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Causal Mapping and Priority Setting for Healthcare Blockchain Adoption

Sağlıkta Blokzincir Benimsenmesine Yönelik Nedensel Haritalama ve Önceliklendirme

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Abstract: This study examines healthcare blockchain adoption determinants within the Technology Organization Environment (TOE) framework using a hybrid fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) and DEMATEL based Analytic Network Process (DANP) approach. Pairwise influence assessments among ten determinants were elicited from fourteen healthcare managers using a five level linguistic scale and encoded as triangular fuzzy numbers. After aggregation, defuzzification, and normalization, fuzzy DEMATEL was applied to compute the total relation matrix, classify determinants into cause and effect groups, and derive influence and dependency indicators. DANP then transformed the causal network into interdependence aware priority weights. Results show that Compliance and Security are the most influential determinants in the cause group, meaning that these factors exert the strongest influence on the rest of the system. By contrast, Interoperability and Complexity appear predominantly in the effect group, meaning that they are shaped more by other determinants than they shape others. The results indicate that the first step in the adoption process should be strengthening security and governance mechanisms and ensuring institutionalized management support.

Keywords: Blockchain Adoption, DANP, Fuzzy DEMATEL, Healthcare Sector, MCDM

JEL Classification: C44, I18, O32

Öz: Bu çalışma, sağlık sektöründe blokzincir benimsenmesini etkileyen faktörleri Teknoloji Organizasyon Çevre (TOE) çerçevesinde incelemekte ve bulanık Karar Verme Deneme ve Değerlendirme Laboratuvarı (DEMATEL) ile DEMATEL tabanlı Analitik Ağ Süreci (DANP) yaklaşımını birlikte kullanmaktadır. Literatürde öne çıkan on faktör arasındaki ikili etki düzeyleri, on dört sağlık yöneticisinden beş düzeyli dilsel ölçekle toplanmış ve değerlendirmeler üçgensel bulanık sayılarla modellenmiştir. Uzman görüşleri birleştirildikten sonra defuzzifikasyon ve normalizasyon işlemleri uygulanmış, ardından bulanık DEMATEL ile toplam ilişki matrisi hesaplanarak faktörler sebep ve etki gruplarına ayrılmış ve etkileme ve etkilenme göstergeleri elde edilmiştir. Daha sonra DANP ile bu nedensel yapı öncelik ağırlıklarına dönüştürülmüştür. Bulgular, Uyum ve Güvenlik faktörlerinin sebep grubunda en güçlü etkiye sahip olduğunu ve diğer faktörleri belirgin biçimde etkilediğini göstermektedir. Buna karşılık Birlikte Çalışabilirlik ve Karmaşıklık ağırlıklı olarak etki grubunda yer almakta, yani bu iki faktör daha çok diğer faktörlerin etkisiyle değişmektedir. Sonuçlar, benimseme sürecinde ilk adımın güvenlik ve yönetişim mekanizmalarının güçlendirilmesi ve yönetim desteğinin kurumsal olarak sağlanması olması gerektiğine işaret etmektedir.

Anahtar Kelimeler: Blokzincir Benimsenmesi, DANP, Bulanık DEMATEL, Sağlık Sektörü, MCDM

JEL Sınıflandırması: C44, I18, O32

1. Introduction

Healthcare teams continue to view blockchain as a way to achieve secure record keeping, privacy preserving data sharing, and fully auditable transactions that extend across organizational boundaries and care settings. In practice, this promise has been translated into initiatives that target longitudinal electronic health records, fine grained consent and access management, integrity controls for clinical trial data and registries, and end to end traceability in pharmaceutical supply chains where provenance and recall management matter for patient safety (Agbo et al. 2019; Dubovitskaya et al. 2018; Kuo et al. 2017). Yet the path from pilot to routine use is uneven. Any ledger service must be aligned with legacy infrastructures and vendor ecosystems while sustaining stable clinical workflows, ensuring continuity of care, and meeting strict regulatory and ethical requirements regarding privacy, data use, and liability. Procurement rules, cross jurisdictional data obligations, and governance arrangements further constrain implementation choices. As a result, adoption cannot be reduced to a single checklist. It requires coordinated attention to interdependent technological, organizational, and environmental considerations that move together in practice, including interoperability standards, perceived security and risk, team and process readiness, leadership sponsorship, and the economic logic that determines whether benefits accrue where costs are incurred (Bazel et al. 2025).

Prior studies repeatedly surface similar barriers and enablers, including interoperability, security, complexity, leadership support, and regulatory uncertainty, but most accounts consider these determinants independently or prioritize them without modeling feedback among factors (Clohessy & Acton 2019; Esmaeilzadeh 2022; Handayani et al. 2023; Hau & Chang 2021). Recent work continues to show that barriers remain multi dimensional across governance, regulation, and implementation, which strengthens the case for interdependence based analyses rather than independent factor lists (Govindarajan et al. 2025). Moreover, widely used adoption frameworks are often applied in a generic manner and are not sufficiently tailored to the constraints of health data governance and institutional accountability, limiting their practical utility for project selection and roadmap design (Mettler 2016). Accordingly, healthcare decision makers need a theory guided and decision ready model that reveals where influence originates, where it accumulates, and which levers should be activated first.

To address this need, this study grounds the analysis in the Technology Organization Environment (TOE) framework and models causal relationships using the fuzzy Decision Making Trial and Evaluation Laboratory. TOE provides a coherent lens for grouping determinants into technology, organization, and environment, which is essential in healthcare, where security and interoperability are technology concerns, readiness and sponsorship are organizational concerns, and regulation and incentives are environmental constraints (Tornatzky & Fleischer 1990; Baker 2012). Fuzzy Decision Making Trial and Evaluation Laboratory

(DEMATEL) captures expert judgments under uncertainty and yields a total relation matrix from which we derive influence and dependence, overall importance, and net effect for each determinant (Gabus & Fontela 1972; Hsu et al. 2013). This emphasis on interdependence is also consistent with recent evidence syntheses in healthcare that highlight privacy preservation and compliance requirements as central issues in blockchain based data sharing (Li et al. 2025). We then extend the analysis with the DEMATEL based Analytic Network Process (DANP) to obtain interdependence aware priority weights that support resource allocation.

This study investigates the following research questions. RQ1: What is the TOE aligned causal structure that links key determinants of healthcare blockchain adoption? RQ2: Which factors act as net drivers and which act as net receivers in this structure? RQ3: Given interdependence among factors, which levers should decision makers prioritize to accelerate adoption? To answer these questions, we elicited pairwise influences among ten widely cited determinants from a panel of fourteen healthcare managers using a five level linguistic scale mapped to triangular fuzzy numbers. We aggregated the fuzzy direct relation matrices, derived the total relation matrix, and computed D, R, D + R, and D - R. We then applied DANP to translate the causal network into priority weights.

The study makes three contributions. First, it provides a TOE grounded causal map of healthcare blockchain adoption that clarifies where leverage resides. Security and Compliance emerge as the srongest net drivers, while Complexity is identified as a net reciever. Second, it operationalizes an integrated fuzzy DEMATEL and DANP workflow that is reproducible and suited to uncertain and interdependent managerial judgments. Third, it delivers a ranked set of actionable levers that connect theory to practice by informing the sequencing of investments in security controls, executive sponsorship, complexity reduction, interoperability enablement, and compliance by design (Azaria et al. 2016; Mackey & Nayyar 2017; Roehrs et al. 2019). Together, these contributions address the need for sector specific adoption guidance that is conceptually grounded and decision ready for complex healthcare environments.

The remainder of the paper is organized as follows: Section 2 reviews the determinants of blockchain adoption in healthcare and positions the TOE framework against alternative theoretical lenses. Section 3 presents the research design and the fuzzy DEMATEL and DANP procedures. Section 4 reports the causal results and priority weights. Section 5 discusses theoretical and managerial implications. Section 6 concludes and outlines limitations and further research directions.

2. Literature Review

Research on blockchain in healthcare has progressed from early proof-of-concept systems to exploring questions about when, where, and why adoption actually occurs. Foundational studies show how distributed ledgers can support longitudinal electronic records, consent and access management, integrity of clinical trial data, and pharmaceutical provenance, with privacy, auditability, and data integrity as the core promises in regulated settings (Azaria et al. 2016; Dubovitskaya et al. 2018; Kuo et al. 2017; Agbo et al. 2019). Review articles consistently identify a small set of determinants that recur across projects; what remains less clear is how these determinants interact with one another and which ones concentrate leverage in practice (Mettler 2016; Clohessy & Acton 2019; Roehrs et al. 2019).

TOE framework explains organizational adoption as a function of three interacting contexts: technology characteristics, organizational conditions, and environmental pressures and support (Baker 2012). In the technology context, adoption depends on perceived benefits and fit, such as interoperability, scalability, and complexity (Baker 2012; Tornatzky & Fleischer 1990). In the organizational context, readiness, resources, and top management support shape the ability to implement and sustain the innovation (Baker 2012). In the environmental context, regulatory requirements, partner readiness, vendor ecosystems, and institutional pressures influence feasibility and timing (Tornatzky & Fleischer 1990). Several alternative lenses are also common in health information systems research. The Human Organization Technology (HOT) fit framework evaluates alignment among human, organizational, and technological dimensions of health information systems (Yusof et al. 2008). Diffusion of Innovations theory emphasizes innovation attributes such as relative advantage, compatibility, and complexity (Rogers 2003). Fit Viability models assess whether a technology fits operational needs and is viable economically and institutionally (Liang & Wei 2004). This study selects TOE because it is well suited for organizational adoption decisions in multi stakeholder healthcare ecosystems where governance and regulatory constraints are central, and because it accommodates both internal capabilities and external pressures.

Within the Technology context of TOE, feasibility rests on four conditions that are consistently present across deployments. Interoperability is the keystone because any new service must exchange semantically consistent clinical data with established electronic health records (EHR), which pushes designs toward standards such as Health Level Seven (HL7), Fast Healthcare Interoperability Resources (FHIR) and careful gateway choices with data kept off chain when appropriate (Elangovan et al. 2022; Kuo et al. 2017; Agbo et al. 2019). Complexity arises from day-to-day tasks, such as cryptographic key custody, ensuring safe smart contract behavior, partitioning sensitive attributes, and revisiting clinical workflows; these issues elevate the perceived risk for clinicians (Esmaeilzadeh 2022; Bazel et al. 2023). Scalability concerns, including throughput, latency, and storage growth, are most visible in high-volume clinical and supply chain scenarios, where permissioned networks, batching, and off-chain computation are commonly employed to stay within operational limits (Khan et al. 2021; Adavoudi Jolfaei et al. 2021). Security is both a promise and a constraint: immutability and distribution help with auditing, but real systems must mitigate vulnerabilities at the node, key, and application layers while meeting health privacy laws (Handayani et al. 2023; Atadoga et al. 2024).

Inside a hospital, adoption rises or stalls with people, routines, and the capacity to change them. In this study, Organizational Readiness is treated as a practical bundle of skills, including IT maturity, governance, and process adaptability, that allows experimentation without disrupting care. In real terms, that means clinicians who can trial a new workflow without compromising safety, an integration team that can stand up and monitor interfaces, a change advisory process that can approve small iterations quickly, and data governance that can adjudicate questions about access and use (Altamimi et al. 2024; Clohessy & Acton 2019). Management Support shows up not only as statements about innovation, but as visible sponsorship that releases budget, assigns accountable owners, resolves cross functional disputes, and accepts measured risk when pilots encounter uncertainty. Executives who chair a steering group, clear vendor security questionnaires, and protect time for super users provide the kind of attention that moves projects forward (Akbar et al. 2022; Esmaeilzadeh 2022). Implementation costs extend beyond licensing or hardware and typically include integration work, data standardization, cybersecurity controls, governance processes, and change management efforts needed to align blockchain services with legacy health information systems and clinical workflows (Bazel et al. 2025; Dubovitskaya et al. 2020). Typical line items include interface development and maintenance, vendor professional services, cybersecurity hardening and monitoring, training, and the effort to update standard operating procedures. The literature repeatedly notes that what organizations perceive as "cost" is often a downstream effect of complexity and readiness: the same task is expensive in a brittle environment and routine in a mature one (Roehrs et al. 2019; Adeghe et al. 2024).

Outside the hospital, the rules decide the pace. Regulatory uncertainty persists in many jurisdictions, taking concrete forms, including data residency and sovereignty requirements, consent for the secondary use of data, obligations under privacy law for joint controllers, and the allocation of liability within a consortium. These uncertainties slow procurement cycles, lengthen ethics reviews, and complicate contracting because legal and compliance teams must resolve open questions before a go live (Esmaeilzadeh 2022; Rao & Manvi 2023). For that reason, compliance is treated here as a design input rather than a late checklist. Architecture choices about on chain versus off chain storage, key management policies, encryption at rest and in transit, audit trails, and vendor selection criteria are all shaped by how privacy and security requirements will be met in day to day operation (Li et al. 2025). When compliance requirements are embedded from the design stage through mechanisms such as role based access control, auditable consent management, and traceable data handling rules, projects can reduce audit friction and redesign cycles that otherwise emerge later in implementation (Barbaria et al. 2025). Economic incentives then determine whether the operational benefits justify the effort. Reimbursement rules, procurement terms, and in some settings targeted subsidies change the payoff to interoperability and auditability. For example, fee schedules that reward data exchange, serialization mandates in pharmaceutical supply chains, or bundled payments that require longitudinal visibility can make blockchain enabled audit and traceability economically sensible rather than merely interesting (Li & Liang 2024).

Methodologically, multi criteria decision making tools are increasingly used to structure adoption problems under uncertainty, but most studies stop at factor ranking and do not model feedback among determinants. Fuzzy logic accommodates linguistic judgments from heterogeneous experts and has been combined with methods such as Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to prioritize criteria or alternatives in health information systems. However, when criteria influence each other, simple independence assumptions are unrealistic. DEMATEL was introduced to uncover causal structures in complex systems by estimating a total relation matrix of direct and indirect effects from expert comparisons (Gabus & Fontela 1972; Hsu et al. 2013). Building on this, DEMATEL-based Analytic Network Process translates the influence network into interdependence-aware weights, overcoming the independence limitation of hierarchy-based approaches and yielding priorities consistent with the underlying causal architecture (Tzeng & Huang 2011; Saaty 1996).

In summary, the literature has identified a stable set of technological, organizational, and environmental determinants for healthcare blockchain adoption; however, it has not sufficiently established how these factors causally interact within healthcare's regulatory and operational context, nor how to translate that interaction into implementable priorities. This study closes that gap by mapping ten well supported determinants to the TOE framework, eliciting expert judgments from healthcare managers, and applying fuzzy DEMATEL to derive the causal structure, followed by DANP to obtain priority weights that respect interdependence. The resulting model provides both an explanatory map and a decision ready ranking of levers for managers and policy makers.

3. Methodology

This study follows a structured, reproducible workflow to identify interdependent determinants of blockchain adoption in healthcare and to translate those interdependencies into actionable priorities. Figure 1 summarizes the full methodological pipeline from factor identification to causal analysis and prioritization.

As shown in Figure 1, the workflow proceeds in seven steps. Step 1 identifies the determinant set by mapping widely cited blockchain adoption factors in healthcare to the Technology Organization Environment framework and finalizing ten determinants for evaluation. Step 2 designs the expert elicitation instrument and the linguistic influence scale used to assess pairwise causal influence among determinants. Step 3 collects expert judgments from fourteen healthcare managers and constructs individual fuzzy direct relation matrices using triangular fuzzy numbers. Step 4 aggregates expert matrices and performs defuzzification and normalization to obtain a crisp, directly computable relation matrix. Step 5 computes the total relation matrix and derives the DEMATEL indicators D, R, D + R, and D − R to identify the influence, dependency, prominence, and net causal role for each determinant, and to visualize the cause and effect structure. Step 6 converts the total relation structure into a priority vector using DANP to produce weights that reflect both direct and indirect influence. Step 7 interprets results and formulates managerial implications by translating the causal drivers and priority weights into a sequencing logic for adoption focused investments.

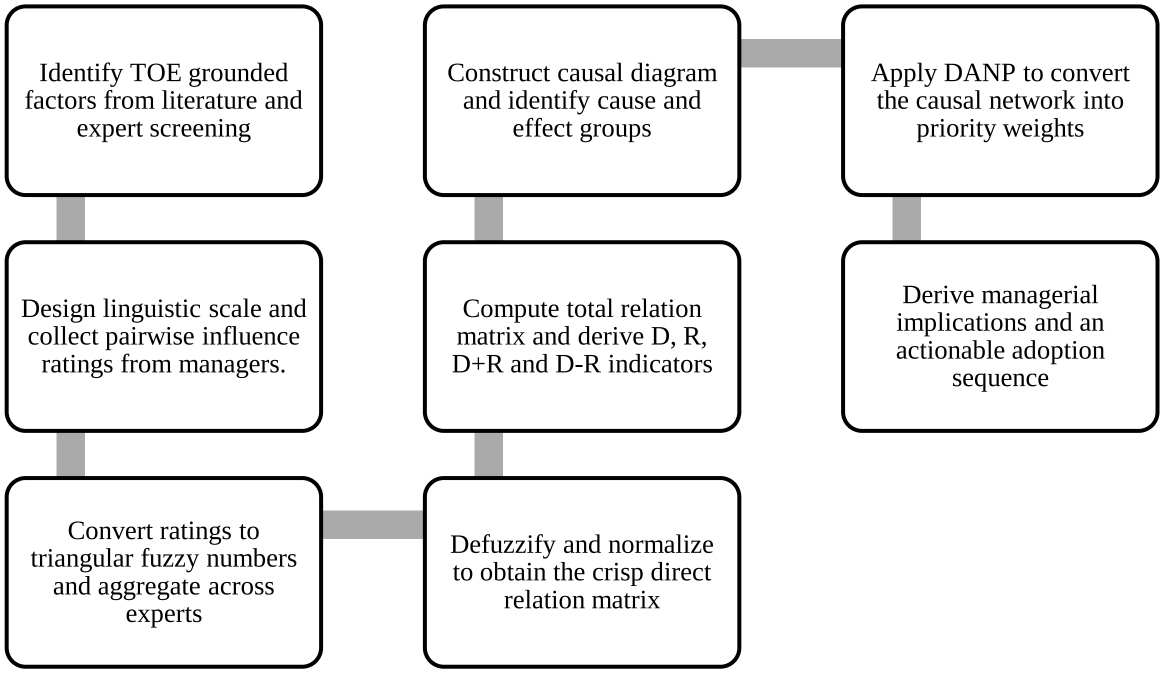

Figure 1. Study workflow and analysis pipeline

This study combines fuzzy DEMATEL and DANP because each method produces a distinct yet complementary output needed for managerial adoption decisions in healthcare. Fuzzy DEMATEL is used first to model causal influence among determinants under linguistic uncertainty, which is appropriate when expert judgments are elicited for complex socio technical settings. Its outputs identify which determinants act as net drivers and which act as net receivers and quantify how strongly influence propagates through the system by means of the total relation matrix and the D and R indicators. However, DEMATEL alone does not provide a final stable priority vector for resource allocation because causal prominence and net effect are not equivalent to interdependence aware weights.

DANP is then applied to convert the DEMATEL total relation structure into priority weights that reflect both direct and indirect influence, including feedback loops. This step is particularly useful when determinants are mutually reinforcing, as is typical in healthcare adoption where governance, security, readiness, and interoperability shape each other over time. In practical terms, the hybrid approach yields two decision ready outputs: a causal map that explains where influence originates and accumulates, and a weight vector that supports prioritization and sequencing of implementation efforts without assuming independence among determinants.

Alternative methods can also address the research objective. Structural equation modeling and Partial Least Squares (PLS) based models can estimate relationships statistically, but they require large samples and measured constructs that are often unavailable for emerging technologies in healthcare. Interpretive structural modeling can map hierarchical relations, but it typically relies on binary reachability rather than graded influence. Standalone AHP can prioritize factors, but it generally assumes independence and cannot represent feedback. Bayesian networks and system dynamics can model dependencies, but they require either rich empirical data or extensive calibration. Given the limited availability of adoption data and the need to represent graded interdependence under uncertainty, the fuzzy DEMATEL-DANP combination offers an appropriate balance among explanatory power, data requirements, and managerial interpretability.

We adopt a theory-guided, expert-elicitation design. Ten determinants of healthcare blockchain adoption: Interoperability (A1), Complexity (A2), Scalability (A3), Security (A4), Organizational Readiness (A5), Management Support (A6), Regulatory Uncertainty (A7), Compliance (A8), Implementation Costs (A9), and Economic Incentives (A10) are organized under the TOE framework (Tornatzky & Fleischer 1990; Baker 2012). The TOE mapping structures instrument design and interpretation by distinguishing technology (A1-A4), organization (A5-A6, A9), and environment (A7-A8, A10).

3.1 Fuzzy DEMATEL

DEMATEL identifies and maps cause and effect relations among system components, and has been widely applied across domains. By translating expert judgments into a structured network, it supports coordinated strategic decisions. DEMATEL offers a visual representation of interdependencies of factors which are positioned as causes or effects, enabling researchers to have a transparent view of how influences spread. The standard procedure below is taken from Wu & Lee (2007).

Step 1: An expert panel conducts pairwise comparisons to assess how much factor i influences factor j. These ratings form the direct-relation matrix Z.

Step 2: Z is scaled to produce the matrix X, which is a normalized direct-relation matrix, using the normalization formulas (1) and (2) so that overall influence levels are comparable across rows.

$$X = s \cdot Z \tag{1}$$

$$s = \frac{1}{max_{\ 1 \le i \le n} \sum_{j=1}^{n} z_{ij}}, \tag{2}$$

Step 3: Form the total correlation matrix. This matrix reflects the total relation between each element.

$$T = X(I - X)^{-1} \tag{3}$$

Step 4: Per Eqs. (5) and (6), R is the aggregate (direct + indirect) influence received by an element from all others, while D is the aggregate influence that an element exerts on all others.

$$T = tij, \quad i,j = 1,2,\ldots,n \tag{4}$$

$$R = \sum_{i=1}^{n} t_{ij}, \tag{5}$$

$$D = \sum_{j=1}^{n} t_{ij}, \tag{6}$$

Step 5: Plot D+R on the horizontal axis and D−R on the vertical axis to obtain a causal diagram that makes the inter-factor relationships visible.

Because expert judgments are imprecise and information may be incomplete or partially missing, a fuzzy approach helps capture vagueness in the data. Fuzzy set theory (Zadeh 1975) models such uncertainty by using linguistic terms instead of exact numbers; these terms are commonly encoded as triangular fuzzy numbers. In this study, the linguistic ratings used in the evaluation are represented by triangular fuzzy numbers (Table 1).

Table 1. Triangular Fuzzy Numbers and Linguistic Terms

Linguistic Term	Triangular Fuzzy Number (l, m, u)
Very Low	(0, 0, 0.25)
Low	(0, 0.25, 0.5)
Medium	(0.25, 0.5, 0.75)
High	(0.5, 0.75, 1)
Very High	(0.75, 1, 1)

We used the converting fuzzy data into crisp scores (CFCS) method from Opricovic & Tzeng (2003) described below:

Step 1: Conduct normalization

$$xl_{ij}^{k} = (l_{ij}^{k} - min\, l_{ij}^{k})/\Delta_{min}^{max}, \quad (7)$$

$$xm_{ij}^{k} = (m_{ij}^{k} - min\, l_{ij}^{k})/\Delta_{min}^{max}, \quad (8)$$

$$xr_{ij}^{k} = (r_{ij}^{k} - min\, l_{ij}^{k})/\Delta_{min}^{max}, \quad (9)$$

Where $\Delta_{min}^{max = max\, r_{ij}^{k} - min\, l_{ij}^{k}}$

Step 2: Calculate left and right normalized values:

$$xls_{ij}^{k} = xm_{ij}^{k}/(1 + xm_{ij}^{k} - xl_{ij}^{k}), \quad (10)$$

$$xrs_{ij}^{k} = xr_{ij}^{k}/(1 + xr_{ij}^{k} - xm_{ij}^{k}). \quad (11)$$

Step 3: Calculate total normalized crisp value:

$$x_{ij}^{k} = \left[xls_{ij}^{k}(1 - xls_{ij}^{k}) + xrs_{ij}^{k}xrs_{ij}^{k}\right]/\left[1 - xls_{ij}^{k} + xrs_{ij}^{k}\right]. \quad (12)$$

Step 4: Calculate the crisp values:

$$z_{ij}^{k} = min\, l_{ij}^{k} + x_{ij}^{k}\Delta_{min}^{max}. \quad (13)$$

Step 5: Integrate the crisp values:

$$z_{ij}^{k} = \frac{1}{p}(z_{ij}^{1} + z_{ij}^{2} + \cdots + z_{ij}^{p}). \quad (14)$$

3.2 DEMATEL-based Analytic Network Process (DANP)

The objective of DANP is to convert the DEMATEL total-relation matrix into interdependence-aware priority weights for the factors. If a factor repeatedly sends influence through the network and that influence tends to circulate back via feedback loops, its steady-state importance is higher.

Step 1: Row-normalize matrix T from DEMATEL (influence propagation matrix):

For each row i, compute $s_i = \sum T_{ij}$ (if $s_i = 0$, set $s_i = 1$ to avoid division by zero) and define the row-stochastic matrix

$$W_{ij} = \frac{Tij}{Si} \quad (15)$$

Each row of W sums to 1. Interpret W as one step of influence propagation from each factor to the others.

Step 2: Steady-state (stationary) priorities:

Start from any probability vector v_0 (e.g., uniform). Iterate until convergence:

$$v_{r+1} = W^T v_r \Rightarrow w = \lim v_r \tag{16}$$

The limit w is the DANP priority vector: $w_i \geq 0$ and $\sum w_i = 1$. These are the global factor weights consistent with the DEMATEL network.

4. Results

Pairwise influences among the ten factors were obtained from fourteen healthcare managers with roles spanning clinical operations, health information technology, compliance and legal, and vendor integration. All self comparisons were set to zero and ratings were expressed on a five level linguistic scale mapped to triangular fuzzy numbers. Individual fuzzy matrices were aggregated component-wise to obtain the group fuzzy direct relation matrix. After defuzzification and normalization by the maximum row sum, the total relation matrix T was computed (Table 2).

Table 2. Total Relation Matrix T

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**
A1	1.390	1.461	1.439	1.426	1.410	1.424	1.381	1.474	1.336	1.496
A2	1.468	1.341	1.411	1.398	1.363	1.411	1.347	1.437	1.322	1.466
A3	1.481	1.452	1.340	1.418	1.407	1.451	1.376	1.457	1.353	1.495
A4	1.554	1.509	1.498	1.387	1.456	1.488	1.423	1.527	1.402	1.531
A5	1.497	1.462	1.425	1.435	1.315	1.429	1.387	1.466	1.354	1.498
A6	1.503	1.486	1.465	1.453	1.416	1.357	1.394	1.476	1.384	1.521
A7	1.466	1.459	1.427	1.434	1.391	1.395	1.274	1.446	1.353	1.456
A8	1.583	1.566	1.538	1.532	1.501	1.510	1.479	1.460	1.442	1.600
A9	1.417	1.388	1.346	1.369	1.352	1.359	1.315	1.404	1.209	1.430
A10	1.490	1.475	1.431	1.422	1.401	1.445	1.365	1.450	1.375	1.396

Table 3 summarizes, for each factor A1–10, the dispatched influence D (row sum of T), the received influence R (column sum), overall prominence D+R, and net effect D−R (driver vs. receiver):

- Drivers (positive D−R): A8 Compliance, A4 Security, A7 Regulatory Uncertainty, A5 Organizational Readiness, A6 Management Support, A9 Implementation Costs.

- Receivers (negative D−R): A3 Scalability, A1 Interoperability, A2 Complexity, A10 Economic Incentives.

Prominence highlights system-salient factors irrespective of direction. The highest values are A8 Compliance (29.810), A10 Economic Incentives (29.138), A1 Interoperability (29.087), and A4 Security (29.050), followed by A6 Management Support (28.724) and A5 Organizational Readiness (28.282). Thus, Compliance is simultaneously the most important (highest D+R) and the strongest driver (highest D−R), whereas Interoperability and Economic Incentives are highly important receivers that absorb upstream influence.

Table 3. Fuzzy DEMATEL Results

Factor Code	Factor Name	D	R	D+R	D-R	Role
A8	Compliance	15.213	14.597	29.810	0.615	Cause
A4	Security	14.775	14.275	29.050	0.500	Cause
A7	Regulatory Uncertainty	14.101	13.743	27.845	0.358	Cause
A5	Organizational Readiness	14.269	14.013	28.282	0.257	Cause
A6	Management Support	14.455	14.269	28.724	0.187	Cause
A9	Implementation Costs	13.588	13.530	27.119	0.058	Cause
A3	Scalability	14.230	14.320	28.550	-0.091	Effect
A1	Interoperability	14.237	14.850	29.087	-0.613	Effect
A2	Complexity	13.965	14.598	28.563	-0.632	Effect
A10	Economic Incentives	14.250	14.888	29.138	-0.638	Effect

To visualize salient pathways, we retained directed arcs i→j with greater than the 75th percentile of the off-diagonal T entries ($T \approx 1.4783$). The resulting graph (Figure 2) shows two dominant emitters: Compliance (A8) and Security (A4). A8 projects a broad, high-strength influence on A10 (Economic Incentives), A1 (Interoperability), A2 (Complexity), A3 (Scalability), A4 (Security), A6 (Management Support), A5 (Organizational Readiness), and A7 (Regulatory Uncertainty). A4 sends strong edges to A1, A10, A8, A2, A3, and A6. A supporting emitter, Management Support (A6), links to A10, A1, and A2; Organizational Readiness (A5) contributes targeted influence to A10 and A1; and Scalability (A3) connects into A10 and A1. On the receiver side, Interoperability (A1) is the principal sink, drawing high-strength inputs from A8, A4, A6, A5, A3, and A10, while Economic Incentives (A10) also concentrates incoming influence (from A8, A4, A6, A5, and A3). Notably, Complexity (A2) receives (from

A8, A4 and A6) but does not emit edges above this threshold; Regulatory Uncertainty (A7) and Implementation Costs (A9) likewise show no outgoing links at this level. Overall, the network backs a TOE consistent structure, where Compliance serves as the environmental driver and Security as the technology driver, acting as upstream levers into organizational governance (Management Support) and into operational outcomes, which are concentrated in Interoperability and Economic Incentives.

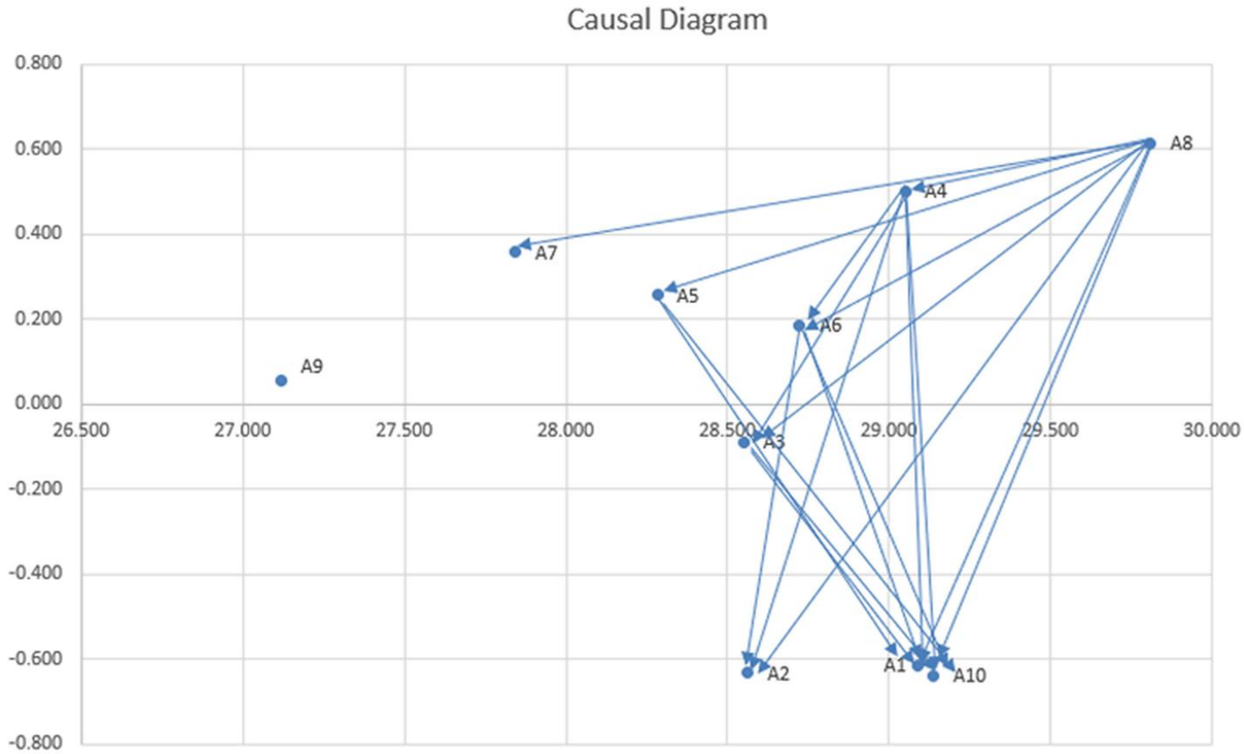

Figure 2. Causal Relation Diagram

Using the transition-matrix DANP procedure, we determine the steady-state importance of each factor, taking into account all feedback paths within the network. Table 4 lists the resulting weights.

Table 4. DANP Weights

Factor Code	Factor Name	DANP Weight
A10	Economic Incentives	0.104029
A1	Interoperability	0.10376
A8	Compliance	0.102047
A2	Complexity	0.101996
A3	Scalability	0.100076
A4	Security	0.099778
A6	Management Support	0.099746
A5	Organizational Readiness	0.097942
A7	Regulatory Uncertainty	0.096062
A9	Implementation Costs	0.094564

Using the transition-matrix DANP, we derive steady-state priorities. The top weights for A10 and A1 indicate where influence accumulates in the network; these are the outcomes most shaped by upstream levers. Although their weights are slightly lower, Compliance (A8) and Security (A4) remain the key drivers in the DEMATEL map and should be used in conjunction with Management Support (A6) and Organizational Readiness (A5) to achieve the high-weight targets. Complexity (A2) and Scalability (A3) remain key priorities, indicating that reducing complexity and optimizing performance are consequential follow-up actions. Practically, sequence actions as: (i) enforce compliance/security and secure sponsorship/readiness, then (ii) drive interoperability and economic value, while (iii) reducing complexity and improving scalability to sustain gains.

This study addressed the research questions as follows: RQ1 (TOE-aligned causal structure): The total-relation matrix T and the high-salience graph reveal a coherent network in which Compliance (A8) and Security (A4) broadcast strong influences across technology, organization, and environment, with dense inflows converging on Interoperability (A1) and Economic Incentives (A10). RQ2 (drivers vs. receivers): Based on D−R, drivers are A8, A4, A7, A5, A6, and A9, while receivers are A3, A1, A2, and A10; prominence D+R is highest for A8, A10, A1, and A4 (Table 3). RQ3 (what to prioritize): DANP steady-state weights concentrate on A10 (0.1040) and A1 (0.1038), followed by A8 (0.1020) and A2 (0.1020) (Table 4), implying a practical sequence: act first on Compliance/Security (with Management Support and

Organizational Readiness) to lift Interoperability and Economic value, then reduce Complexity and improve Scalability to sustain gains.

5. Discussion

This study maps a TOE grounded causal architecture for healthcare blockchain adoption and then converts that network into interdependence-aware priorities. Two results stand out. First, Compliance (A8) and Security (A4) act as the strongest drivers in the DEMATEL map, joined by Regulatory Uncertainty (A7), Organizational Readiness (A5), Management Support (A6), and Implementation Costs (A9) as additional, though weaker, sources of push. Second, the DANP weights concentrate on Economic Incentives (A10) and Interoperability (A1) as the highest steady-state priorities, with Complexity (A2) and Scalability (A3) forming the next tier. This pattern is consistent with prior reviews, which show that in healthcare, secure and compliant designs are necessary conditions that unlock downstream value and facilitate data exchange (Kuo et al. 2017; Agbo et al. 2019; Prokofieva & Miah 2019). It also explains why studies often report slow translation from pilots to enterprise value: upstream compliance and security choices determine whether interoperability and economic payoffs can materialize (Dubovitskaya et al. 2018; Mackey & Nayyar 2017).

Mechanistically, compliance and security dominate because protected health information (PHI) is subject to stringent privacy, consent, and audit regimes; architectures that satisfy these constraints reduce perceived risk and accelerate integration approvals (Prokofieva & Miah 2019; Handayani et al. 2023). In the TOE lens, these are environmental (compliance/regulation) and technological (security) levers that shape organizational behavior (Tornatzky & Fleischer 1990). Our finding that Management Support (A6) and Organizational Readiness (A5) are positive-net drivers, but not top DANP priorities, echoes digital-health evidence: leadership sponsorship and governance unlock resources and cross-functional coordination, yet the accumulated influence still resides where benefits are realized, interoperability and economic value (Clohessy & Acton 2019; Esmaeilzadeh 2022). The receiver status of Interoperability (A1) is also aligned with the EHR-integration literature, which stresses that standardization and interface gateways only succeed after security/compliance guardrails are in place (Kuo et al. 2017).

Managerial implications follow a clear sequence. Phase 1 Levers: Institutionalize compliance-by-design (data-sharing agreements, consent/audit templates, DPIAs) and security hardening (zero-trust access, key management, privacy-preserving logging), while formalizing executive sponsorship and readiness (governance board, clinical champions, vendor playbooks). Phase 2 High-weight targets: drive measurable gains in interoperability (HL7 FHIR coverage, application programming interface (API) uptime, time-to-retrieve records) and economic incentives (reconciliation cost reduction, claim-processing cycle time), which our DANP results identify as the most influential endpoints. Phase 3 Friction removal: reduce complexity (interface standardization, vendor consolidation, smart contract safety checks) and improve scalability (permissioned consensus tuning, off-chain computation), locking in benefits and enabling wider rollout. This staged approach converts the DEMATEL "drivers to receivers" logic into an operations plan with KPIs, consistent with prior multi criteria decision making (MCDM) guided health-IT roadmaps (Hsu et al. 2013; Tzeng & Huang 2011).

For policymakers and vendors, this study suggests two strategies. Regulators can speed safe experimentation by providing pre-approved compliance patterns (model consent artifacts, audit trails, cross-institution data-use templates) and sandbox regimes that reduce uncertainty without relaxing safeguards (Mettler 2016; Mackey & Nayyar 2017). Vendors can package reference architectures that front-load security and compliance, thereby shortening procurement and ethics cycles and raising adoption likelihood. Because Economic Incentives (A10) carries the highest DANP weight, payers and health systems should align incentive programs with observable outcomes (e.g., fewer duplicate tests, faster record reconciliation, and counterfeit prevention in pharmaceutical supply chains), thereby reinforcing the network locations where benefits accumulate (Agbo et al. 2019).

From a theoretical perspective, the results show how TOE determinants align with core Diffusion of Innovations attributes. Economic Incentives operationalizes relative advantage, Interoperability reflects compatibility with existing standards and workflows, and Complexity captures perceived difficulty. The causal map indicates that these Diffusion of Innovations (DOI) aligned outcomes are shaped upstream by Compliance and Security and by governance related environmental conditions, supporting the view that organizational adoption depends on both innovation attributes and the institutional and operational context in which they are evaluated.

6. Conclusion

This study develops a theory guided and decision ready model for blockchain adoption in healthcare by combining the Technology Organization Environment lens with fuzzy DEMATEL and DANP. Using judgments from 14 healthcare managers, we map a causal network in which

Compliance and Security act as the principal drivers that exert influence on key outcomes. DANP reveals that Economic Incentives and Interoperability have the highest steady state priorities, indicating where benefits and impacts accumulate when upstream levers are activated. Taken together, the findings suggest an executable order of steps: build compliance into the design and put security controls in place; secure visible backing from leadership and confirm organizational readiness; then pursue interoperability and measurable economic value while trimming complexity and planning for scale.

This study contributes to the literature on healthcare blockchain adoption in three ways. First, it provides a TOE grounded causal architecture that distinguishes upstream drivers from downstream receivers, addressing a key limitation of prior studies that report determinants as independent lists. Second, it offers a transparent hybrid fuzzy DEMATEL and DANP procedure that yields both an interpretable causal map and interdependence aware priority weights, which is suitable for expert panel settings typical in healthcare. Third, it translates the results into an actionable adoption sequence that connects compliance and security governance to downstream interoperability and measurable economic value.

This work has limitations that should guide interpretation. Expert elicitation is inherently subjective, and the panel size, role mix, and jurisdiction may influence the structure of the panel. Factor definitions and the linguistic scale, while grounded in the literature, may still omit context specific determinants. Modeling choices, such as defuzzification, the normalization rule, and the percentile threshold for graph sparsification, can shift marginal ties even if the identity of dominant drivers remains stable. Finally, the study suggests that leverage comes from expert structure rather than observed outcomes, so external validation in live deployments remains necessary.

Future research can extend this work in several directions. First, the causal structure implied by the DEMATEL results should be tested using larger samples and statistical models, for example through survey based structural equation approaches or longitudinal adoption data that can capture changes in readiness, governance maturity, and ecosystem conditions over time. Second, qualitative research should be used to unpack the mechanisms behind the strongest drivers and receivers identified in this study. Semi structured interviews and focus groups with key stakeholder groups such as clinicians, data governance officers, compliance and privacy leads, and technology vendors can clarify how compliance and security requirements are operationalized, how leadership sponsorship is translated into resources and decisions, and how interoperability initiatives are implemented across systems. Third, multi site case studies across different jurisdictions and organizational types can compare how regulatory regimes, procurement practices, and vendor ecosystems shape adoption pathways and outcomes. Fourth, mixed methods designs can link these qualitative findings to refined constructs and measurement items, and then validate them quantitatively, improving both explanatory depth and generalizability. Finally, future work can broaden the determinant set to include patient centered considerations and ecosystem readiness variables and can evaluate robustness by comparing expert subgroup judgments and conducting sensitivity analysis across alternative factor definitions.

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