Future of Work and Digital Management Journal

Article type:
Original Research

Article history:
Received 05 January 2026
Revised 04 February 2026
Accepted 10 March 2026
Published online 01 December 2026

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How to cite this article:
Hasanshahi, J., Ghodrati, H., Kianoosh, D., Arabzadeh, M., & Mohaghgheghi, M. (2025). Modeling and Leveling the Drivers of Blockchain Technology Adoption in Financial Services of the National Banking Network. *Future of Work and Digital Management Journal,4*(4),1-19.
https://doi.org/10.61838/fwdmj.66

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Modeling and Leveling the Drivers of Blockchain Technology Adoption in Financial Services of the National Banking Network

ABSTRACT

The banking sector has undergone significant transformation over time due to the adoption of information and communication technologies. This transformation has been further strengthened by the continuous advancement of artificial intelligence and blockchain technologies. In recent years, technology has played a crucial role in major developments within the banking industry, and users have become highly dependent on information technology for utilizing and purchasing banking services. Accordingly, the main objective of this study is to model and level the drivers influencing the adoption of blockchain technology in the financial services of the national banking network. In terms of purpose, this research is applied, and regarding data collection, it follows a descriptive design. The study was conducted in two phases: in the first phase, literature review was employed to identify influential drivers, and in the second phase, the Interpretive Structural Modeling (ISM) approach was used to analyze the relationships among the drivers. The statistical population consisted of banking experts and researchers in the national banking sector, among whom fifteen participants were selected using a non-probability purposive sampling method based on accessibility. The interpretive structural approach was applied to level the components. In this stage, twenty drivers affecting the adoption of blockchain technology in financial services of the national banking network were analyzed and categorized into five hierarchical levels. The findings indicated that drivers related to technology accessibility, structural characteristics, market and customer factors, and the realistic formulation of policies were positioned at the first level, while the driver of macro economic–political policy revision was placed at the fifth level.

Keywords: Blockchain, Financial Technology (FinTech), National Banking Network, Interpretive Structural Modeling (ISM).

Introduction

The rapid transformation of the global financial system in recent decades has been strongly influenced by technological innovation, digitalization, and the emergence of intelligent financial infrastructures. Among these innovations, blockchain technology has attracted considerable scholarly and practical attention due to its capacity to fundamentally reshape financial intermediation, transaction verification, and trust mechanisms within banking ecosystems. Traditional banking models, historically dependent on centralized architectures, hierarchical verification processes, and institutional trust, increasingly face structural limitations in responding to demands for transparency, efficiency, security, and real-time financial services. Consequently, financial institutions worldwide are exploring blockchain technology as a strategic solution capable of enabling decentralized, transparent, and tamper-resistant financial operations [1, 2].

Blockchain technology represents more than a technological upgrade; it constitutes a paradigm shift in how financial value is created, exchanged, and governed. By integrating distributed ledger systems, cryptographic verification, and consensus protocols, blockchain reduces reliance on intermediaries and enables secure peer-to-peer transactions across institutional boundaries. These characteristics enhance operational efficiency, reduce transaction costs, and improve data integrity across financial networks [3, 4]. The banking industry, as one of the most information-intensive sectors, has therefore become a primary arena for blockchain experimentation and adoption. Emerging financial technologies increasingly integrate blockchain with artificial intelligence, data analytics, and digital platforms to develop next-generation financial services capable of supporting complex financial ecosystems [5, 6].

The diffusion of blockchain in banking is closely associated with the broader development of Financial Technology (FinTech), which emphasizes innovation in payment systems, lending, investment management, and digital asset governance. FinTech adoption has demonstrated the ability to enhance financial inclusion, improve operational agility, and facilitate collaboration between banks and technology startups. Strategic cooperation between banking systems and FinTech firms enables institutions to leverage technological innovation while maintaining regulatory compliance and financial stability [7, 8]. Within this transformation, blockchain acts as a foundational infrastructure supporting smart contracts, decentralized finance, secure identity verification, and automated financial processes.

Despite its recognized advantages, blockchain adoption in banking organizations remains uneven across countries and institutions. Adoption decisions are shaped not only by technological readiness but also by organizational, environmental, regulatory, and behavioral factors. Previous studies indicate that institutional readiness, legal frameworks, managerial resilience, and financial governance structures significantly influence technological innovation adoption within financial organizations [9, 10]. Furthermore, financial performance outcomes associated with blockchain implementation depend on how effectively organizations align technological innovation with strategic management capabilities and risk governance structures.

One critical dimension influencing blockchain adoption is macroeconomic and financial uncertainty. Digital technologies such as blockchain have been shown to improve investment efficiency and risk management by enhancing information transparency and reducing asymmetric information within markets [11]. Blockchain-based financial infrastructures also contribute to reducing supply chain disruption risks by enabling traceability, secure data exchange, and automated financial settlement mechanisms [12]. These benefits highlight blockchain's systemic implications extending beyond banking operations toward broader economic resilience and sustainable financial development.

From an organizational perspective, blockchain adoption requires significant structural transformation within banking institutions. Human capital readiness, technological competence, and workforce adaptation play decisive roles in enabling successful implementation. The transition toward Banking 4.0 demands new digital skills, interdisciplinary expertise, and strategic leadership capable of managing technological complexity and innovation uncertainty [13]. Banks must therefore invest in training, organizational learning, and technological integration strategies to overcome internal resistance and capability gaps.

Regulatory and policy environments represent another fundamental determinant of blockchain diffusion. Policymaking related to emerging banking technologies requires balancing innovation promotion with financial stability and risk mitigation. Regulatory strategies must address issues such as data governance, cybersecurity, interoperability, and legal recognition of

blockchain transactions. Game-theoretic analyses of banking technology policy emphasize the importance of coordinated regulatory frameworks and stakeholder collaboration in fostering innovation ecosystems [14]. Without supportive regulatory infrastructures, technological adoption may remain limited despite technological readiness.

Transparency and trust also constitute central motivations for blockchain integration in financial services. Blockchain enhances accountability by providing immutable transaction records and reducing opportunities for fraud and manipulation. Studies examining supply chain finance and information transparency demonstrate that blockchain and Internet of Things integration can significantly improve trust among stakeholders and increase operational transparency [15]. In banking contexts, enhanced transparency strengthens customer confidence and contributes to financial stability, which remains a primary objective for financial regulators and institutions [16].

Market dynamics and customer behavior further influence adoption patterns. Increasing digital expectations among consumers require banks to provide faster, more secure, and personalized financial services. Social attitudes toward technology usage, perceived usefulness, and ease of use remain key determinants shaping acceptance of financial technologies. Adoption research consistently highlights customer readiness, cultural acceptance, and technological awareness as critical drivers of FinTech diffusion [8, 17]. As digital ecosystems expand, customer demand increasingly pressures banks to modernize infrastructure and integrate blockchain-enabled services.

In addition to organizational and social dimensions, infrastructure development and technological accessibility significantly affect blockchain adoption feasibility. Advanced digital infrastructures, standardized technological frameworks, and interoperability among systems enable scalable blockchain implementation across financial networks. Technological hotspot analysis demonstrates that blockchain innovation evolves rapidly alongside complementary technologies, reinforcing the importance of continuous research and development investments [5]. Infrastructure limitations, however, remain a key barrier in many banking systems, particularly within developing financial environments.

Strategic financial planning and organizational governance also contribute to adoption success. Financing structures influence innovation capacity by determining investment allocation, risk tolerance, and strategic flexibility within organizations [18]. Managerial decision-making, institutional resilience, and governance mechanisms therefore shape how banks evaluate technological risks and opportunities associated with blockchain adoption. Financial institutions must integrate innovation strategies with long-term organizational objectives to achieve sustainable technological transformation.

The relationship between blockchain adoption and sustainable development has also received growing scholarly attention. Digital investments contribute to environmental performance improvements and resource efficiency by enabling transparent tracking systems and reducing operational inefficiencies [19]. Similar findings in digital transformation research emphasize that technological adoption supports broader sustainability objectives across industries, including tourism and financial services [20]. Blockchain's ability to facilitate transparent reporting and automated compliance processes further strengthens its relevance for sustainable financial systems.

Nevertheless, multiple challenges continue to hinder large-scale blockchain deployment. Technical complexity, scalability limitations, regulatory uncertainty, interoperability challenges, and organizational resistance remain persistent barriers. Decentralized autonomous finance models illustrate both the transformative potential and the institutional constraints associated with blockchain adoption in financial markets [21]. These challenges highlight the necessity of systematic modeling approaches capable of identifying interrelationships among adoption drivers and prioritizing strategic interventions.

Data-driven decision-making has become increasingly essential in understanding technological adoption trends. Advances in data mining and financial trend prediction demonstrate how analytical approaches can reveal patterns shaping technological innovation diffusion within financial systems [22]. Similarly, organizational characteristics such as firm size, governance structures, and institutional oversight influence innovation implementation timelines and strategic decision processes [23]. Integrating analytical modeling with expert knowledge therefore provides a robust methodological foundation for evaluating blockchain adoption dynamics.

Given the multidimensional nature of blockchain adoption, scholars emphasize the importance of holistic frameworks that incorporate technological, organizational, environmental, and policy factors simultaneously. The complexity of banking ecosystems requires analytical methods capable of identifying causal relationships among multiple drivers rather than examining variables independently. Interpretive Structural Modeling and related systems approaches enable researchers to identify hierarchical relationships among adoption factors, revealing foundational drivers and dependent outcomes within complex systems [17, 18]. Such approaches support policymakers and banking managers in prioritizing strategic initiatives aligned with systemic transformation goals.

In summary, blockchain technology represents a transformative innovation capable of reshaping banking services, financial governance, and economic systems through enhanced transparency, efficiency, and decentralization. However, successful adoption depends on an interconnected set of technological readiness factors, organizational capabilities, regulatory frameworks, market dynamics, and societal acceptance conditions. Understanding the hierarchical relationships among these drivers is essential for designing effective strategies that facilitate blockchain integration within national banking networks while ensuring financial stability and sustainable development [2, 9, 12].

Therefore, the aim of this study is to model and level the drivers influencing the adoption of blockchain technology in financial services of the national banking network.

Methodology

According to the classification of research based on purpose, the present study is categorized as applied research, and based on the method of data collection, it is classified as descriptive research. Furthermore, regarding the approach to problem analysis, this study adopts a quantitative modeling approach, employing Interpretive Structural Modeling (ISM) as the analytical method. The research was conducted in two stages. In the first stage, through an extensive literature review and background analysis, 20 factors were identified as key drivers influencing the adoption of blockchain technology in the financial services of the national banking network. These drivers are presented in Table 1. In the second stage, the interpretive structural modeling approach was applied to determine the hierarchical levels of the drivers. Participants in this phase consisted of 15 banking experts selected through non-probability purposive sampling.

Table 1

Drivers Influencing the Adoption of Blockchain Technology in Financial Services of the National Banking Network

No.	Drivers	Supporting Sources
1	Establishment of legal frameworks and formulation of supportive regulations	Zarei et al. (2024); Habibi et al. (2024)
2	Information exchange	Marvat et al. (2024); Sheikheh et al. (2023)
3	Market and customers	Veisi et al. (2024); Sheikheh et al. (2023)
4	Societal attitude toward usage	Marvat et al. (2024); Sheikheh et al. (2023)
5	Acceptance culture and adaptability	Zarei et al. (2024); Sheikheh et al. (2023)
6	Ease of use and perceived usefulness	Marvat et al. (2024); Sheikheh et al. (2023)

7	Technology accessibility	Ansari et al. (2024); Sheikheh et al. (2023)
8	Availability of blockchain specialists	Zarei et al. (2024); Aghamohammadi & Enayati Hatkeloui (2024)
9	Technical expertise in blockchain system standardization	Ansari et al. (2024); Aghamohammadi & Enayati Hatkeloui (2024); Sheikheh et al. (2023)
10	Research and development	Marvat et al. (2024); Sheikheh et al. (2023)
11	Change in governmental attitudes	Zarei et al. (2024); Veisi et al. (2024)
12	Infrastructure development	Ansari et al. (2024); Sheikheh et al. (2023)
13	Structural characteristics	Ansari et al. (2024); Marvat et al. (2024); Sheikheh et al. (2023)
14	Accurate financial resource planning	Ansari et al. (2024); Veisi et al. (2024); Marvat et al. (2024)
15	Expansion of blockchain role in monetary and financial systems	Veisi et al. (2024); Silspour et al. (2023); Sheikheh et al. (2023)
16	Realistic policy formulation	Habibi et al. (2024); Veisi et al. (2024); Silspour et al. (2023); Sheikheh et al. (2023)
17	Technological performance evaluation	Ansari et al. (2024); Veisi et al. (2024); Silspour et al. (2023); Sheikheh et al. (2023)
18	Revision of macro economic–political policies	Zarei et al. (2024); Habibi et al. (2024); Veisi et al. (2024); Silspour et al. (2023)
19	Public trust and security	Aghamohammadi & Enayati Hatkeloui (2024); Marvat et al. (2024); Rahdar & Asgharian (2023); Sheikheh et al. (2023)
20	Transparency and accountability	Aghamohammadi & Enayati Hatkeloui (2024); Rahdar & Asgharian (2023); Sheikheh et al. (2023)

Findings and Results

Interpretive Structural Modeling analyzes relationships among drivers by decomposing them into multiple hierarchical levels and identifying interdependencies among individual and collective factors. The ISM procedure was implemented in several stages. In the first stage, the Structural Self-Interaction Matrix (SSIM) was constructed. In the second stage, the initial reachability matrix was developed. In the third stage, the final reachability matrix was derived, followed by level partitioning of the drivers. Finally, MICMAC analysis and graphical modeling of the final structure were performed. The stages of the interpretive–structural approach are presented below.

Step 1: Formation of the Structural Self-Interaction Matrix (SSIM)

Table 2 presents the Structural Self-Interaction Matrix.

Table 2

Structural Self-Interaction Matrix (SSIM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	-	O	V	V	O	O	O	O	A	X	O	A	O	O	O	O	O	A	O	O
2		-	V	O	O	A	O	O	A	O	O	A	O	O	O	O	O	O	O	O
3			-	O	O	A	O	O	O	O	O	A	O	O	O	O	O	O	A	O
4				-	O	O	O	O	O	O	O	O	V	O	O	O	O	O	O	O
5					-	O	O	A	O	O	O	O	V	O	O	O	O	O	O	O
6						-	V	O	O	O	O	O	V	V	O	O	A	O	O	
7							-	O	O	O	O	O	O	O	O	A	A	O	O	
8								-	V	V	A	A	O	X	X	V	O	O	O	A
9									-	O	O	X	O	O	V	O	O	O	O	
10										-	X	A	O	V	V	V	A	A	O	O
11											-	A	O	O	O	V	O	O	O	V
12												-	V	V	V	V	O	O	O	O
13													-	A	A	O	O	O	O	O
14														-	A	O	A	A	A	O
15															-	O	O	O	O	O
16																-	O	O	O	O
17																	-	A	O	O
18																		-	O	O
19																			-	O
20																				

The Structural Self-Interaction Matrix (SSIM) is formed based on the dimensions and indicators of the study through comparison using four types of conceptual relationships. This matrix is completed by experts and specialists in the banking sector. The obtained information was aggregated according to the Interpretive Structural Modeling (ISM) methodology,

resulting in the final Structural Self-Interaction Matrix. The logic of interpretive structural modeling relies on non-parametric methods and operates based on the mode of frequencies.

Step 2: Formation of the Initial Reachability Matrix

In the second step, the Initial Reachability Matrix is developed by converting the Structural Self-Interaction Matrix into binary values (0 and 1). The results are presented in Table 3.

Table 3

Initial Reachability Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	1	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
6	0	1	1	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0
7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	1	1	1	0	0	0	1	1	1	0	0	0	0
9	1	1	0	0	0	0	0	0	1	0	0	1	0	1	1	0	0	0	0	0
10	1	0	0	0	0	0	0	0	0	1	1	0	0	1	1	1	0	0	0	0
11	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	1	0	0	0	1
12	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0
15	0	0	0	0	0	0	0	1	0	0	0	0	1	1	1	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
17	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	1	0	0	0
18	1	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	1	1	0	0
19	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0
20	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1

Step 3: Formation of the Consistent Initial Reachability Matrix

After obtaining the Initial Reachability Matrix, its internal consistency must be established. For example, if Variable 1 leads to Variable 2 and Variable 2 leads to Variable 3, then Variable 1 must also lead to Variable 3. If such a relationship does not exist in the reachability matrix, corrective adjustments are required. Consistency is achieved by adding secondary transitive relationships that may not initially appear in the matrix. The Consistent Initial Reachability Matrix is presented in Table 4.

Table 4

Consistent Initial Reachability Matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	Driving Power
1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	15
2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
4	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2
5	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	17
7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
8	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	15
9	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	15
10	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	15
11	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	15
12	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	15
13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
14	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	15

15	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	0	0	0	0	1	15
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
17	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	0	1	17
18	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	19
19	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	1	1	16
20	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	15
Dependence	13	14	15	14	14	2	4	13	13	13	13	13	16	13	13	14	2	1	1	13	

Step 4: Determining the Levels of the Factors

In this step, the input (prerequisite/antecedent) set and the output (reachability) set are calculated for each criterion, and then the intersection set (common elements) is identified. A criterion is assigned to the highest level when its output (reachability) set is equal to its intersection set. After identifying this variable (or variables), its corresponding row and column are removed from the tables, and the procedure is repeated for the remaining criteria. The input and output sets are extracted from the consistent initial reachability matrix (Table 5). To do so, the number of ones in each row represents the output (driving) set, and the number of ones in each column represents the input (dependence) set; the results of the level partitioning are reported in Table 5.

Table 5

Level Partitioning of the Model Drivers

Drivers	Output Set (Reachability)	Input Set (Antecedent)	Intersection Set	Level
1	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-18-19-20	1-8-9-10-11-12-14-15-20	Third
2	2	1-2-6-8-9-10-11-12-14-15-17-18-19-20	2	Second
3	3	1-2-3-6-8-9-10-11-12-14-15-17-18-19-20	3	First
4	4	1-4-6-8-9-10-11-12-14-15-17-18-19-20	4	Second
5	5	1-5-6-8-9-10-11-12-14-15-17-18-19-20	5	Second
6	6	6-18	6	Fourth
7	7	6-7-17-18	7	First
8	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-18-19-20	1-8-9-10-11-12-14-15-20	Third
9	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-18-19-20	1-8-9-10-11-12-14-15-20	Third
10	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-17-19-20	1-8-9-10-11-12-14-15-20	Third
11	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-18-19-20	1-8-9-10-11-12-14-15-20	Third
12	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-18-19-20	1-8-9-10-11-12-14-15-20	Third
13	13	1-4-5-6-8-9-10-11-12-13-14-15-17-18-19-20	13	First
14	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-18-19-20	1-8-9-10-11-12-14-15-20	Third
15	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-18-19-20	1-8-9-10-11-12-14-15-20	Third
16	16	1-6-8-9-10-11-12-14-15-16-17-18-19-20	16	First
17	17	17-18	17	Fourth
18	6-17-18	18	18	Fifth
19	19	19	19	Fourth
20	1-8-9-10-11-12-14-15-20	1-6-8-9-10-11-12-14-15-17-18-19-20	1-8-9-10-11-12-14-15-20	Third

Step 5: MICMAC Analysis

The direct influence matrix and the potential direct influence matrix are considered as MICMAC input elements, whereas the indirect influence matrix and the potential indirect influence matrix represent the derived results of the analyses that require interpretation. The first output of MICMAC relates to the general characteristics of the studied matrix, which are presented in Table 6.

Table 6

General Characteristics of the Studied Matrix

Indicator	Value
Matrix size	20
Number of iterations	4
Number of zeros	166
Number of ones	40

Number of twos	69
Number of threes	125
Number of P	0
Total	234
Filled-cell rate	58.5

Further MICMAC outputs (generated by the MICMAC software) are presented below.

1) Direct Influence Matrix

This matrix contains the structural variables of the system, positioned across the rows and columns of the corresponding table. It describes the direct relationships that exist among the variables within the system. Another MICMAC output in this section is the matrix-sum table, in which two values are reported for each variable: one is the column sum and the other is the row sum. The row sum indicates the driving power (influence) of the variable, whereas the column sum indicates its dependence (being influenced). The matrix-sum table for direct influences is reported in Table 7.

Table 7

Sum Table for the Direct Influence Matrix

No.	Study Variables	Row Sum (Driving Power)	Column Sum (Dependence)
1	Establishment of a legal framework and supportive regulations	34	35
2	Information exchange	30	18
3	Market and customers	34	30
4	Societal attitude toward usage	38	22
5	Acceptance culture and adaptability	34	30
6	Ease of use and perceived usefulness	31	3
7	Technology accessibility	14	12
8	Availability of blockchain specialists	38	17
9	Technical expertise in standardizing different blockchain systems	34	23
10	Research and development	28	31
11	Change in governmental attitudes	34	46
12	Infrastructure development	11	50
13	Structural characteristics	33	49
14	Accurate financial resource planning	9	49
15	Expansion of blockchain's role in the monetary and financial system	20	46
16	Realistic policy formulation	30	26
17	Technological performance evaluation	27	5
18	Revision of macro economic–political policies	36	7
19	Public trust and security	17	23
20	Transparency and accountability	21	31

Based on the results in Table 7, the variables societal attitude toward usage and availability of blockchain specialists rank first in terms of driving power, while infrastructure development ranks first in terms of dependence. Another MICMAC software output for this section is the table related to system stability. The summarized results are presented in Table 8.

Table 8

System Stability Results for the Direct Influence Matrix

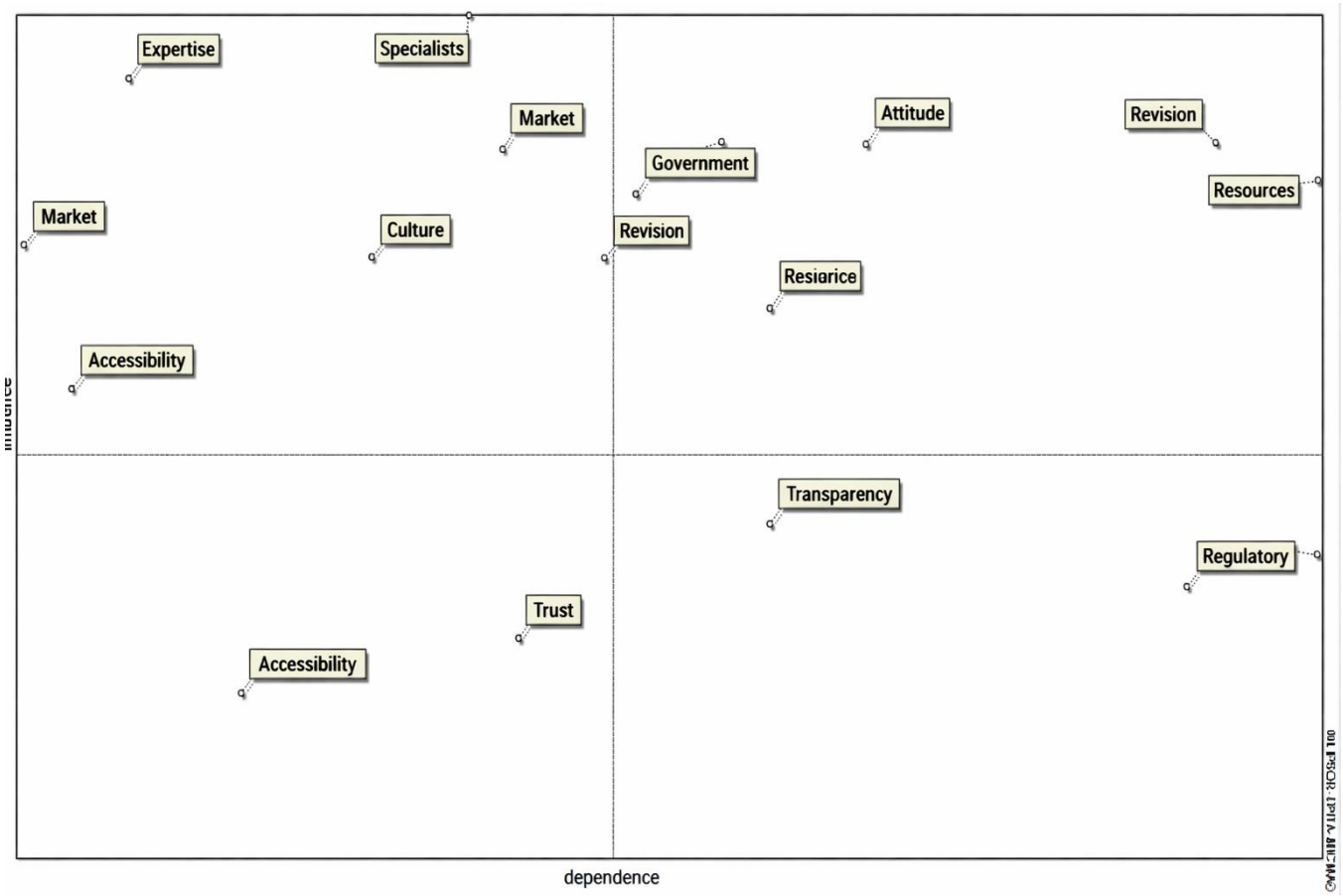
No.	Iteration	Influence (Stability)	Dependence (Stability)
1	First	94%	95%
2	Second	96%	99%
3	Third	99%	100%
4	Fourth	100%	100%

In this section, the standard number of iterations required to reach system stability is four. In the first iteration, the system's influence is 94% and dependence is 95%. In the second iteration, influence increases to 96% and dependence to

99%. In the third iteration, influence reaches 99% and dependence 100%. Finally, in the fourth iteration, both influence and dependence reach 100%. Figure 1 presents the MICMAC diagram for the direct influence matrix.

Figure 1

MICMAC diagram for the direct influence matrix



To analyze the four quadrants of Figure 1, it is necessary to consider the general characteristics shown in Figure 2. This diagram comprises four categories: driving (influential) variables, linkage (bi-dimensional) variables, dependent variables, and autonomous (independent) variables.

The first quadrant, which includes the driving variables, has the following characteristics: these variables exert high influence and have low dependence; they are located in the northwest part of the diagram; they are the most critical components of the system; they are considered input variables of the system; they generally include environmental variables; and they are typically not controllable by the system.

The second quadrant includes the linkage (bi-dimensional) variables, which have the following characteristics: these variables are simultaneously highly influential and highly dependent; they are located in the northeast part of the diagram; their nature is associated with instability; and they are divided into two groups: risk variables and target variables.

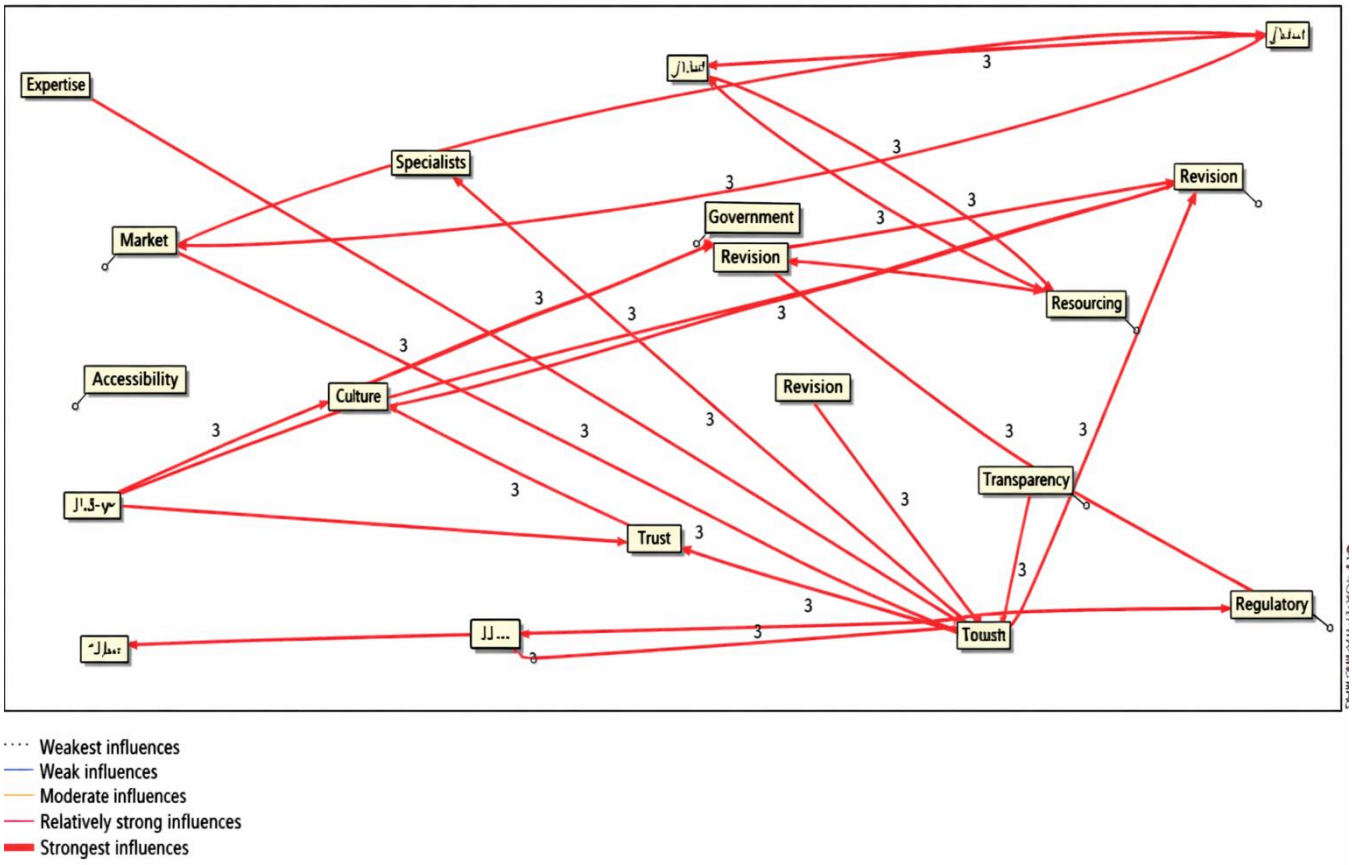
The third quadrant includes the dependent variables, which have the following characteristics: dependent variables are located in the southeast part of the diagram; they have low influence and very high dependence; they are highly sensitive to the evolution of driving and linkage variables; and they are considered system outputs.

The fourth quadrant includes the autonomous (independent) variables, which have the following characteristics: these variables neither influence other variables nor are influenced by them; they are located in the southern part of the diagram and have very limited connection to the system; they neither halt a main variable nor drive the development and progress of a variable in the system; and they consist of two subtypes, namely discrete and regulatory variables.

Based on the analysis of the four quadrants, the strategic key variables are the linkage variables. These variables are manipulable and influence the system's dynamics and change. They have high influence yet are not controllable. Figure 2 presents the direct influence matrix.

Figure 2

Diagram of the direct influence matrix.



2) Potential Direct Influence Matrix

The indirect influence matrix is a matrix corresponding to the direct influence matrix that has been strengthened through successive iterations. The sum table for the potential direct influence matrix is presented in Table 9.

Table 9

Sum Table for the Potential Direct Influence Matrix

No.	Study Variables	Row Sum (Influence)	Column Sum (Dependence)
1	Establishment of a legal framework and supportive regulations	1.477415E+07	1.641775E+07
2	Information exchange	1.318744E+07	8206824
3	Market and customers	1.517113E+07	1.040364E+07
4	Societal attitude toward usage	1.709597E+07	7598959
5	Acceptance culture and adaptability	1.474623E+07	1.009294E+07
6	Ease of use and perceived usefulness	1.528279E+07	2175276
7	Technology accessibility	4939776	7928299

8	Availability of blockchain specialists	1.843427E+07	4654235
9	Technical expertise in standardizing different blockchain systems	1.421252E+07	1.366982E+07
10	Research and development	1.328796E+07	1.308359E+07
11	Change in governmental attitudes	1.422902E+07	1.955793E+07
12	Infrastructure development	4154751	2.265499E+07
13	Structural characteristics	1.362988E+07	2.197756E+07
14	Accurate financial resource planning	4188333	2.291945E+07
15	Expansion of blockchain's role in the monetary and financial system	6989936	1.930158E+07
16	Realistic policy formulation	1.358386E+07	1.155007E+07
17	Technological performance evaluation	1.353068E+07	1397872
18	Revision of macro economic–political policies	1.617708E+07	2148486
19	Public trust and security	5742998	1.170301E+07
20	Transparency and accountability	8449739	1.436622E+07

In any research project, the researcher may define a number of iterations and consider them to enhance system stability. If the researcher does not specify a particular number of iterations, MICMAC software displays, by default, the required number of iterations to reach stability. The identification of hidden variables is conducted by multiplying the applied matrix within the indirect classification. In this section, the MICMAC software output includes the matrix-multiplication table in the classification, where two values are reported for each variable: one corresponds to the column sum and the other corresponds to the row sum. The row sum represents the indirect influence of variables, and the column sum represents the indirect dependence (or indirect susceptibility) of the respective variables. The sum table for the indirect effects is presented in Table 9.

Figure 3 presents the MICMAC diagram for the indirect influence matrix.

Figure 3

MICMAC diagram for the indirect influence matrix.

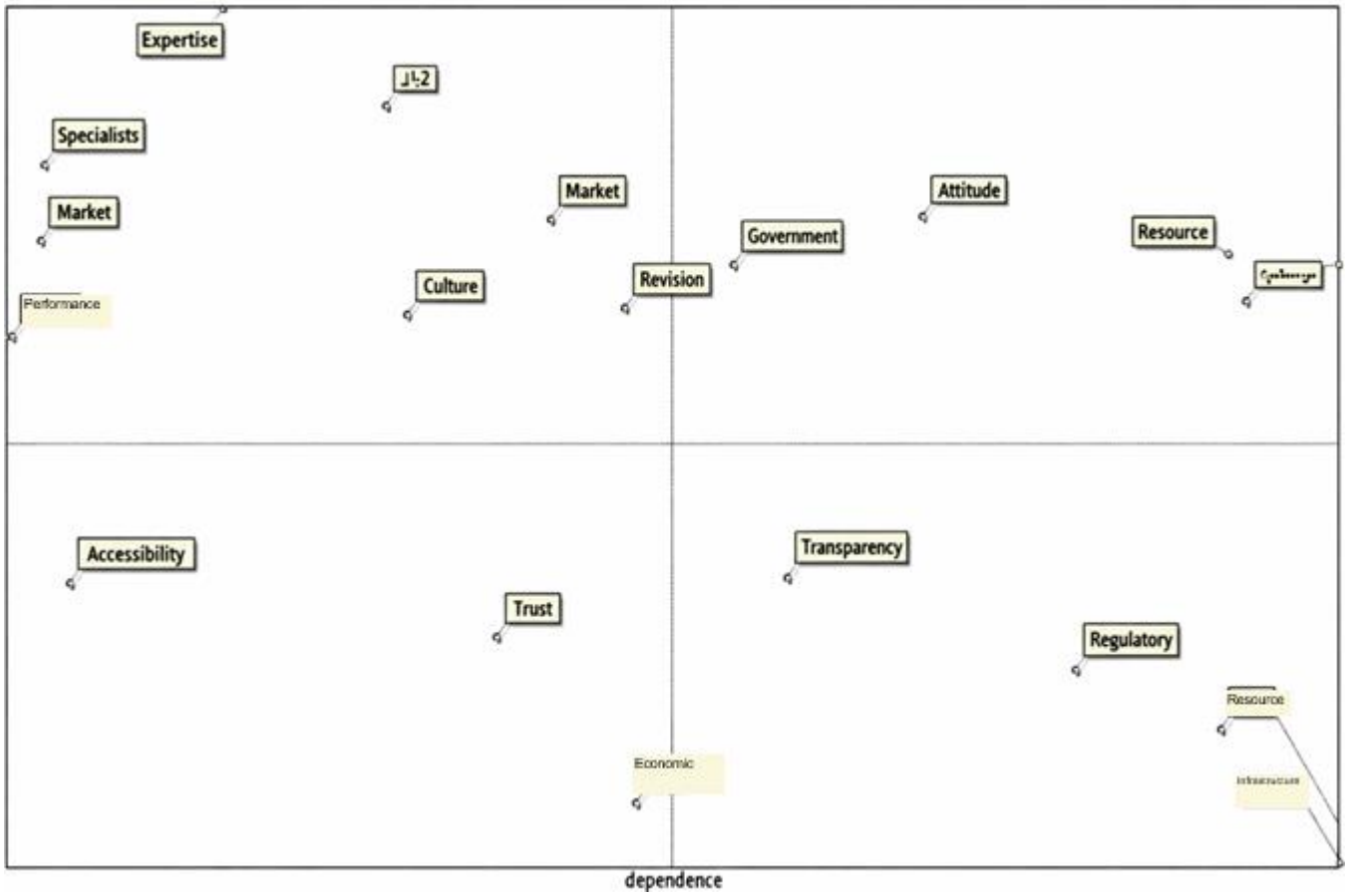
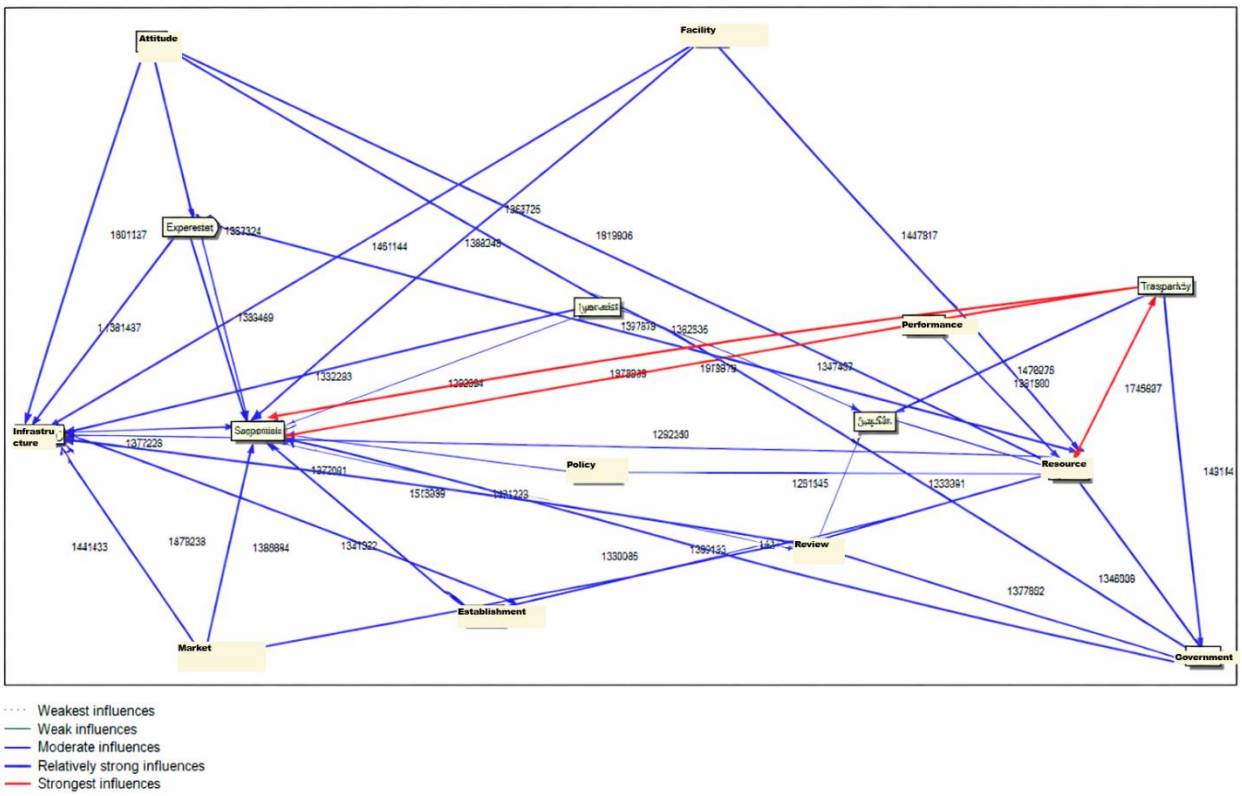


Figure 4 presents the diagram of the indirect influence matrix.

Figure 4

Diagram of the direct influence matrix.



3) Potential Direct Influence Matrix

The potential direct influence matrix also corresponds to the potential indirect influence matrix through successive iterations. In this section as well, the researcher may define the number of iterations deemed necessary to enrich system stability. Based on all variables, an overall ranking was conducted, and the results are presented in Table 10.

Table 10

Overall Ranking of Influence and Dependence in the Matrix

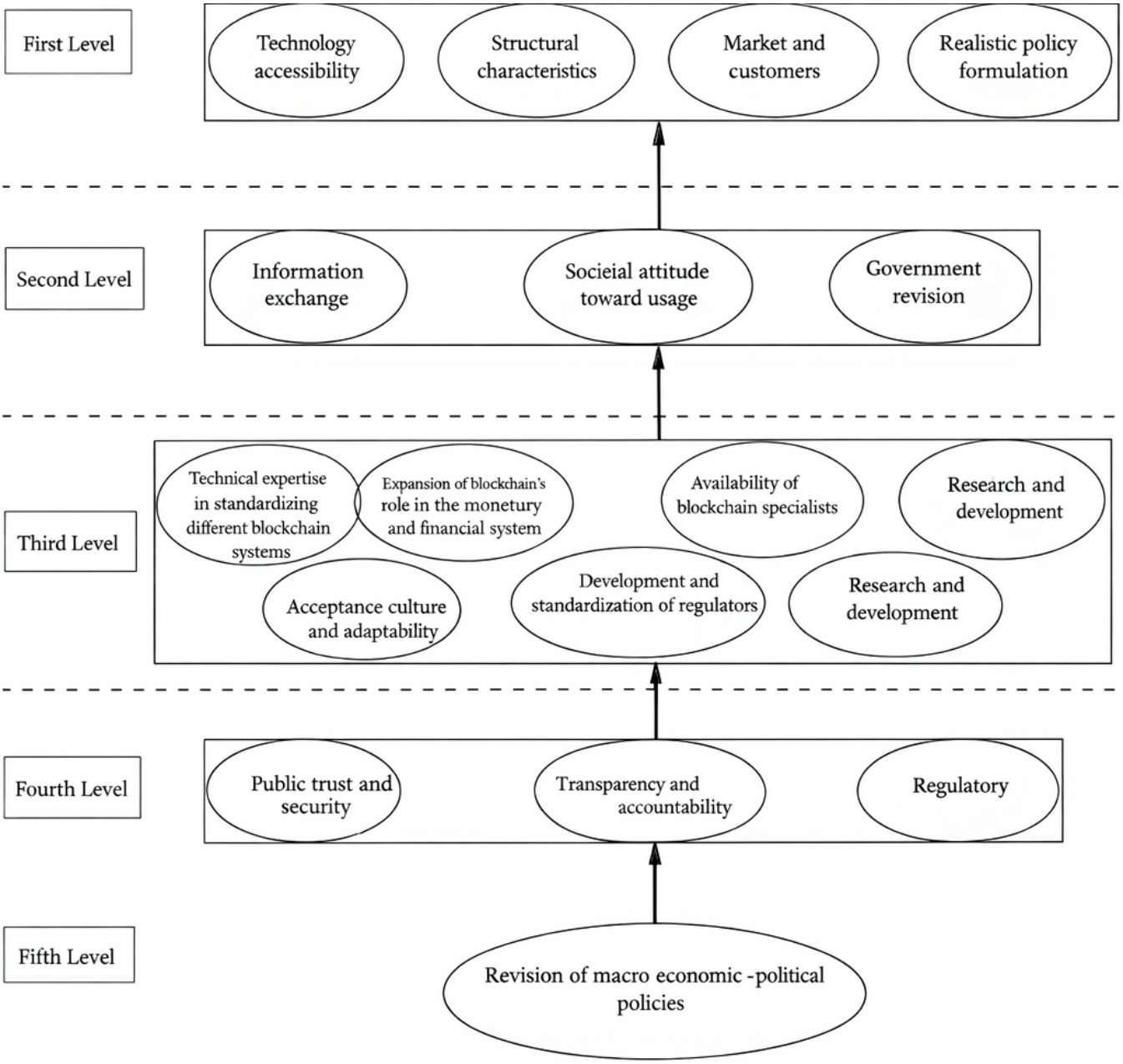
Rank	Drivers (Direct Influence)	Direct Influence	Drivers (Direct Dependence)	Direct Dependence	Drivers (Indirect Influence)	Indirect Influence	Drivers (Indirect Dependence)	Indirect Dependence
1	Attitude	687	Infrastructure	904	Specialists	762	Resources	947
2	Specialists	687	Structural	886	Attitude	707	Infrastructure	936
3	Revision	650	Resources	886	Revision	669	Structural	908
4	Establishment	614	Government	831	Ease of use	632	Government	808
5	Market	614	Blockchain	831	Market	627	Blockchain	798
6	Culture	614	Establishment	632	Establishment	610	Establishment	678
7	Expertise	614	R&D	560	Culture	609	Transparency	594
8	Government	614	Transparency	560	Government	588	Expertise	565
9	Structural	596	Market	542	Expertise	587	R&D	541
10	Ease of use	560	Culture	542	Structural	563	Trust	483
11	Exchange	542	Policy	470	Policy	561	Policy	477
12	Policy	542	Expertise	415	Performance	559	Market	430
13	R&D	506	Trust	415	R&D	549	Culture	417
14	Performance	488	Attitude	397	Exchange	545	Exchange	339
15	Transparency	379	Exchange	325	Transparency	349	Accessibility	327
16	Blockchain	361	Specialists	307	Blockchain	289	Attitude	314
17	Trust	307	Accessibility	216	Trust	237	Specialists	192
18	Accessibility	253	Revision	126	Accessibility	204	Ease of use	89
19	Infrastructure	198	Performance	90	Resources	173	Revision	88
20	Resources	162	Ease of use	54	Infrastructure	171	Performance	57

In this section, based on the obtained results, the drivers influencing the adoption of blockchain technology in the financial services of the national banking network were level-partitioned. Accordingly, the drivers identified through the literature

review and background analysis were classified into five levels. The results showed that the drivers of technology accessibility, structural characteristics, market and customers, and finally realistic policy formulation were placed at the first level, while the driver of revision of macro economic–political policies was positioned at the fifth level. Figure 5 presents the multi-level model of the drivers.

Figure 5

ISM model and level partitioning of the drivers influencing the adoption of blockchain technology in the financial services of the national banking network.



Discussion and Conclusion

The findings of this study provide a structured and systemic understanding of the drivers influencing the adoption of blockchain technology in financial services within the national banking network. Using interpretive structural modeling and MICMAC analysis, the results demonstrated that blockchain adoption is not a purely technological decision but rather a multidimensional phenomenon shaped by hierarchical interactions among environmental, organizational, technological, regulatory, and socio-behavioral factors. The classification of drivers into five hierarchical levels reveals that foundational macro-level variables exert strong indirect influence over operational and behavioral adoption outcomes. This systemic perspective aligns with contemporary research emphasizing that blockchain transformation in financial systems emerges from complex socio-technical ecosystems rather than isolated technological implementation [1, 2].

At the deepest level of the model, the revision of macro economic–political policies emerged as the most fundamental driver influencing blockchain adoption. This finding highlights the decisive role of governance structures and national policy orientation in enabling financial innovation. Regulatory uncertainty, institutional rigidity, and policy misalignment have been identified as major barriers preventing blockchain diffusion in banking systems. Previous studies demonstrate that effective policymaking frameworks are necessary to balance innovation incentives with financial stability concerns, particularly in emerging financial technologies [14]. Similarly, analyses of decentralized finance indicate that institutional and legal infrastructures significantly determine whether blockchain-based financial systems can scale beyond pilot stages [21]. The present findings therefore reinforce the argument that technological readiness alone cannot ensure adoption without supportive macroeconomic governance.

The fourth level of the model identified public trust and security, technological performance evaluation, and transparency and accountability as key intermediate drivers. These results underscore the centrality of trust-building mechanisms in blockchain adoption. Blockchain's core promise lies in enhancing transparency and reducing information asymmetry through immutable transaction records. Empirical research confirms that blockchain integration improves information transparency and strengthens trust among stakeholders across financial ecosystems [15]. Moreover, financial stability studies indicate that trust, risk monitoring, and governance quality significantly influence banking system resilience [16]. The strong positioning of transparency and security in this study demonstrates that adoption is closely tied to stakeholders' confidence in technological reliability and institutional safeguards.

Another important finding concerns the role of technological performance evaluation as a driving mechanism. Banks appear to prioritize performance validation before committing to large-scale adoption. This result is consistent with innovation adoption theories suggesting that perceived performance benefits and risk reduction strongly influence organizational acceptance of new technologies. Blockchain adoption research shows that firms evaluate operational efficiency, transaction speed, and cost reduction outcomes prior to investment decisions [9]. Furthermore, blockchain-enabled financial transformation has been shown to improve investment efficiency under conditions of macroeconomic uncertainty, reinforcing managerial incentives for adoption [11].

The third level of the hierarchy contained a broad set of organizational and technological capability drivers, including research and development, availability of blockchain specialists, technical expertise in standardization, financial resource planning, expansion of blockchain roles in financial systems, legal framework establishment, and infrastructure development. The prominence of these drivers indicates that organizational readiness plays a decisive role in blockchain diffusion. Human

capital capability, digital skills, and technological expertise are increasingly recognized as prerequisites for Banking 4.0 transformation. Studies examining AI-driven banking evolution highlight the growing importance of specialized talent and interdisciplinary competencies in managing digital financial innovation [13]. Similarly, technological hotspot analyses demonstrate that blockchain adoption accelerates in environments characterized by strong research investment and infrastructure maturity [5].

Infrastructure development, in particular, exhibited strong dependence relationships in the MICMAC analysis, indicating its role as an enabling rather than initiating factor. This finding supports previous research suggesting that infrastructure functions as a transmission mechanism through which policy, investment, and technological capability translate into operational adoption outcomes [17]. Supply chain finance studies also confirm that blockchain effectiveness depends heavily on technological integration across interconnected systems rather than isolated implementation [24]. Therefore, infrastructure development represents a critical but interdependent driver within the adoption ecosystem.

The inclusion of legal frameworks and supportive regulations among the influential drivers further validates regulatory alignment as a necessary adoption condition. Banking innovation policies must address data governance, interoperability, compliance requirements, and risk management simultaneously. Regulatory game-theory analyses emphasize that technological diffusion occurs when regulators, financial institutions, and technology providers achieve strategic balance and cooperation [14]. Without coordinated regulatory adaptation, even technologically advanced banking systems may hesitate to adopt blockchain solutions.

At the second level, information exchange, acceptance culture and adaptability, and societal attitudes toward technology use were identified as behavioral and social adoption drivers. This result highlights the significance of cultural readiness and user perception in financial innovation acceptance. FinTech adoption studies consistently show that perceived usefulness, social acceptance, and organizational culture strongly influence technological diffusion processes [8]. The presence of these variables confirms that blockchain adoption depends not only on institutional strategy but also on collective behavioral change among employees, customers, and stakeholders.

The role of societal attitudes toward technology is particularly notable. As financial services increasingly shift toward digital platforms, users demand faster, secure, and transparent services. Research on digital transformation indicates that customer expectations and digital trust significantly accelerate innovation adoption across industries [20]. Likewise, collaboration between banking institutions and FinTech startups enhances innovation diffusion by fostering adaptive organizational cultures and knowledge exchange mechanisms [7]. Therefore, behavioral readiness serves as a bridge connecting institutional policies with operational implementation.

At the first level of the hierarchy, technology accessibility, structural characteristics, market and customer factors, and realistic policy formulation emerged as the most immediate drivers influencing blockchain adoption outcomes. These variables directly shape implementation feasibility within banking operations. Market pressure and customer expectations increasingly compel banks to modernize financial infrastructures and introduce digital services. Structural organizational characteristics—including governance flexibility, operational processes, and strategic orientation—determine how effectively institutions respond to technological change [18]. Furthermore, realistic policymaking ensures that innovation initiatives remain aligned with institutional capabilities and economic realities.

The strong positioning of market and customer factors aligns with studies demonstrating that blockchain financial transformation reduces supply chain disruption risks and enhances service responsiveness, ultimately improving organizational competitiveness [12]. Market demand therefore acts as a direct catalyst translating strategic readiness into practical adoption. Additionally, blockchain technology has been associated with improvements in sustainability performance and digital investment outcomes, further reinforcing organizational motivation for adoption [19].

The MICMAC analysis further revealed the presence of linkage variables characterized by high influence and high dependence. These variables function as strategic leverage points capable of accelerating or destabilizing system transformation. Prior literature emphasizes that technological innovation systems often hinge on such linkage variables, where small policy or organizational adjustments can produce significant systemic effects [22]. The identification of these variables provides valuable managerial insight by highlighting areas where targeted interventions can maximize adoption effectiveness.

Overall, the results confirm that blockchain adoption in banking systems represents a layered transformation process beginning with macro-level governance reform, progressing through institutional capability development, and culminating in behavioral acceptance and operational implementation. This hierarchical pattern supports earlier findings indicating that financial innovation adoption follows systemic diffusion pathways shaped by environmental, organizational, and technological interactions [1, 2]. The present study extends prior research by empirically modeling these relationships and demonstrating how different drivers operate across multiple levels of influence.

Despite its contributions, this study has several limitations. First, the research relied on expert judgment within a specific national banking context, which may limit the generalizability of findings to other financial systems with different regulatory structures or technological maturity levels. Second, interpretive structural modeling captures perceived relationships among variables rather than causal relationships verified through longitudinal empirical data. Third, the relatively small sample size of experts, although acceptable for ISM methodology, may introduce subjective bias. Finally, rapid technological evolution in blockchain and financial technologies means that identified drivers may change over time as new innovations emerge.

Future studies can expand this research by employing quantitative validation methods such as structural equation modeling or longitudinal panel analysis to test causal relationships among adoption drivers. Comparative cross-country studies could also examine how institutional environments influence blockchain adoption pathways across developed and developing economies. Researchers may further integrate artificial intelligence readiness, cybersecurity maturity, and digital governance indicators into future adoption models. Additionally, examining customer-level adoption behavior alongside organizational readiness could provide a more comprehensive understanding of blockchain diffusion dynamics.

Banking policymakers should prioritize regulatory reform and macroeconomic alignment to create supportive innovation ecosystems for blockchain adoption. Financial institutions are encouraged to invest strategically in human capital development, technological infrastructure, and research capabilities to enhance organizational readiness. Managers should promote transparent governance practices and strengthen public trust mechanisms to facilitate stakeholder acceptance. Finally, collaborative partnerships between banks, FinTech firms, regulators, and technology providers can accelerate blockchain integration while reducing implementation risk and ensuring sustainable financial transformation.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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