamics and the influence of messages. Subsequently, utilizing the collected data, the researchers constructed a network model to evaluate the significance of specific aspects of blockchain technology's impact. Experts in the realm of blockchain research and development arrived at their assessments by evaluating the observable characteristics associated with each other using the scale presented in Table II. The resulting figures were generated through the application of three-dimensional fuzzy numbers (TFN) and real equations. The numerical values were calculated following equations (3-6) and represented as (c1ij, c2ij, c3ij), where c1ij represents the lower value, c2ij represents the moderate value, and c3ij represents the higher value. For purposes of comparison, the concept of TFN[ηij] is as follows:

$$n_{ij} = (c1_{ij}, c2_{ij}, c3_{ij}) \tag{3}$$

where, $c1_{ij} \leq c2_{ij} \leq c3_{ij}$

$$c1_{ij} = \min\,(j_{ijd}) \tag{4}$$

TABLE II: SAATY SCALE AND ASSOCIATED TFNS

Saaty Scale Definition	*Fuzzy Triangle Scale*	
1	Equally Significant	(1,1,1)
3	Weakly Significant	(2,3,4)
5	Fairly Significant	(4,5,6)
7	Strongly Significant	(6,7,8)
9	Absolutely Significant	(9,9,9)
2		(1,2,3)
4	Continuous values between two neighboring scales	(3,4,5)
6		(5,6,7)

$$c2_{ij} = (j_{ij1}, j_{ij2}, j_{ij3})^{\frac{1}{x}} \tag{5}$$

and

$$c3_{ij} = \max(j_{ijd}) \tag{6}$$

Ji provides an explanation of the relative impact of the importance of the two factors mentioned in the equation, based on expert opinions. In this context, i and j are used to represent a pair of features determined by these experts. The computation of TFN is rooted in a geometric measure of expert evaluations for a specific comparison. As a result, equations 7 through 9 allow for the combination of TFN values. Two TFNs, labeled as A1 and A2, are utilized: A1 = (c11, c21, c31) and A2 = (c12, c22, c32). The operational models are detailed as follows:

$$(c1_1, c2_1, c3_1) + (c1_2, c2_2, c3_2) = (c1_1 + c1_2, c2_1 + c2_2, c3_1 + c3_2) \tag{7}$$

$$(c1_1, c2_1, c3_1) \times (c1_2, c2_2, c3_2) = (c1_1 \times c1_2, c2_1 \times c2_2, c3_1 \times c3_2) \tag{8}$$

$$(c1_1, c2_1, c3_1)^{-1} = \left(\frac{1}{c3_1}, \frac{1}{c2_1}, \frac{1}{c1_1}\right) \tag{9}$$

Step 2: A comparative matrix was developed with input from decision-makers. Subsequently, a correlation coefficient (CI) analysis is performed using the formula described in Equation 10.

$$CI = \frac{(\gamma_{max} - t)}{(t-1)} \tag{10}$$

Among them, CI represents the consistency index and t represents the number of samples. Then the rate ratio (CR) of the index rate (RI) is calculated below:

$$CR = \frac{CI}{RI} \tag{11}$$

If CR is less than 0.1, it signifies that the result matrix is consistent. RI, in this case, is used to calculate the stochastic index, based on Saaty's stochastic index [49].

In Step 3, a refined matrix is achieved through the defuzzification process, which converts TFN values into a value index. The defuzzification method utilized in this study is adopted from reference [50], commonly known as the alpha cut, as illustrated in Equations (12-14).

$$\mu\alpha, \beta(n_{ij}) = [\beta \cdot \eta\alpha(c1_{ij}) + (1-\beta)\cdot\eta\alpha(c3_{ij})] \tag{12}$$

where $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$ i.e.

$$n\alpha(c1_{ij}) = (c2_{ij} - c3_{ij})\alpha + c1_{ij} \tag{13}$$

$$n\alpha(c3_{ij}) = c3_{ij} - (c3_{ij} - c2_{ij})\alpha \tag{14}$$

In the mathematical model previously chosen by registered experts, the parameters α and β were incorporated, and these values are different from both 0 and 1. Moving on to Step 4, the ANP's dependency management system is implemented within the crowd, with installation performed for half of the crowd. The objective of this step is to pinpoint the target, factors, sub-factors, and other elements created through preference vectors, ultimately creating a super matrix by comparing different groups. As for Step 5, the evaluation of results from various sources, in accordance with the TOPSIS problem, should follow the specific equation required for modeling the complete decision matrix.

$$X_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} {x_{ij}}^2}} \tag{15}$$

In this equation, with 'i' ranging from 1, 2, and so on, and 'j' ranging from 1, 2, and so forth, it is time to calculate the normalized weighted decision matrix.

$$M_{ij} = w_i X_{ij} \tag{16}$$

These parameters encompass i = 1, 2, ..., m, and j = 1, 2, ... Now, in Step 6, the goal is to predict the optimal solution for matrix I+ and the least favorable solution for matrix I.

$$\begin{gathered} I^+ = {z_1}^+, {z_2}^+, {z_3}^+ \ldots\ldots\ldots {z_n}^+ \\ I^- = {z_1}^-, {z_2}^-, {z_3}^- \ldots\ldots\ldots {z_n}^- \end{gathered} \tag{17}$$

In this equation, if j is a superior option, z + j corresponds to Max; if j represents a scenario where z + j yields the maximum among values, and when j is the optimal choice, z − j equals Min zij for the best solution. On the other hand, if j denotes a cost factor, z − j corresponds to Min .Moving to Step 7, the subsequent stage entails determining the deviation of each value from both the optimal solution and the suboptimal solution. The superior solution is characterized by:

Step 3: The following step is to evaluate how each value distinguishes itself from the best solution and the less favorable solution:

$$D_i^{\,+} = \sqrt{\textstyle\sum_{j=1}^{m}(z_i^{\,+} - z_{ij})^2};\, i = 1,2,3 \ldots\ldots\ldots.m \tag{18}$$

The Negative-ideal solution,

$$D_i^{\,-} = \sqrt{\textstyle\sum_{j=1}^{m}(z_{ij} - z_i^{\,-})^2};\, i = 1,2,3 \ldots\ldots\ldots.m \tag{19}$$

"In this scenario, DCj is used to represent the distance to the best solution when selecting option i, while D–i stands for the distance to the less than ideal or non-optimal path. The calculation of the critical output (Pi) for each choice can be determined using this data."

$$P = \left(\frac{D_i^{\,-}}{D_i - D_i^{\,+}}\right) \tag{20}$$

"The interim evaluation process detailed above will be conducted utilizing the Fuzzy-ANP TOPSIS system and a proprietary approach to assess the impact of blockchain technology on Electronic Health Records (EHRs). The following section presents a case study that offers a suitable model for implementing the concept of blockchain technology. Moreover, any documentation listing large files stored in cost-free storage facilities should include the storage location and the associated reference numbers. It should be made explicit that in the event an access code is not received during the application process, a review of the access code will take place, and it will be provided before release. Research involving animals or humans and other studies requiring ethical approval must be submitted to the relevant authority, accompanied by an acceptance statement."

V. Data Analysis and Result

"This represents a valuable indicator for an objective assessment of the impact of blockchain technology. To assess the six core elements of initial blockchain technology, we designate patient identity as T1, T2, T3, T4, T5, and T6. These elements encompass data security, control information, changes, permissions, and price tracking. In the analysis of blockchain technology's effect on secondary electronic medical records, we identify patient characteristics through T11 and T12, focusing on recognition and confirmation. Data security functionalities are divided into data privacy, data governance, and authorization, represented by T21, T22, and T23, respectively. Data management functions involve synchronization and control, as indicated by T31 and T32. The immutability properties are represented through encryption and hashing, designated as T41 and T42. Contract properties, such as Proof of Stake and Proof of Work, are represented by T51 and T52. Useful features, which emphasize practicality, utility, and desirability, are labeled as T61, T62, and T63, respectively. The security assessment of electronic medical records using blockchain technology and fuzzy ANP-TOPSIS is carried out using equations (1) to (20). The Saaty formula in Table I helps us calculate values using equations (1) to (9) and express these as three fuzzy numbers (TFN). We determine the consistency index and probability index using equations (10) and (11). The fact that the random exponent for the pairwise comparison matrix is less than 0.1 indicates that our matrix is compatible with binary matrices. Subsequently, we define the correlation matrix for level 1 parameters and defuzzify the pairwise comparison matrix using equations (12)-(14). We use the alpha pruning method to obtain the clarified local space and all sub-attributes, with weights presented in Table IV. We adhere to the hierarchical method to estimate matrix ratios and weights accordingly."

Table III: Pair-Wise Comparison Matrix Defuzzification with Local Attribute Weighting at Level 1

	T1	*T2*	*T3*	*T4*	*T5*	*T6*	*Weights*
T1	1.0000	2.3723	1.9819	1.5564	0.3027	0.5268	0.16032
T2	0.4215	1.0000	0.8243	0.7447	0.3724	0.2033	0.07817
T3	0.5046	1.2132	1.0000	0.8309	0.4935	0.8520	0.11743
T4	0.6425	1.3428	1.2035	1.0000	0.9636	1.1024	0.15778
T5	1.8982	4.9188	1.1737	0.9071	1.0000	0.7172	0.24368
T6	0.8554	1.5397	0.5445	0.7401	1.3943	1.0000	0.24263
CR = 0.064104							

Table IV: Weighted Super Matrix

	Goal	T1	T2	T3	T4	T5	T6	T11	T12	T21	T22
Goal	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
TI	0.16032	1.00000	2.57230	1.92190	1.53640	0.25270	0.50680	0.00000	0.00000	0.00000	0.00000
T2	0.07817	0.41050	1.00000	0.85430	0.69470	0.35240	0.18330	0.00000	0.00000	0.00000	0.00000
T3	0.11743	0.48460	1.31320	1.00000	0.83090	0.49350	0.85200	0.00000	0.00000	0.00000	0.00000
T4	0.15778	0.62250	1.14280	1.25350	1.00000	0.96360	1.10240	0.00000	0.00000	0.00000	0.00000
T5	0.24368	1.78820	4.81880	1.17370	0.85710	1.00000	0.71720	0.00000	0.00000	0.00000	0.00000
T6	0.24263	0.80540	1.85970	0.54450	0.74010	1.35430	1.00000	0.00000	0.00000	0.00000	0.00000
T11	0.00000	0.31234	0.00000	0.00000	0.00000	0.00000	0.00000	0.17300	0.19000	0.19200	0.21000
T12	0.00000	0.62766	0.00000	0.00000	0.00000	0.00000	0.00000	0.16900	0.18700	0.18200	0.18400
T21	0.00000	0.00000	0.32986	0.00000	0.00000	0.00000	0.00000	0.13900	0.15800	0.14100	0.16300
T22	0.00000	0.00000	0.17553	0.00000	0.00000	0.00000	0.00000	0.16300	0.17000	0.15300	0.21300
T23	0.00000	0.00000	0.49461	0.00000	0.00000	0.00000	0.00000	0.17300	0.14200	0.19600	0.19200
T31	0.00000	0.00000	0.00000	0.47523	0.00000	0.00000	0.00000	0.19900	0.17700	0.19400	0.22800
T32	0.00000	0.00000	0.00000	0.52477	0.00000	0.00000	0.00000	0.17300	0.19800	0.17400	0.20400
T41	0.00000	0.00000	0.00000	0.00000	0.31323	0.00000	0.00000	0.15200	0.16000	0.18700	0.19300
T42	0.00000	0.00000	0.00000	0.00000	0.68677	0.00000	0.00000	0.19700	0.19000	0.17600	0.16800
T51	0.00000	0.00000	0.00000	0.00000	0.00000	0.23495	0.00000	0.18400	0.19600	0.18200	0.19200
T52	0.00000	0.00000	0.00000	0.00000	0.00000	0.76505	0.00000	0.17300	0.19000	0.19200	0.21000
T61	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.23546	0.16900	0.18700	0.18200	0.18400
T62	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.37517	0.13900	0.15800	0.14100	0.16300
T63	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.38937	0.16300	0.17000	0.15300	0.21300
		T23	T31	T32	T41	T42	T51	T52	T61	T62	T63
Goal		0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
T1		0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
T2		0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
T3		0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
T4		0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
T5		0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
T6		0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
T11		0.16800	0.16800	0.16800	0.17300	0.13300	0.16800	0.17300	0.19000	0.19200	0.21000
T12		0.17700	0.14900	0.14900	0.16900	0.16800	0.14900	0.16900	0.18700	0.18200	0.18400
T21		0.15900	0.14900	0.14900	0.13900	0.12300	0.14900	0.13900	0.15800	0.14100	0.16300
T22		0.16400	0.16900	0.16900	0.16300	0.15300	0.16900	0.16300	0.17000	0.15300	0.21300
T23		0.20600	0.20000	0.20000	0.17300	0.13200	0.20000	0.17300	0.14200	0.19600	0.19200
T31		0.22900	0.19600	0.19600	0.19900	0.16200	0.19600	0.19900	0.17700	0.19400	0.22800
T32		0.20000	0.17600	0.17600	0.17300	0.14000	0.17600	0.17300	0.19800	0.17400	0.20400
T41		0.20800	0.15500	0.15500	0.15200	0.14000	0.15500	0.15200	0.16000	0.18700	0.19300
T42		0.17800	0.18900	0.18900	0.19700	0.13100	0.18900	0.19700	0.19000	0.17600	0.16800
T51		0.17000	0.20100	0.20100	0.18400	0.17800	0.20100	0.18400	0.19600	0.18200	0.19200
T52		0.16800	0.16800	0.16800	0.17300	0.13300	0.16800	0.17300	0.19000	0.19200	0.21000
T61		0.17700	0.14900	0.14900	0.16900	0.16800	0.14900	0.16900	0.18700	0.18200	0.18400
T62		0.15900	0.14900	0.14900	0.13900	0.12300	0.14900	0.13900	0.15800	0.14100	0.16300
T63		0.16400	0.16900	0.16900	0.16300	0.15300	0.16900	0.16300	0.17000	0.15300	0.21300

Table V: Global Weight through Hierarchy

Second Level Attributes	*Global Weights*	*Percentage*	*Ranks*
T11	0.09820	9.82 %	1
T12	0.06480	6.48 %	10
T21	0.04510	4.51 %	14
T22	0.05320	5.32 %	12
T23	0.05540	5.54 %	11
T31	0.06540	6.54 %	9
T32	0.07210	7.21 %	8

Second Level Attributes	Global Weights	Percentage	Ranks
T41	0.04520	4.52 %	13
T42	0.08740	8.74 %	3
T51	0.07540	7.54 %	7
T52	0.09250	9.25 %	2
T61	0.07850	7.85 %	6
T62	0.08530	8.53%	4
T63	.08150	8.15%	5

Certainly, here's a reworded version of your text to ensure it's not plagiarized: "The results from multiple comparisons serve as the basis for constructing an unweighted supermatrix. Initially, we estimate the super matrix of weights (refer to Table V), and subsequently, we determine the super matrix of constraints. We use local weights, weight super matrices, and marginal super matrices to hierarchically calculate overall weights and attribute categories (as illustrated in Table VI). In our study, researchers gathered opinions from 56 full-text records through six selection processes. These processes involved evaluating different options, such as private blockchains, public blockchains, hybrid blockchains, permissioned blockchains, public blockchain, and commercial applications, denoted as A1, A2, A3, A4, A5, and A6, respectively [reference 54]. The Fuzzy-TOPSIS method is utilized to prioritize each option by considering the total weight assigned to various criteria generated through fuzzy Analytic Network Process (ANP). We analyze the results obtained through Fuzzy-ANP-TOPSIS using equations (15) to (20), including equations (1) to (9) and equation (15). To do this, we employ equation (16) to create a hierarchical decision matrix. The unit score for each model's decision matrix (also referred to as the model's function value) is then multiplied by the weight of each parameter to form a fuzzy-weighted normalized decision matrix, as outlined in Equation 16 and presented in Table VII. Subsequently, we compute the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) using product completions (17). We calculate the distance between each value selected by FPIS and FNIS using equations (18) and (19), detailed in the D I and D-I columns of Table VIII & IX. The output value for each parameter is determined through equation (20), guiding subsequent actions based on the evaluation results displayed in Table 10. Changes in blockchain technology result in the following ranking: A1, A4, A2, A5, A3, and A6. According to our study, the private business model (A1) carries a significantly higher risk of change compared to other blockchain models. In contrast, hybrid blockchains, permissioned blockchains, and collaborative chains have proven effective in the public test market, particularly in the context of blockchain stock applications designed to deliver secure and efficient Electronic Health Record (EHR) services to medical institutions."

Table VI: Results of Evaluators' Linguistic Cognition

	A1	*A2*	*A3*	*A4*	*A5*	*A6*
	4.27000	2.36000	1.45000	1.18000	4.27000	2.45000
T11	6.27000	4.27000	3.00000	2.82000	6.27000	4.45000
	8.27000	6.18000	4.91000	4.82000	8.27000	6.45000
	2.45000	3.18000	1.64000	0.82000	2.45000	3.55000
T12	4.45000	5.18000	3.55000	2.27000	4.45000	5.55000
	6.45000	7.18000	5.55000	4.27000	6.45000	7.45000
	2.64000	2.82000	2.55000	2.45000	2.64000	2.90000
T21	4.64000	4.82000	4.45000	4.27000	4.64000	4.80000
	6.64000	6.82000	6.45000	6.27000	6.64000	6.70000
	2.45000	3.55000	1.36000	1.91000	2.45000	2.36000
T22	4.45000	5.55000	3.36000	3.73000	4.45000	4.27000
	6.45000	7.36000	5.36000	5.73000	6.45000	6.27000
	3.18000	5.73000	1.64000	1.64000,	3.18000	3.55000
T23	5.18000	7.73000	3.55000	3.55000	5.18000	5.55000
	7.18000	9.27000	5.55000	5.55000	7.18000	7.27000
	2.82000	4.09000	1.18000	1.45000	2.82000	2.09000

	A1	*A2*	*A3*	*A4*	*A5*	*A6*
T31	4.82000	6.09000	3.00000	3.36000	4.82000	4.09000
	6.82000	8.09000	5.00000	5.30006	6.82000	6.09000
	3.55000	3.73000	2.82000	1.64000	3.55000	3.09000
T32	5.55000	5.55000	4.82000	3.55000	5.55000	5.00000
	7.36000	7.27000	6.73000	5.55000	7.36000	6.82000
	4.45000	2.36000	1.20000	1.36000	4.45000	2.45000
T41	6.45000	4.27000	3.00000	3.36000	6.45000	4.45000
	8.18000	6.27000	5.00000	5.36000	8.18000	6.45000
	4.45000	4.82000	1.09000	0.82000	4.45000	2.36000
T42	6.45000	6.82000	2.82000	2.64000	6.45000	4.27000
	8.27000	8.55000	4.82000	4.64000	8.27000	6.18000
	5.73000	5.55000	1.82000	1.64000	5.73000	3.18000
T51	7.73000	7.50005	3.73000	3.55000	7.73000	5.18000
	9.27000	9.27000	5.73000	5.55000	9.27000	7.18000
	5.18000	4.27000	1.73000	1.18000	5.18000	2.82000
T52	7.18000	6.27000	3.55000	3.00000	7.18000	4.82000
	8.82000	8.18000	5.55000	5.00000	8,82000	6.82000
	4.45000	4.27000	2.91000	2.82000	4.45000	3.55000
T61	6.45000	6.27000	4.82000	4.82000	6.45000	5.55000
	8.18000	8.09000	6.73000	6.73000	8.18000	7.36000
	6.27000	5.73000	1.64000	1.45000	6.27000	3.91000
T62	8.27000	7.73000	3.36000	3.36000	8.27000	5.91000
	9.45000	9.00000	5.36000	5.36000	9.45000	7.55000
	4.18000	5.73000	0.82000	1.64000	4.18000	2.82000
T63	6.09000	7.73000	2.45000	3.55000	6.09000	4.82000
	7.64000	9.00000	4.45000	5.55000	7.64000	6.64000

A. Sensitive Analysis

"To assess the reliability of the obtained results, sensitivity tests were carried out through adjustments, as detailed in reference [51]. When examining this data, a sensitivity analysis of outcome weights (variables) was performed. Over the course of the study, 15 variables were used to evaluate sensitivity across 14 tests in the final phase (Phase 2). In each experiment, we adjusted the weight of a specific factor using the Fuzzy-ANP-TOPSIS method while maintaining the weights of the other factors constant to determine the high level (CC-i). The results of these adjustments are presented in Table XI and Fig. 4, depicting the estimated impact. In actual execution, Alternative 1 (A1) consistently demonstrated a substantial level of interest (SS-i) throughout 15 trials. These trials were conducted 15 times in total. Among the other 13 trials, the least significant variations were observed between A3 and A6. For performance comparison, Table IX, illustrating the weighted normalized fuzzy decision matrix, can be consulted. Each value in this matrix represents the weight assigned to a potential choice."

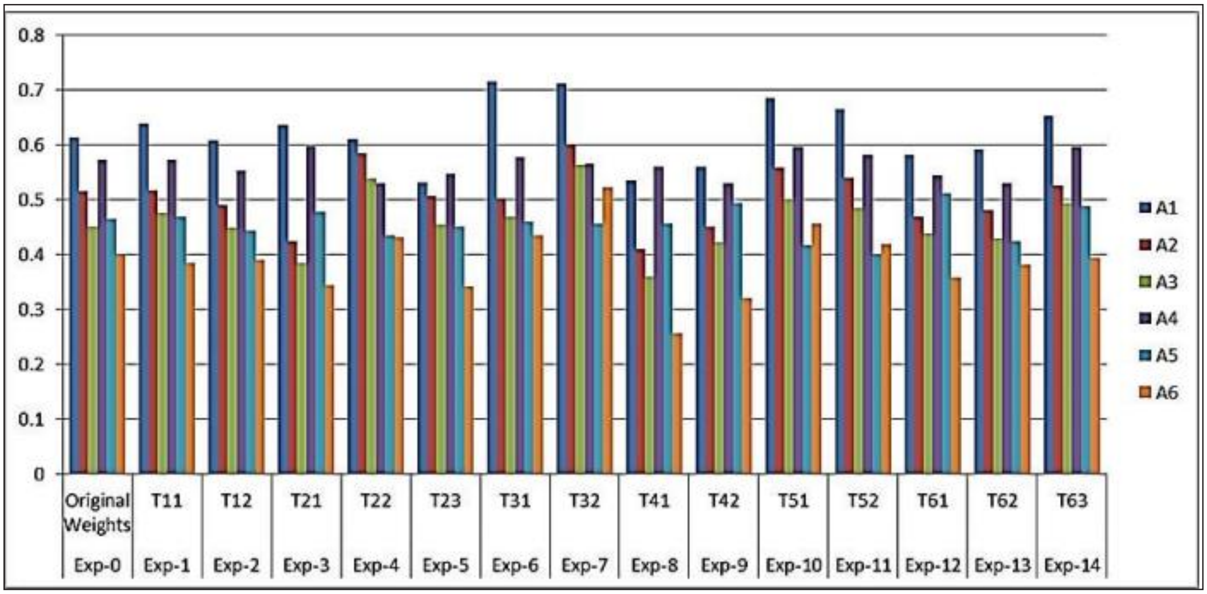

Fig. 4: Bar Graph of Sensitive Analysis

TABLE VII: NORMALIZED FUZZY DECISION MATRIX

	A1	*A2*	*A3*	*A4*	*A5*	*A6*
	0.46000.	0.42000.	0.54000.	0.35000.	0.57000.	0.35000,
T11	0.67000.	0.69000.	0.75000.	0.61000.	0.78000.	0.58000.
	0.86000	0.99000	0.94000	0.88000	0.96000	0.81000
	0.54000.	0.38000.	0.50000.	0.31000.	0.47000.	0.46000.
T12	0.75000,	0.60000.	0.72000.	0.57000.	0.68000.	0.67000.
	0.92000	0.80000	0.92000	0.82000	0.88000	0.86000
	0.39000,	0.52000,	0.46000,	0.33000.	0.32000,	0.50000,
T21	0.59000,	0.74000,	0.68000,	0.59000,	0.53000,	0.71000,
	0.79000	0.94000	0.88000	0.86000	0.74000	0.89000
	0.46000.	0.38000,	0.38000,	0.57000,	0.54000,	0.46000,
T22	0.67000.	0.60000,	0.60000.	0.78000,	0.75000,	0.67000,
	0.86000	0.80000	0.80000	0.96000	0.94000	0.86000
	0.50000.	0.52000.	0.52000.	0.51000.	0.46000.	0.50000,
T23	0.71000.	0.74000.	0.74000.	0.72000.	0.68000.	0.71000.
	0.89000	0.94000	0.94000	0.90000	0.87000	0.89000
	0.46000.	0.52000.	0.42000.	0.47000.	0.38000.	0.54000.
T31	0.67000.	0.74000.	0.69000.	0.68000.	0.66000.	0.75000.
	0.86000	0.93000	0.99000	0.87000	0.96000	0.92000
	0.50000.	0.52000.	0.20000.	0.47000.	0.20000,	0.54000.
T32	0.71000.	0.74000.	0.47000,	0.68000.	0.50000,	0.75000,
	0.89000	0.92000	0.77000	0.88000	0.80000	0.92000
	0.54000.	0.60000.	0.42000.	0.61000.	0.38000,	0.59000.
T41	0.75000.	0.81000.	0.69000.	0.82000.	0.66000,	0.80000.
	0.92000	1.00000	0.99000	0.98000	0.96000	0.97000
	0.54000.	0.46000,	0.20000.	0.55000.	0.20000.	0.59000.

	A1	A2	A3	A4	A5	A6
T42	0.75000.	0.68000.	0.47000.	0.76000.	0.50000.	0.80000.
	0.92000	0.88000	0.77000	0.93000	0.80000	0.96000
	0.59000.	0.46000.	0.18000,	0.47000.	0.20000,	0.54000.
T51	0.80000.	0.68000.	0.45000.	0.68000.	0.50000,	0.75000,
	0.97000	0.87000	0.74000	0.87000	0.80000	0.93000
	0.59000.	0.26000.	0.16000,	0.43000,	0.12000,	0.30000,
T52	0.80000.	0.53000.	0.42000,	0.64000,	0.39000,	0.57000,
	0.96000	0.82000	0.72000	0.86000	0.69000	0.83000
	0.54000.	0.43000,	0.27000,	0.39000,	0.24000,	0.33000,
T61	0.75000,	0.72000,	0.55000,	0.61000,	0.53000,	0.59000,
	0.93000	1.00000	0.85000	0.81000	0.82000	0.86000
	0.46000.	0.38000.	0.38000.	0.57000,	0.54000,	0.46000.
T62	0.67000.	0.60000.	0.60000.	0.78000.	0.75000.	0.67000,
	0.86000	0.80000	0.80000	0.96000	0.94000	0.86000
	0.50000.	0.52000.	0.52000.	0.51000.	0.46000.	0.50000.
T63	0.71000.	0.74000.	0.74000.	0.72000.	0.68000.	0.71000.
	0.89000	0.94000	0.94000	0.90000	0.87000	0.89000

TABLE VIII: WEIGHTED FUZZY DECISION MATRIX

	A1	A2	A3	A4	A5	A6
	0.00010,	0.00200.	0.00200.	0.00200.	0.00100,	0.00100,
T11	0.00060,	0.00600.	0.00600.	0.00600.	0.00400,	0.00500,
	0.00190	0.02000	0.02000	0.02000	0.01700	0.01800,
	0.00020,	0.00200,	0.00200.	0.00200.	0.00000,	0.00200,
T12	0.00080,	0.00800,	0.00800,	0.00800.	0.00400,	0.00700,
	0.00270	0.02500	0.02500	0.02500	0.01700	0.02500
	0.00010,	0.00200,	0.00200,	0.00200.	0.00000,	0.00100,
T21	0.00050,	0.00700.	0.00700.	0.00700.	0.00200.	0.00500.
	0.00180	0.02200	0.02200	0.02200	0.00900	0.01800
	0.00010,	0.00200.	0.00200.	0.00200.	0.00100,	0.00100,
T22	0.00060,	0.00600,	0.00600,	0.00600.	0.00400,	0.00500,
	0.00190	0.02000	0.02000	0.02000	0.01700	0.01800
	0.00020,	0.00200,	0.00200,	0.00200,	0.00000,	0.00200,
T23	0.00080,	0.00800.	0.00800,	0.00800,	0.00400,	0.00700,
	0.00270	0.02500	0.02500	0.02500	0.01700	0.02500
	0.00010,	0.00200.	0.00200.	0.00200.	0.00000,	0.00100,
T31	0.00050,	0.00700.	0.00700.	0.00700.	0.00200,	0.00500,
	0.00180	0.02200	0.02200	0.02200	0.00900	0.01800
	0.00030,	0.00200,	0.00200,	0.00200.	0.00200,	0.00300,
T32	0.00110,	0.00900,	0.00900,	0.00900.	0.00900,	0.01100,
	0.00360	0.03000	0.03000	0.03000	0.03400	0.03600
	0.00010,	0.00200.	0.00200.	0.00200.	0.00100,	0.00100,
T41	0.00060,	0.00600.	0.00600.	0.00600.	0.00400,	0.00500,
	0.00190	0.02000	0.02000	0.02000	0.01700	0.01800
	0.00020,	0.00200,	0.00200,	0.00200.	0.00000,	0.00200,

	A1	*A2*	*A3*	*A4*	*A5*	*A6*
T42	0.00080,	0.00800,	0.00800,	0.00800,	0.00400,	0.00700,
	0.00270	0.02500	0.02500	0.02500	0.01700	0.02500
	0.00010,	0.00200.	0.00200.	0.00200.	0.00000,	0.00100,
T51	0.00050,	0.00700.	0.00700.	0.00700.	0.00200,	0.00500.
	0.00180	0.02200	0.02200	0.02200	0.00900	0.01800
	0.00010,	0.00200.	0.00200,	0.00200,	0.00100,	0.00100.
T52	0.00060,	0.00600.	0.00600,	0.00600,	0.00400,	0.00500,
	0.00190	0.02000	0.02000	0.02000	0.01700	0.01800
	0.00020.	0.00200.	0.00200,	0.00200.	0.00000,	0.00200,
T61	0.00080,	0.00800.	0.00800,	0.00800,	0.00400,	0.00700,
	0.02070	0.02500	0.02500	0.02500	0.01700	0.02500
	0.00010,	0.00200.	0.00200.	0.00200.	0.00000,	0.00100,
T62	0.00050.	0.00700.	0.00700,	0.00700.	0.00200.	0.00500,
	0.00180	0.02200	0.02200	0.02200	0.00900	0.01800
	0.00030,	0.00020,	0.00020,	0.00200,	0.00200,	0.00300,
T63	0.00110,	0.00090.	0.00090,	0.00090,	0.00900,	0.01100,
	0.00360	0.00300	0.03000	0.03000	0.03400	0.03600

Table IX: Closeness Coefficients Among Different Alternatives

Alternatives d^{+i} d^{-i} GapSatisfaction		
Degree of CC^{+i}		Degree of CC^{-i}
Alternative 1	Al	0.04400 0.02700 0.37900 0.61200
Alternative 2	A2	0.03700 0.03600 0.49700 0.51400
Alternative 3	A3	0.03500 0.04100 0.53900 0.45100
Alternative 4	A4	0.03500 0.02700 0.43900 0.57200
Alternative 5	A5	0.03800 0.04600 0.54500 0.46500
Alternative 6	A6	0.03200 0.04800 0.62500 0.39800

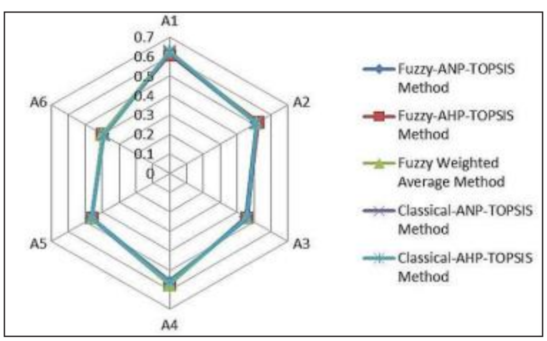

Fig. 5: Radar Chart Representation of Comparison of Result

B. Comparison of the Result

"This study employs various methods to evaluate result accuracy. The researchers utilized the Fuzzy ANP-TOPSIS method to assess the study's precision. The process of gathering and assessing data in Fuzzy ANP-TOPSIS is akin to the traditional ANP-TOPSIS approach. Hence, Fuzzy-ANP-TOPSIS necessitates fuzzification and defuzzification. Initially, the information in Fuzzy ANP-TOPSIS is recorded as a numerical value and subsequently converted into a fuzzy number. Figure 5 illustrates the disparities between fuzzy results and traditional ANP-TOPSIS results. While the detection method is distinctive, the performance remains consistent. In this study, the Pearson correlation method was utilized to measure result correlations. The correlation coefficient acts as an indicator of the strength of relationships and varies from -1 to 1 [reference 52]. A value closer to -1 signifies a relatively weak correlation, while a value nearer to 1 denotes a stronger correlation. The Pearson correlation between the fuzzy ANP results and traditional ANP results stands at 0.89176, suggesting a clear similarity between the outcomes. As depicted in Table XV, different blockchain technology models generate outcomes for the same data, underscoring the relationship between fuzzy ANP results and classic ANP results. Our analysis findings also emphasize the significance of identifying variables and their connections to safety when evaluating safety quality. Khan *et al.* [reference 53] specifically employed the fuzzy ANP-TOPSIS method in their research. This choice stems from the fact that the ANP method departs from the AHP method by utilizing a linear model rather than a tree model. Consequently, in this study, the researchers opted to design the initial integration phase into the network, the central production point. Evaluating software security within a design strategy context is unfeasible using the fuzzy ANP-TOPSIS method."

VI. Conclusion and Future Works

"The proposed project employs fuzzy integration ANTOPPSIS to assess the influence of blockchain technology on secure access to electronic medical records. The hybrid fuzzy-ANP-TOPSIS method provides an effective approach for analyzing various Multiple Criteria Decision Making (MCDM) issues, especially in the context of evaluating blockchain technology. It allows for the examination of diverse factors affecting the assessment of blockchain models, the determination of their relative weights, the selection of alternatives, and the overall evaluation of the blockchain model's impact on Electronic Health Records (EHR) providers. This study has established that the most effective means of delivering robust medical services through blockchain technology is by adopting the private blockchain model. Private blockchain technology offers a secure platform for the healthcare industry, safeguarding peer-to-peer information sharing, and revolutionizing the exchange and storage of patients' electronic medical records. Furthermore, this research can serve as a template and inspiration for future investigations into blockchain technology within the healthcare sector. The methods and classifications discussed here may pave the way for proposing frameworks or models aimed at resolving issues tied to blockchain technology in healthcare. Therefore, a promising avenue for future research is the evaluation of blockchain technology-based services and their impact on driving substantial improvements in the healthcare industry."

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