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ORIGINAL RESEARCH ARTICLE

Integrating blockchain in the healthcare sector: Adoption and challenges for sustainable waste management

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Abstract: Healthcare waste management suffers from limited transparency, weak traceability, and compliance challenges, leading to significant environmental and public health risks. Blockchain technology offers a potential solution by enabling secure, immutable, and auditable waste-tracking systems. This study examines the key factors influencing the adoption of blockchain in sustainable healthcare waste management and assesses suitable blockchain platforms for implementation. An integrated multi-method framework—fuzzy best–worst method, interpretive structural modeling, decision-making trial and evaluation laboratory (DEMATEL) was applied to analyze expert judgments from healthcare, industry, academia, and blockchain specialists. The findings indicate that data privacy concerns, scalability limitations, a lack of organizational support, and regulatory ambiguity are the most significant barriers. DEMATEL identifies organizational support and regulatory clarity as major causal drivers. The study offers actionable insights for policymakers and healthcare organizations to prioritize regulatory reforms, capacity-building, and infrastructure investment to enable blockchain-driven waste management systems.

Keywords: Blockchain technology; Healthcare waste management; Sustainability; Decision-making trial and evaluation laboratory method; Analytic network process; Regulatory compliance

1. Introduction

The healthcare sector is crucial in ensuring public health and economic development. At the same time, the sector contributes significantly to environmental challenges due to the large volume of waste it generates.[1,2] Healthcare waste comprises biomedical, pharmaceutical, chemical, and electronic waste, requiring proper handling and disposal to prevent environmental contamination and public health risks.[3] Improper waste management can lead to severe consequences, such as spreading infectious diseases, causing water pollution, and releasing toxic substances into the environment.[4] Traditional waste management systems in healthcare facilities often suffer from inadequate tracking mechanisms, a lack of transparency, and weak regulatory enforcement.[5] These issues necessitate the adoption of innovative technologies to enhance traceability, accountability, and sustainability in healthcare waste management.[6]

Blockchain technology has emerged as a promising solution to address these challenges by offering a decentralized, immutable, and transparent digital ledger system.[7,8] It ensures that all transactions are securely recorded and cannot be altered, making it particularly useful for tracking healthcare waste from its point of generation to its final disposal.[9] Blockchain's ability to provide real-time monitoring of waste disposal activities can reduce instances of illegal dumping, fraud, and mismanagement.[10,11] In addition, smart contracts, self-executing contracts with predefined rules, can automate regulatory compliance and ensure that all stakeholders adhere to environmental laws without requiring manual intervention.[12] By integrating blockchain into healthcare waste management, healthcare institutions, regulatory bodies, and waste management companies can collaborate more effectively, reducing environmental hazards and improving compliance.

Despite its transformative potential, blockchain adoption in healthcare waste management faces significant barriers.[13] These include technological complexity, high implementation costs, regulatory uncertainties, and interoperability issues with existing healthcare systems.[7] In addition, resistance to change among stakeholders, the lack of digital infrastructure, and concerns over data privacy pose further challenges.[14] Given these complexities, a structured approach is required to identify, categorize, and analyze the factors influencing blockchain adoption and to determine the most suitable blockchain platforms for implementation.[15] While prior studies have explored blockchain adoption challenges in healthcare waste management, their focus was primarily limited to identifying and ranking barriers conceptually.[13] The current study differs in three critical ways: (i) It employs an integrated multi-method framework (Fuzzy Best–Worst method [FBWM], interpretive structural modeling [ISM], decision-making trial and evaluation laboratory [DEMATEL], and analytic network process [ANP]) that systematically accounts for both causal relationships and hierarchical dependencies; (ii) it bases its analysis on primary data collected from a multidisciplinary panel of experts across academia, industry, healthcare, and blockchain technology; and (iii) it extends the scope beyond barriers to evaluate and rank blockchain platforms (Ethereum, Hyperledger Fabric, and Corda), offering practical decision-making insights. These distinctions strengthen the originality and practical utility of our work.

Unlike traditional ranking methods, ANP considers the complex interrelationships between various criteria, making it suitable for evaluating blockchain adoption decisions.[16] Given the availability of multiple blockchain platforms, such as Ethereum, Hyperledger Fabric, and Corda, each with different strengths in terms of scalability, security, cost, and compliance, ANP helps prioritize the most suitable platform for sustainable healthcare waste management.[17] This approach provides a comprehensive decision-making framework for healthcare institutions looking to integrate blockchain into their waste management systems.

The novelty of this research lies in combining multiple decision-making methodologies (FBWM, ISM, DEMATEL into a single integrated framework applied to healthcare waste management, supported by primary expert data, and extended to include blockchain platform ranking—an approach not previously attempted in the literature. The platform comparison aligns with the study by Tripathi *et al*.,[9] which cautioned against the use of public blockchains for sensitive healthcare data due to privacy risks. By ranking Hyperledger Fabric above Ethereum, the current study empirically validated these concerns in the specific context of waste management. In addition, Miron *et al*.[18] highlighted scalability challenges in blockchain applications for smart cities.

For blockchain technology to be successfully integrated into healthcare waste management, it is crucial to provide actionable insights for healthcare organizations and policymakers on its adoption.[19,20] The insights generated from the DEMATEL analyses offer a data-driven understanding of the enablers and inhibitors of blockchain implementation. These findings can assist healthcare facilities in developing strategies to overcome technical and regulatory challenges while optimizing waste disposal practices.[21] Moreover, policymakers can use these insights to formulate regulatory frameworks that encourage blockchain adoption while ensuring environmental sustainability and compliance with waste management laws.[22]

This study is situated primarily within the context of developing and emerging healthcare systems, where regulatory ambiguity, limited digital infrastructure, and resource constraints intensify blockchain adoption challenges. The expert panel was drawn from regions characterized by such constraints, making the findings particularly relevant for low- and middle-income countries. While some barriers, such as data privacy and scalability, are universal, others, including organizational readiness and regulatory enforcement, differ markedly across development contexts. This contextual grounding enhances the interpretability of the findings and provides clearer guidance for future comparative research.

This study aims to achieve two key objectives: First, to identify and categorize the critical factors influencing blockchain adoption using the DEMATEL method; and second, to provide actionable insights for healthcare organizations and policymakers on adopting blockchain for sustainable waste management.

Given the multifaceted and uncertain nature of blockchain adoption in healthcare waste management, this study employed an integrated multi-method decision-making framework. Specifically, the FBWM was used to capture expert judgment uncertainty and prioritize adoption barriers; ISM was applied to establish hierarchical relationships among these barriers; DEMATEL identified causal and effect relationships. This integrated approach enables a comprehensive analysis that simultaneously addresses importance, hierarchy, causality, and platform selection—an advancement over prior single-method or dual-method studies. Based on the above objectives, this study addresses the following research questions (RQs):

i. RQ1: What are the critical factors influencing blockchain adoption in sustainable healthcare waste management?
ii. RQ2: How do these factors interact and influence each other within a causal and hierarchical framework?
iii. RQ3: Which blockchain platforms are most suitable for adoption in the healthcare waste management sector, considering scalability, compliance, and cost?

2. Literature review

This section reviews prior studies on blockchain adoption in healthcare waste management, with particular emphasis on technological, organizational, financial, and regulatory barriers. The review synthesizes findings from recent empirical and methodological studies to identify recurring challenges and methodological gaps, thereby establishing the foundation for the integrated analytical framework employed in this study.

2.1. Technological challenges

The integration of blockchain technology in sustainable healthcare waste management presents multiple challenges spanning technological, organizational, and regulatory dimensions.[23,24] One of the primary technological barriers is the lack of standardized protocols and regulatory frameworks governing blockchain adoption in healthcare waste management.[14] The absence of uniform standards leads to interoperability issues between different blockchain platforms and existing waste management systems, thereby impeding seamless data exchange and operational efficiency.[25] Furthermore, concerns regarding the scalability of blockchain networks and the substantial computational resources required for implementation pose significant technical constraints.[26]

2.2. Organizational and strategic challenges

In addition to technological barriers, organizational challenges further hinder the adoption of blockchain in healthcare waste management. Many healthcare institutions lack adequate expertise in blockchain technology, resulting in a skill gap that limits the effective deployment and maintenance of blockchain-based waste tracking systems.[14,27] Resistance to change among healthcare personnel, who may be accustomed to traditional waste management practices, further complicates implementation efforts.[28]

2.3. Financial and economic challenges

The high initial investment costs associated with blockchain infrastructure present a financial burden, particularly for healthcare facilities operating with limited resources.[29,30]

2.4. Regulatory and governance challenges

Regulatory and legal concerns also pose significant obstacles to blockchain adoption in healthcare waste management. Given the stringent data protection regulations governing the healthcare sector, ensuring compliance with policies such as the general data protection regulation and the Health Insurance Portability and Accountability Act becomes challenging.[31] The immutable nature of blockchain records may conflict with data protection laws that grant individuals the right to modify or erase personal data, necessitating legal frameworks that balance data integrity with privacy concerns.[32] Addressing these challenges requires a multidisciplinary approach involving technological advancements, policy adaptations, and capacity-building initiatives to facilitate blockchain adoption in sustainable healthcare waste management.[23]

Recent studies have advanced the understanding of sustainable healthcare waste management through technology-enabled frameworks. For example, Lotfi *et al*.[33] designed an antifragile and sustainable healthcare waste chain network incorporating blockchain and resilience-based optimization. Similarly, Trivedi *et al*.[34] proposed a goal-programming-based design for COVID-19 immunization waste management, emphasizing efficiency and risk minimization. These works highlight the critical role of digital innovations but focus primarily on optimization models rather than adoption dynamics.

In contrast, several 2024–2025 studies have examined blockchain adoption challenges across several sectors. Riedel[23] explored pharmaceutical blockchain adoption for sustainability, while Souissi *et al*.[35] linked blockchain uptake to financial distress and information asymmetry. Dhingra *et al*.[13] analyzed healthcare waste management barriers using Best–Worst Method (BWM)–DEMATEL, and Najati[36] evaluated blockchain project failures through commons theory.

The current study extends these efforts by integrating fuzzy, structural, and causal analyses and by ranking blockchain platforms to provide actionable guidance for healthcare organizations.

A comprehensive literature review revealed several critical challenges associated with integrating blockchain technology in sustainable healthcare waste management. These challenges span across technological, organizational, regulatory, and financial domains, impacting the feasibility and scalability of blockchain adoption in this sector. Table 1 categorizes and summarizes the significant adoption challenges identified from the literature, providing a structured overview of the complexities of implementing blockchain-based waste management solutions.

3. Research methodology and data collection

In this study, data were collected through a survey from a panel of experts (n = 10). The panel comprises academia, industry, healthcare, and blockchain technology experts. A structured questionnaire was developed and distributed to the selected experts. The questionnaire included a list of challenges related to blockchain integration in sustainable healthcare waste management based on an extensive literature review. FBWM was utilized to derive fuzzy pairwise comparisons, allowing for the computation of relative weights for each challenge while effectively addressing the inherent uncertainty in expert judgments. Following this, the ISM approach was applied to examine the hierarchical structure and interdependencies among the challenges, thereby reinforcing the robustness and interpretability of the FBWM-derived rankings.

3.1. Steps of the FBWM

In this study, a hybrid FBWM formulation was adopted. Expert judgments were initially expressed using linguistic variables and modeled as triangular fuzzy numbers (TFNs). These fuzzy values were

Table 1. Adoption challenges of blockchain integration in sustainable healthcare waste

No.	Adoption challenge	Description	References
E1	Lack of organizational vision and support	Absence of clear goals, strategic planning, and leadership commitment for blockchain adoption.	13,14
E2	Resistance and lack of awareness	Reluctance to adopt blockchain due to limited understanding of its benefits and fear of transitioning from traditional systems.	7,36,37
E3	Financial barriers	High implementation, maintenance, and infrastructure costs associated with blockchain adoption.	13,14,29,38-41
E4	Uncertain return on investment	Doubts about blockchain adoption's financial viability and measurable benefits hinder its implementation.	13,38,41
E5	Infrastructure and design limitations	Inadequate digital infrastructure and complex system design requirements hinder blockchain integration.	13,37,42,43
E6	Scalability challenges	Difficulty in managing increasing data volumes and transaction loads as blockchain-based systems expand.	29,37,44-46
E7	Data privacy and security concerns	Risks of unauthorized access, data breaches, and challenges in protecting sensitive healthcare and waste-related data.	13,36,47,48
E8	Lack of technical expertise	Insufficient blockchain-related skills among stakeholders to develop, implement, and manage blockchain systems effectively.	13,36,43,49
E9	Interoperability and coordination issues	Challenges in integrating blockchain with existing healthcare and waste management systems and coordinating among stakeholders.	13,37,40
E10	Lifecycle management gaps	Inadequate monitoring and control across all stages of the healthcare waste lifecycle, from generation to final disposal.	13,36,42,43
E11	Regulatory ambiguity and stakeholder trust issues	Unclear regulations and low stakeholder trust hinder governance, compliance, and adoption of blockchain solutions.	7,13,35,36,50-52
E12	Health and environmental risks	Risks arising from improper waste handling and the environmental footprint of energy-intensive blockchain operations.	10,36,53
E13	Data access and integrity issues	Limited data accessibility, poor data quality, and challenges in ensuring data accuracy and integrity across stakeholders.	41,47,48

subsequently defuzzified into crisp scores prior to optimization to enhance numerical stability and enable seamless integration with ISM and DEMATEL. While some FBWM formulations retained fuzzy arithmetic throughout, the adopted approach aligns with studies that prioritize interpretability and integration across multiple multi-criteria decision-making techniques. The steps are as follows:

- Step 1: Identification of criteria and best/worst selection: Challenges to blockchain integration for sustainable healthcare waste management are identified from the detailed literature review, as shown in Table 1. Each expert selects the most critical (best) and the least critical (worst) challenge based on their expertise.
- Step 2: Fuzzy pairwise comparisons: After the identification of the best and worst challenges, experts provide pairwise comparisons of these challenges using linguistic variables (e.g., very high, moderate, and low) to evaluate the relative importance of the best challenge (most critical challenge) over all others, and of all challenges relative to the worst factor (least critical challenge). These qualitative assessments are then converted into fuzzy numbers using fuzzy scales to quantify the inherent uncertainty in expert judgments. In the next step, these fuzzy numbers are converted into crisp values using a defuzzification technique.
- Step 3: Construction of comparison vectors: Two comparison vectors are then constructed—one for comparing the best factor (most critical challenge) with the other factors, and another for comparing all factors with the worst factor (least critical challenge). These vectors serve as the foundational data for deriving the relative weights.
- Step 4: Optimization model formulation and solution: The next step is to formulate an optimization model to determine the optimal weights $\{w_1, w_2,\ldots, w_n\}$. This is achieved by minimizing the maximum absolute deviation ξ between the derived weight ratios and the provided preference values. The model is expressed as:

  $min\ \xi$

  subject to:

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \le \xi, \qquad \forall_j = 1,2,\ldots\ldots,n \tag{1}$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \le \xi, \qquad \forall_j = 1,2,\ldots\ldots,n \tag{2}$$

and the normalization constraints:

$$\sum\nolimits_{j=1}^{n} w_j = 1, \qquad w_j \ge 0,\ \forall_j \tag{3}$$

Where w_B, w_W, and w_j denote the weights of the best, worst, and j[th] factors, respectively; a_{Bj} indicates how much more important the best factor is compared to factor j; and a_{jW} indicates how important factor j is compared to the worst factor.

The above linear programming model was solved using appropriate optimization techniques or software. The solution yielded the optimal weights w_j and the minimized deviation ξ, ensuring the weight ratios closely reflect the expert judgments. In this study, the optimization models and weight calculations were executed using Microsoft Excel Solver, while fuzzy number defuzzification and ISM matrix processing were supported by MATLAB scripts (MATLAB R2023a, MathWorks, USA).

3.2. Steps of ISM

The steps are as follows:

- Step 1: Identification of variables: The variables or elements involved in the decision-making or evaluation process are identified. These are typically gathered from expert opinions, literature, or preliminary research.
- Step 2: Construction of structural self-interaction matrix (SSIM): The relationships between each pair of elements or variables are identified by experts using a predefined set of symbols:
  - (i) V (element i influences element j)
  - (ii) A (element j influences element i)
  - (iii) X (both elements influence each other)
  - (iv) O (no relationship between the elements)
- Step 3: Creation of initial reachability matrix: The SSIM is then used to create an Initial Reachability Matrix by replacing symbols with binary digits (1 for relationships, 0 for no relationship). Diagonal elements are typically set to 1.
  - (i) V replaced as 1
  - (ii) A replaced as 0
  - (iii) X replaced as 1
  - (iv) O replaced as 0
- Step 4: Development of final reachability matrix: In the next step, transitive relationships are identified and incorporated. If element A influences B, and B influences C, then A indirectly influences C. Such indirect relationships are reflected in the Final Reachability Matrix through transitive closure.

- Step 5: Level partitioning: Next, the levels of the variables or factors are determined based on reachability and antecedent sets. Elements with identical reachability and intersection sets form a level and are removed from subsequent analyses. The process is repeated iteratively to define hierarchical levels.
- Step 6: Building the ISM model: A hierarchical directed graph (ISM diagram) is prepared using identified levels. The lowest levels represent foundational elements (causes), and the higher levels represent dependent elements (effects). The results are further explained and supported by the matrix impact cross-multiplication applied to a classification (MICMAC) analysis, which categorizes the variables into four categories: autonomous, driver, dependent, and linkage variables.

3.3. Steps of the DEMATEL method

The steps are as follows:

- Step 1: Construct a direct-relation matrix: Experts assess the degree of influence of one challenge over another using a linguistic scale (no influence, low, medium, high, and very high).
- Step 2: Normalize the direct-relation matrix: Each expert's assessments are normalized to ensure comparability of influence levels.
- Step 3: Derive a total relation matrix: The normalized matrix is extended to capture both direct and indirect influences among challenges.
- Step 4: Calculate cause–effect relationships: For each challenge, the summation of rows (D, the degree a factor influences others) and the summation of columns (R, the degree a factor is influenced) are computed. Factors with $D - R > 0$ are identified as causal drivers, whereas those with $D - R < 0$ are dependent barriers.
- Step 5: Visualize interdependencies: A causal diagram is plotted, mapping the strength and direction of relationships among barriers.

This process enables the identification of the most influential and dependent challenges for blockchain adoption.

3.4. Steps of the ANP

The steps are as follows:

- Step 1: Model construction: The decision problem is structured into clusters of criteria (scalability, security, compliance, and cost) and alternatives (Ethereum, Hyperledger Fabric, and Corda).
- Step 2: Pairwise comparisons: Experts compare criteria and alternatives using Saaty's 1–9 scale to capture relative importance.
- Step 3: Supermatrix formation: A supermatrix is constructed to represent interdependencies among criteria and alternatives.
- Step 4: Weighted supermatrix and limit supermatrix: The supermatrix is normalized (weighted) and raised to limiting powers to derive stable priority weights.
- Step 5: Selection of best alternative: The final weights are aggregated, and blockchain platforms are ranked according to suitability for healthcare waste management.

3.5. Integration of FBWM and DEMATEL results

The FBWM consistency ratios were within acceptable thresholds for all expert responses, indicating a high level of judgmental consistency. The aggregated consistency index value was below the recommended cutoff, confirming the reliability of the derived weights.

Integrating the hierarchical ISM structure with the weights obtained from FBWM provides a comprehensive understanding of the elements' importance, causality, and hierarchical relationships.

The integration of FBWM, ISM, and DEMATEL was deliberately designed to address different analytical needs within a complex adoption environment (Figure 1). FBWM captures uncertainty in expert judgments and derives consistent importance weights. ISM structures these factors hierarchically, while DEMATEL identifies cause–effect relationships among them. Selective fuzzification was applied only at the judgment–elicitation stage (FBWM), while crisp methods were used in ISM, DEMATEL to preserve interpretability and computational stability, consistent with prior healthcare and sustainability studies.

Although the ANP is incorporated within the proposed integrated methodological framework, the present study primarily reports empirical findings from the FBWM, ISM, DEMATEL, and MICMAC analyses. ANP is retained to demonstrate the extensibility of the framework and to support future model enhancements.

4. Results

Data were systematically gathered from a diverse panel of experts specializing in academia, industry, healthcare, and blockchain technology. These experts,

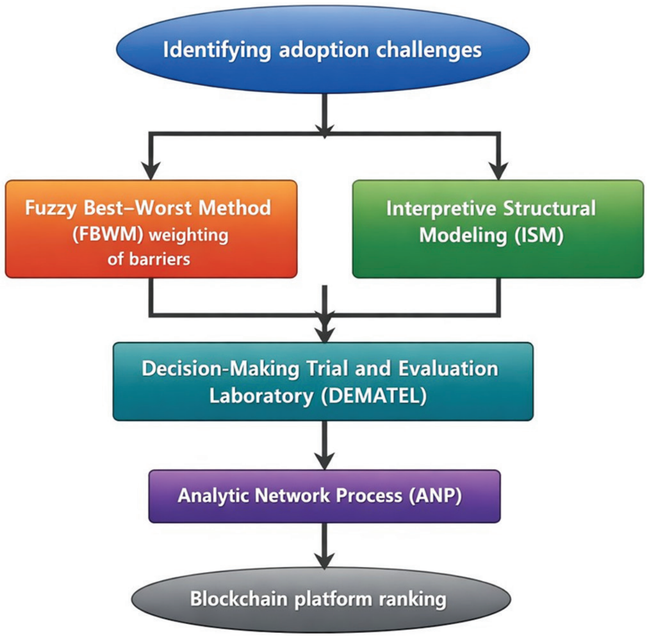

Figure 1. Integrated methodological flow of the study
Abbreviations: ANP: Analytic network process; DEMATEL: Decision-making trial and evaluation laboratory; ISM: Interpretive structural modeling.

selected for their substantial experience in the relevant fields, provided valuable insights into the significance of various challenges and their interconnections. Detailed information about the experts, including their areas of expertise and years of professional experience, is provided in Table S1. Although the challenges were categorized thematically for conceptual clarity, all identified factors were compared simultaneously within the FBWM framework. The categorization did not restrict or influence the pairwise comparison process.

These experts were asked to identify the most critical and least critical challenges of blockchain adoption for sustainable healthcare waste management, as shown in Table S2. After the identification of these challenges (termed as best and worst factors), experts were asked to create two sets of comparison sets, one for comparing the best with all the other factors (B_2O) and another comparing the others with the worst factor using linguistic terms (very low, low, medium, high, very high, and extremely high). Then, these linguistic terms were converted into fuzzy numbers using TFNs (Table S3). The expert panel was purposefully selected to ensure balanced representation from key stakeholder groups: academia (researchers in sustainability, healthcare, and blockchain systems), industry (supply chain and hospital administration professionals), healthcare practitioners (medical and waste management experts), and blockchain consultants. To ensure credibility of responses, all participants had at least 4 years of relevant professional experience, and those classified under blockchain expertise had prior exposure to blockchain deployment or consultation projects. This mix provided both technical and practical perspectives on blockchain adoption in healthcare waste management.

The data obtained from all the experts were aggregated for further analysis. Each of the 10 experts provided a TFN A_k for a given factor, denoted as:

$$A_k = (L_k, M_k, N_k) \tag{4}$$

Where k denotes 1, 2,…, n; L_k is the lower bound (minimum perceived value); M_k is the most likely or peak value; and N_k is the upper bound (maximum perceived value).

Aggregation was done using the following formulae:

$$\bar{L} = \frac{1}{n}\sum_{j=1}^{n} L_k \tag{5}$$

$$\bar{M} = \frac{1}{n}\sum_{j=1}^{n} M_k \tag{6}$$

$$\bar{N} = \frac{1}{n}\sum_{j=1}^{n} N_k \tag{7}$$

$$\text{Aggregated } \tilde{A} = (\bar{L}_k, \bar{M}_k, \bar{N}_k) \tag{8}$$

Then these fuzzy aggregated numbers were converted into crisp numbers (Table S4) using the following formula:

$$Crisp\ value = \frac{\bar{L} + 4\bar{M} + \bar{N}}{6} \tag{9}$$

In the next step, a linear optimization model was developed as mentioned in Step 4 in Section 3.1. This model was solved using Excel to calculate the weights of the factors (Table 2).

After the weights were calculated, ISM was used to identify the interdependencies among these challenges. Data were collected from the same experts as described in Step 1 in Section 3.2 and aggregated to calculate the aggregated SSIM (Table S5). Aggregation was done using the following formula:

$$\bar{X}_{ij} = \frac{1}{n}\sum_{k=1}^{n} x_{ij}^{(k)} \tag{10}$$

Where $x_{ij}^{(k)}$ is the *k-th* expert's rating of $i \to j$, and $\bar{X}_{ij}$ is the aggregated rating for $i \to j$.

This aggregated SSIM was then converted into the Initial Reachability Matrix with a cutoff value of 0.7

(Table S6). The following formulae were used for this purpose:

If $\bar{X}_{ij} \geq 0.7$, $a_{ij} = 1$ (11)

And $\bar{X}_{ij} < 0.7$, $a_{ij} = 0$ (12)

After obtaining the Initial Reachability Matrix, the Final Reachability Matrix was calculated according to Step 4 in Section 3.2. This matrix was then used to identify the reachability, antecedent, and intersection sets. These sets were then used to identify the challenges at different levels. Table 3 shows the identified sets and levels of the challenges. Table 4 presents the dependence and driving power.

The ISM digraph was then developed based on these findings (Figure 2). MICMAC analysis is a structural method used to assess and categorize variables based on their level of influence and dependence within a system. It helps identify key drivers, dependent variables, and autonomous factors that shape the dynamics of a complex system. The analysis is conducted with the help of the transitivity matrix, which accounts for direct and indirect relationships among elements. The results are typically plotted on a two-dimensional graph, where high-influence and low-dependence variables are considered driving factors. In contrast, high-dependence and low-influence variables are dependent factors. Autonomous elements have low influence and dependence, indicating minimal impact on the system, whereas linking variables exhibit both strong influence and dependence, making them crucial in system evolution. MICMAC analysis is widely used in strategic planning, policymaking, and risk assessment, allowing decision-makers to prioritize key factors and effectively understand the interconnections within a system.

The MICMAC analysis revealed that E13 (data access and integrity issues) was dependent, whereas E1 (lack of organizational vision and support) constituted an autonomous challenge (Figure 3). E3 (financial barriers), E5 (infrastructure and design limitations), E6 (scalability challenges), E7 (data privacy and security concerns), and E12 (health and environmental risks) were the driver challenges. At the same time, linkage challenges include E2 (resistance and lack of

Table 2. Weights of the factors

No.	Challenges	Weights
E1	Lack of organizational vision and support	0.012
E2	Resistance and lack of awareness	0.120
E3	Financial barriers	0.075
E4	Uncertain return on investment	0.035
E5	Infrastructure and design limitations	0.051
E6	Scalability challenges	0.076
E7	Data privacy and security concerns	0.231
E8	Lack of technical expertise	0.095
E9	Interoperability and coordination issues	0.071
E10	Lifecycle management gaps	0.137
E11	Regulatory ambiguity and stakeholder trust issues	0.041
E12	Health and environmental risks	0.037
E13	Data access and integrity issues	0.020

Table 3. Reachability, antecedent, and intersection sets, as well as the challenge levels

No.	Reachability set	Antecedent set	Interaction set	Level
E1	1	1, 3, 6	1	1
E2	2, 4, 8, 9, 10, 11, 13	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	2, 4, 8, 9, 10, 11	2
E3	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13	3, 6	3, 6	4
E4	2, 4, 8, 9, 10, 11, 13	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	2, 4, 8, 9, 10, 11	2
E5	2, 4, 5, 18, 9, 10, 11, 13	3, 4, 5	4, 5	5
E6	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13	3, 6	3, 6	4
E7	2, 4, 7, 8, 9, 10, 11, 13	7	7	3
E8	2, 4, 8, 9, 10, 11, 13	2, 4, 7, 8, 9, 10, 11, 12	2, 4, 8, 9, 10, 11	2
E9	2, 4, 8, 9, 10, 11, 13	2, 4, 7, 8, 9, 10, 11, 12	2, 4, 8, 9, 10, 11	2
E10	2, 4, 8, 9, 10, 11, 13	2, 4, 7, 8, 9, 10, 11, 12	2, 4, 8, 9, 10, 11	2
E11	2, 4, 8, 9, 10, 11, 13	2, 4, 7, 8, 9, 10, 11, 12	2, 4, 8, 9, 10, 11	2
E12	2, 4, 8, 9, 10, 11, 12, 13	3, 12	12	3
E13	13	2, 4, 7, 8, 9, 10, 11, 12, 13	13	1

Table 4. Driving and dependence powers of the challenges

Challenges	Driving power	Dependence power
E1	1	3
E2	7	11
E3	12	2
E4	7	11
E5	8	3
E6	12	2
E7	8	1
E8	7	11
E9	7	11
E10	7	11
E11	7	11
E12	8	3
E13	1	12

awareness), E4 (uncertain return on investment), E8 (lack of technical expertise), E9 (interoperability and coordination issues), E10 (lifecycle management gaps), and E11 (regulatory ambiguity and stakeholder trust issues).

Figure 4 presents the DEMATEL results by plotting the adoption barriers (E1–E13) against prominence (D + R) on the x-axis and relation index (D − R) on the y-axis. Barriers with positive relation index values fall into the causal (driver) group, while those with negative values fall into the dependent group. This visualization clarifies the interrelationships among the barriers and highlights the dominant drivers.

5. Discussion

This study integrated findings from FBWM, ISM, and DEMATEL to provide a comprehensive understanding of blockchain adoption in healthcare waste management.

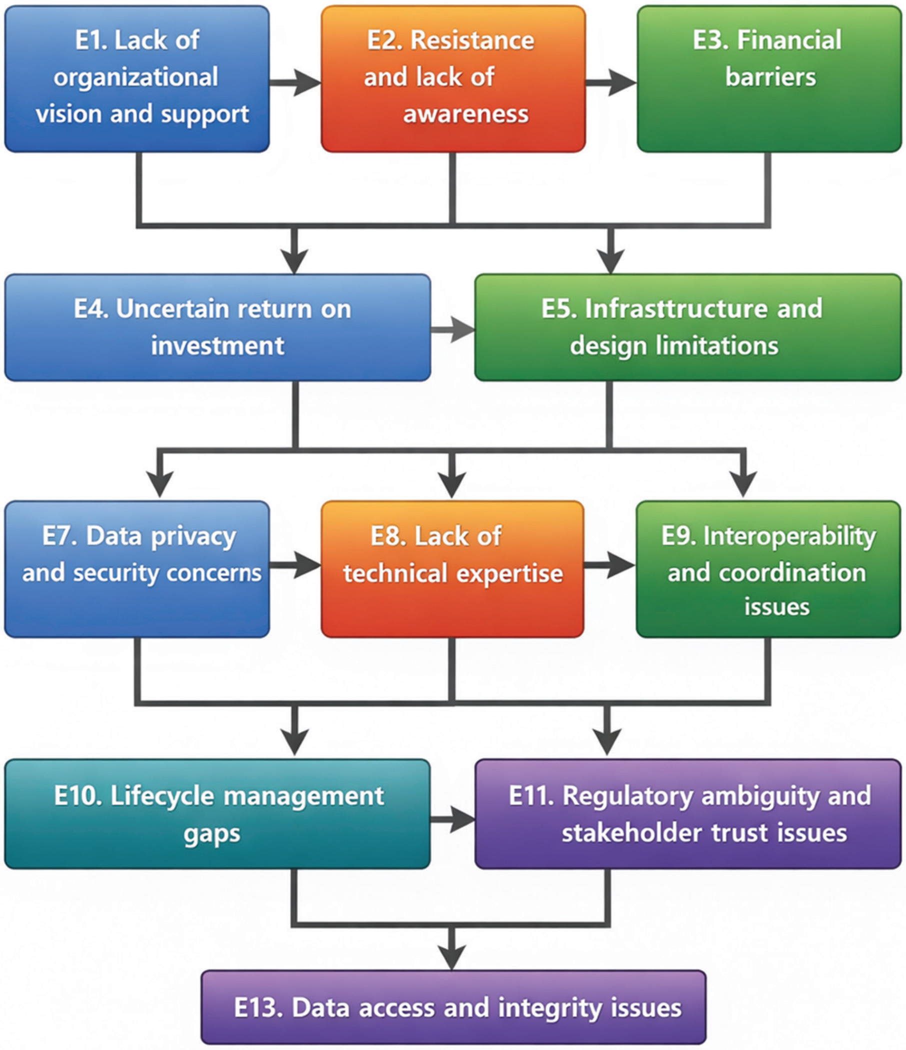

Figure 2. Interpretive Structural Modeling-based hierarchical structure of blockchain adoption challenges

FBWM highlighted the relative importance of barriers, ISM revealed their hierarchical structure, and DEMATEL identified causal relationships evaluated blockchain platform suitability. Together, these methods offer complementary insights that extend beyond prior single-method studies. This study aimed to (i) identify and categorize critical factors influencing blockchain adoption using the DEMATEL method, (ii) provide actionable insights for healthcare organizations and policymakers. This discussion interprets the study's findings compared to previous research, highlighting the contributions and implications of blockchain adoption in healthcare waste management.

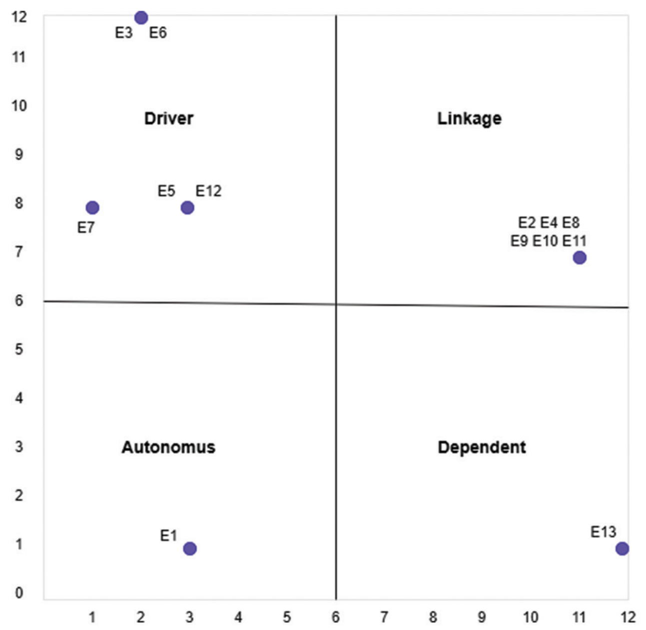

Figure 3. Matrix impact cross-multiplication applied to a classification graph

5.1. Identification and categorization of key factors influencing blockchain adoption

The study's first objective was to identify and categorize the critical factors influencing blockchain adoption in healthcare waste management. Based on the DEMATEL analysis (Figure 4), barriers with positive relation index (D − R) values are classified as causal (driver) barriers, whereas those with negative values are categorized as dependent barriers. In this study, E7 (Data privacy and security concerns) exhibits a positive D − R value and therefore acts as a key causal barrier influencing other adoption challenges. In contrast, E1 (Lack of organizational vision and support) and E11 (Regulatory ambiguity and stakeholder trust issues) have negative D − R values, indicating that they are predominantly influenced by other barriers rather than acting as primary drivers. These findings resonate with

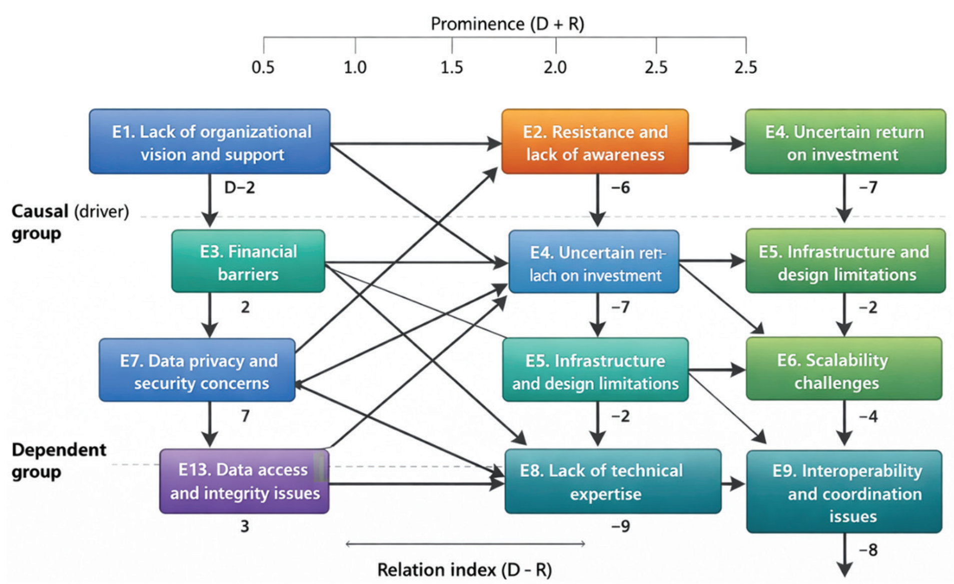

Figure 4. Decision-making trial and evaluation laboratory (DEMATEL)-based causal relationship diagram of blockchain adoption challenges. The diagram illustrates the causal relationships among 13 blockchain adoption challenges (E1–E13) in sustainable healthcare waste management using the DEMATEL method. The horizontal axis represents the relation index (D − R), which distinguishes causal (driver) barriers with positive values from dependent barriers with negative values, while the vertical axis represents prominence (D + R), indicating the overall importance of each challenge within the system.

studies by Singh *et al*.,[43] who also identified multi-layered challenges in blockchain adoption, particularly financial, technological, and institutional barriers. However, while they focused on construction supply chains, our study extended the analysis to healthcare waste management and established the causal pathways among barriers. Furthermore, Souissi *et al*.[35] emphasized the role of financial distress and information asymmetry in hindering blockchain uptake. Our results complement this perspective by showing that financial barriers (E3), while significant, function as driver challenges with high driving power, influencing organizational, technological, and regulatory constraints associated with blockchain adoption. This distinction offers a more actionable framework for prioritizing interventions. These findings are also consistent with previous studies, such as those of Dhingra *et al*.,[13] who found that regulatory uncertainties and legal framework gaps hinder blockchain adoption in healthcare.

A key contribution of this study is establishing causal relationships among adoption challenges. Unlike prior research that primarily identified barriers without distinguishing their influence levels, this study differentiates between causal and dependent challenges. The DEMATEL results indicate that lack of organizational vision and support (E1) functions as a dependent barrier, shaped by upstream financial, technological, and regulatory constraints, rather than acting as a root cause. This insight is valuable for decision-makers prioritizing strategic interventions for blockchain adoption.

In addition, the study confirmed the importance of financial feasibility as a determinant of blockchain adoption, aligning with the study by Souissi *et al*.,[35] which noted that high implementation costs and uncertain return on investment are significant barriers in digital transformation initiatives. However, this study extends previous findings by demonstrating that financial constraints (E3) function as driver challenges with strong influence across the system, rather than merely being dependent outcomes. The MICMAC results indicate that financial limitations actively shape organizational, technological, and regulatory barriers associated with blockchain adoption. This distinction suggests that improving organizational commitment and regulatory clarity could indirectly mitigate financial challenges.

5.2. Ranking of blockchain platforms for healthcare waste management

The second objective was to rank blockchain platforms for their suitability for healthcare waste management. The results indicate that Hyperledger Fabric is the most suitable platform due to its permissioned architecture, which enhances data security and regulatory compliance. This aligns with the findings of Wang and Qin,[54] who noted that Hyperledger's modular design makes it ideal for enterprise applications, including healthcare data tracking.

In contrast, Ethereum was found to have robust smart contract functionality but raised concerns over data privacy due to its public blockchain structure. These findings align with the work of Tripathi *et al*.,[9] who pointed out that public blockchains may not be suitable for sensitive data management. While Ethereum's decentralized nature enhances transparency, it also introduces risks related to unauthorized data access, making it less ideal for healthcare waste management.

Corda, which is primarily designed for financial transactions, was found to have limited scalability for large-scale waste-tracking applications, supporting the arguments made by Miron *et al*.[18] These findings suggest that while Corda offers strong security, its narrow focus on financial use cases limits its applicability in the broader context of waste management.

A key contribution of this study is its quantitative ranking of blockchain platforms, which prioritizes scalability, compliance, and cost-effectiveness rather than just theoretical assessments. Unlike previous studies that have compared blockchain platforms qualitatively, this study provides a structured decision-making framework for selecting the most effective blockchain solutions in healthcare waste management.

5.3. Actionable insights for healthcare organizations and policymakers

Actionable insights from this study emphasize three priorities: (i) Develop clear regulatory frameworks to reduce uncertainty; (ii) invest in technical capacity-building to address the skills gap; and (iii) leverage financial incentives and public–private partnerships to overcome cost barriers. These measures will provide a practical foundation for accelerating blockchain adoption in healthcare waste management.

Beyond identifying challenges, this study contributes methodologically by employing DEMATEL to establish causal relationships among barriers, thereby distinguishing between primary drivers and dependent challenges.

Dhingra *et al*.[13] investigated blockchain adoption challenges in healthcare waste management using a BWM–DEMATEL framework. While their study provided a useful barrier prioritization, it did not establish hierarchical relationships or evaluate blockchain platforms. Our study extended their approach by (i) using a fuzzy version of BWM (FBWM) to reduce judgmental uncertainty, (ii) integrating ISM and DEMATEL to combine structural and causal analyses under interdependent criteria. This integrated framework thus offers a more comprehensive and prescriptive tool for decision-making in sustainable healthcare waste management.

The findings offer integrated theoretical, practical, and sustainability implications. Theoretically, the study advances blockchain adoption research by combining fuzzy prioritization with causal and network-based evaluation. Practically, healthcare managers are advised to prioritize organizational readiness and regulatory clarity before technological investments. From a sustainability perspective, blockchain-enabled waste tracking can enhance traceability, reduce illegal dumping, and support environmentally responsible healthcare operations.

6. Conclusion

This study investigated the barriers to blockchain adoption in healthcare waste management using an integrated multi-method decision-making framework. By combining FBWM, ISM, and DEMATEL the study simultaneously captured uncertainty in expert judgments, hierarchical relationships among barriers, causal interactions, and the relative suitability of blockchain platforms. This integrated approach represents a methodological advancement over prior studies that relied on single or dual analytical techniques.

The results indicate that organizational readiness and regulatory clarity are the most influential barriers, acting as root causes that shape technological and financial challenges. The causal structure revealed by DEMATEL further highlights that addressing upstream governance and institutional factors can significantly reduce downstream operational barriers.

From a practical perspective, the findings suggest that policymakers and healthcare managers should prioritize institutional capacity building, regulatory frameworks, and stakeholder coordination before investing in blockchain infrastructure. From a sustainability standpoint, blockchain-enabled traceability can enhance accountability, reduce environmental risks, and support circular healthcare waste management practices.

Despite its contributions, this study has limitations. The analysis was based on expert judgments drawn primarily from developing and emerging healthcare system contexts, which may limit generalizability. Future research could extend this framework to comparative cross-country studies, incorporate dynamic adoption modeling, or explore emerging blockchain architectures and integration with Internet of Things-enabled waste tracking systems.

Overall, this study provides a structured and context-sensitive decision-support framework that can guide both researchers and practitioners in advancing sustainable and transparent healthcare waste management systems.

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Conflict of interest

The author declares has no competing interests.

Author contributions

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Availability of data

The data that support the findings of this study are available from the corresponding author on reasonable request.

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