A Model of Electronic Banking Services' Impact on Iraq's Financial System Development

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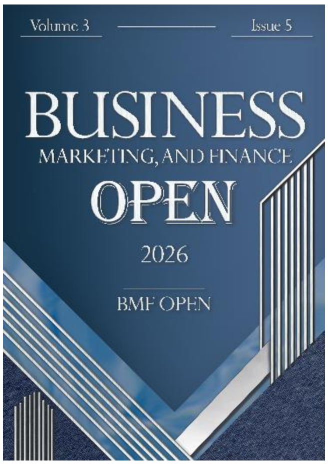

Citation: Shakir, G. H., Madanchi Zaj, M., & Kordlouie, H. (2026). A Model of Electronic Banking Services' Impact on Iraq's Financial System Development. *Business, Marketing, and Finance Open*, 3(5), 1-20.

Received: 15 October 2025
Revised: 14 January 2026
Accepted: 21 January 2026
Initial Publication: 08 February 2026
Final Publication: 01 September 2026

Abstract: This study aims to propose a model to examine the impact of electronic banking services on the development of Iraq's financial system. Electronic banking, through the introduction of channels such as online banking, mobile banking, and digital wallets, has enhanced accessibility, speed, and convenience in financial service delivery. This transformation has not only improved customer experience and reduced operational costs for banks but has also played a pivotal role in advancing financial inclusion, increasing financial literacy, and fostering economic growth. In this research, leveraging Fuzzy Delphi Method (FDM), Interpretive Structural Modeling (ISM), and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique, key factors influencing electronic banking were identified, and their causal relationships were analyzed. Subsequently, using Structural Equation Modeling (SEM), a comprehensive model illustrating the impact of these services on Iraq's financial system was developed. The findings revealed that components such as trust, security, digital innovation, and IT infrastructure serve as driving forces, significantly influencing user adoption and service efficacy. These factors indirectly affect other dimensions, including service quality, regulatory frameworks, and financial inclusion. Ultimately, the proposed model underscores the necessity of an integrated approach to digital banking development through infrastructure enhancement, trust-building, innovation, and legal reforms. This framework can serve as a guideline for policymakers, bank executives, and technology stakeholders in transitioning toward a more efficient and transparent financial system in Iraq.

Keywords: Electronic Banking, Financial System Development, Interpretive Structural Modeling (ISM), Fuzzy Delphi Method (FDM), Digital Innovation.

1. Introduction

The rapid diffusion of information and communication technologies has transformed banking from a branch-centered, paper-intensive service industry into a data-driven platform for payments, savings, lending, and customer relationship management. Within this transition, electronic banking (e-banking)—including internet banking, mobile banking, card-based transactions, and digital wallet ecosystems—has increasingly become a strategic capability that shapes how financial institutions compete, reduce transaction frictions, and serve households and firms. Recent scholarship indicates that e-banking is no longer an auxiliary delivery channel; rather, it is a multidimensional system that integrates service quality, security architecture, process innovation, and customer experience design into a unified model of value creation [1, 2]. This transformation has accelerated because users' expectations have shifted toward immediacy, personalization, and continuous availability, while banks' operational models have moved toward automation, real-time risk controls, and digitally mediated engagement mechanisms [3, 4]. As a result, understanding e-banking's contribution to broader financial system development requires moving beyond descriptive discussions and examining how underlying determinants—such as infrastructure readiness, adoption behavior, service quality, and trust—interact within a structured causal framework.

From a financial development perspective, digitalization can influence the financial system through multiple pathways. First, it can expand functional reach by lowering geographic and informational barriers to financial access, thereby strengthening inclusion. Second, it can enhance allocative efficiency by improving transaction speed, data quality, and service integration, which reduces intermediation costs and increases the reliability of payment and settlement mechanisms. Third, it can increase transparency by digitizing financial traces and improving monitoring capacity, which may contribute to reduced fraud, enhanced compliance, and better risk governance. Research that links e-banking to transparency and the mitigation of illicit behaviors emphasizes that electronic trails, automated controls, and standardized digital processes can strengthen financial integrity, support resource allocation, and reduce vulnerabilities to money laundering and banking crimes [5]. At the institutional level, e-banking also becomes closely tied to customer relationship management and loyalty dynamics because digital service delivery is repeatedly experienced and evaluated by customers, making satisfaction and perceived performance central to sustained use [6, 7]. Consequently, financial system development in a digital era is increasingly co-determined by both supply-side investment in digital capability and demand-side acceptance, trust, and usage behaviors.

The contemporary e-banking literature has matured along several interconnected themes. One major stream concentrates on modeling e-banking as a set of service dimensions that shape customer satisfaction and, ultimately, behavioral outcomes such as continued usage and loyalty. Empirical work using structural equation modeling shows that e-banking dimensions frequently exert their strongest effects indirectly, operating through customer satisfaction as a mediator between perceived service performance and outcomes such as retention, usage intensity, and recommendation behaviors [1]. Related studies extend this logic by examining service quality attributes as antecedents of satisfaction and loyalty. Evidence from multiple banking contexts suggests that higher perceived service quality—reflecting reliability, responsiveness, convenience, and usability—significantly predicts customer satisfaction and electronic loyalty, supporting the argument that quality is not merely an operational metric but a strategic driver of digital adoption and continued use [4, 8-10]. Complementing this, a dual-dimensional approach to electronic banking loyalty highlights that loyalty is both attitudinal and behavioral, requiring banks to address cognitive evaluations and repeated digital experiences simultaneously [7]. Collectively, these findings imply that a financial system's modernization through e-banking is likely to depend on sustained customer-level engagement processes rather than one-time adoption.

A second stream of research focuses on the determinants of adoption and intention to use e-banking, often drawing on the Technology Acceptance Model (TAM) and related behavioral frameworks. In this literature, perceived usefulness, perceived ease of use, and attitude formation are central explanatory constructs, frequently shaped by contextual factors such as cybercrime concerns, risk perceptions, and social influence. Recent evidence integrating TAM with a cybercrime perspective demonstrates that security threats and perceived risk can meaningfully alter adoption intentions, reinforcing the view that the benefits of digitization must be weighed against trust and safety concerns in the user's decision calculus [11]. In addition, work on antecedents of attitudes and behavioral intention shows that the impact of conventional adoption predictors can be contingent on moderating variables, including social influence and individual customer traits, suggesting that adoption is not uniform across user segments and should be modeled as a socially embedded behavior [12]. These findings are highly relevant for banking systems in transitional environments, where trust deficits, uneven digital literacy, and concerns about fraud may significantly condition adoption trajectories.

A third stream emphasizes how digital customer engagement and innovation features reshape the meaning of service delivery in financial contexts. As e-banking interfaces become richer and more interactive, banks are experimenting with advanced experience technologies to increase engagement, enhance perceived modernity, and strengthen relationship quality. Research on augmented reality in e-banking indicates that immersive and interactive technologies can enhance customer engagement, suggesting that digital banking is increasingly competing not only on functional efficiency but also on experiential differentiation [3]. In parallel, broader organizational and productivity perspectives show that e-banking can be associated with organizational performance through channels such as innovativeness, employee productivity, and the reconfiguration of operational processes, implying that the consequences of e-banking extend beyond customers to internal performance systems [13]. These insights align with the view that financial system development is influenced by the organizational capacity of banks to innovate and scale digital services, while also maintaining service reliability and workforce readiness.

A fourth stream concentrates on assessing and benchmarking e-banking development across regions or institutional environments, often using quantitative classification methods and indicator-based measurement. Research employing principal component and cluster analysis to evaluate electronic banking indicators across provinces illustrates that digital banking readiness is spatially uneven and that regions can be meaningfully segmented based on infrastructure and service performance patterns [14]. Such approaches are valuable for policymakers because they provide a diagnostic map of where digital interventions are most needed and where returns to investment may be highest. Similarly, the literature has proposed frameworks for technology transfer in electronic banking, highlighting that the diffusion of digital banking capabilities often depends on the structured movement of knowledge, processes, and technological assets, rather than the mere acquisition of hardware or software [15]. These contributions collectively suggest that a national financial system's digital modernization requires coordinated capability-building across institutions, geographies, and stakeholder networks.

While the above streams provide critical insights, they also reveal persistent gaps—particularly in linking e-banking expansion to the macro-level development of a financial system in transitional economies. Much of the adoption and service-quality literature is oriented toward customer-level outcomes (satisfaction, loyalty, usage intention), whereas the financial development question requires connecting these customer outcomes to system-level dimensions such as efficiency, inclusion, transparency, and institutional robustness. Studies on profitability and performance provide part of the system-level perspective, yet they are often restricted to specific banking models or regions. For instance, evidence from Sub-Saharan Africa on Islamic bank profitability suggests that e-banking can influence financial performance through identifiable determinants, but the findings also underscore that the effects of e-banking are context-sensitive and mediated by institutional conditions [16]. In other words, e-banking's contribution to financial system development cannot be assumed to be linear or universal; rather, it depends on the structure of the banking sector, regulatory maturity, cyber risk environment, and consumer trust norms.

This contextual dependency is particularly salient in environments facing post-conflict reconstruction, institutional fragmentation, and uneven infrastructure—conditions that closely resemble the operating realities of

Iraq's banking sector. In such environments, e-banking is simultaneously an opportunity and a risk: it can improve access, increase payment efficiency, and strengthen formal financial participation, yet it can also amplify vulnerabilities if cybersecurity, legal frameworks, and operational controls are insufficient. The adoption-focused literature highlights how cybercrime perceptions and trust concerns may become dominant inhibitors, implying that policy strategies must integrate safety, transparency, and consumer protection to realize the developmental promise of e-banking [11, 17]. The service-quality stream similarly implies that if digital services are unreliable, slow, or difficult to use, customers may not transition from cash-based or in-person transactions to digital alternatives, limiting system-level gains [8, 18]. Thus, in Iraq, the developmental outcomes of e-banking plausibly depend on a network of interdependent conditions: infrastructure adequacy, regulatory enforcement, trust and privacy safeguards, service quality, customer satisfaction, and sustained adoption.

At the same time, recent studies suggest that digital banking diffusion is widening across demographic groups, including younger and more digitally educated segments whose financial habits may shape future financial system structure. Evidence on the growth of e-banking among educated teenagers points to generational shifts in banking behavior and the potential for long-term expansion of digital-first financial participation [19]. Such findings matter for financial system development because youth adoption can create durable behavioral norms around digital payments and savings, which may increase the velocity and traceability of transactions over time. However, generational diffusion alone will not deliver system development if broader societal trust, digital literacy, and service reliability are not simultaneously addressed. The literature on loyalty further implies that even after initial adoption, continued use depends on stable satisfaction experiences, credible security, and perceived relational value, which necessitates continuous service improvement and customer engagement strategies [1, 3, 7].

Given these complexities, a purely linear modeling approach is unlikely to capture the structural realities of e-banking's role in financial system development. What is required is an integrated framework that (a) identifies the key determinants of e-banking development and effectiveness, (b) clarifies the causal structure and hierarchy among these determinants, and (c) tests how these interrelated dimensions translate into financial system development outcomes. Bibliometric mapping of e-banking scholarship shows that the field is expanding rapidly and increasingly multi-disciplinary, spanning marketing, information systems, risk management, and financial economics—yet it also indicates that integrative, system-level causal modeling remains comparatively limited, especially for under-studied contexts [2]. Accordingly, a methodological strategy that combines expert-driven indicator identification with causal structure modeling and empirical validation is well-aligned with the current research frontier.

In response to these needs, the present article is positioned at the intersection of three complementary research traditions. First, it builds on the service-quality and satisfaction tradition by treating perceived service performance as a central determinant of usage continuity and system-level benefits [4, 8, 9]. Second, it incorporates the adoption and intention tradition by acknowledging that technology acceptance is conditioned by security risks, privacy perceptions, and social influences, which shape customers' attitudes and behavioral intentions [11, 12, 17]. Third, it integrates innovation and capability perspectives by recognizing that digital banking transformation requires structured technology transfer, regional capability assessment, and organizational innovation that translate into improved operational performance and financial sector modernization [13-15]. In addition, the article aligns with governance and integrity arguments emphasizing that digital banking can strengthen transparency and compliance capacity, thereby supporting developmental outcomes in resource allocation and financial crime mitigation when appropriately governed [5]. The combined implication is that e-banking's developmental impact in Iraq is best understood as a system of interacting drivers and mediators rather than a single-factor effect.

The study's specific context—developing Iraq's financial system—further strengthens the relevance of such integrative modeling. Iraq's banking sector is characterized by a need to expand inclusion, improve service efficiency, rebuild trust, and align regulatory capacity with the growing complexity of digital transactions. International experience suggests that even where digital services are introduced, the absence of effective security assurance and privacy protection can constrain trust and reduce the sustainability of adoption, weakening potential financial system gains [11, 17]. Likewise, evidence across banking contexts indicates that satisfaction and engagement are not automatic by-products of digitization; they must be engineered through high-quality service design, reliable performance, and meaningful relational interaction, which jointly shape loyalty and long-term digital usage [1, 3, 7]. Therefore, policymakers and bank executives require not only descriptive insights but also a structured decision model that can prioritize interventions among infrastructure, innovation, service quality, regulation, and trust-building.

Accordingly, this article contributes by proposing and validating an integrated model that links electronic banking services to financial system development in Iraq through a structured sequence of identification, causal structuring, and empirical testing, consistent with contemporary methodological calls to connect e-banking drivers to both customer outcomes and broader system-level development implications [2, 16, 18].

The aim of this study is to develop and validate a comprehensive model explaining how electronic banking services influence the development of Iraq's financial system through the structured interaction of infrastructure readiness, service quality, trust and security, user adoption dynamics, regulatory support, financial inclusion, and digital innovation.

2. Methodology

This study represents a hybrid of fundamental and applied research. On one hand, it aims to design and validate a conceptual framework elucidating the role of electronic banking in developing Iraq's financial system. On the other hand, its findings provide practical guidance for and economic policymakers to enhance financial and digital infrastructure. The research adopts a mixed-methods approach (qualitative-quantitative) and implements analytical phases through deductive-inductive reasoning. As an exploratory and developmental study, it combines content analysis by experts, interpretive structural modeling (ISM), fuzzy DEMATEL causal relationship analysis, and Likert-scale questionnaires.

The study population comprises domain experts in digital banking, finance, and investment with specialized knowledge and practical experience in Iraq's digital financial services. Participants were categorized into three groups: (1) senior executives of (2) banking IT specialists, and (3) finance and investment faculty members. A hybrid sampling technique combining judgmental and snowball sampling was employed. Initially, highly qualified participants were selected through judgmental sampling, who then recommended other qualified experts (snowball sampling) until theoretical saturation was achieved. The fuzzy Delphi process involved 20 experts, whose inputs were also used for ISM and fuzzy DEMATEL analyses. Data collection instruments included a 7-point linguistic scale fuzzy Delphi questionnaire, where expert opinions (e.g., "very high," "high," "medium," "low") were converted to triangular fuzzy numbers (see Table 1 for fuzzy number equivalents).

Table 1: 7-point fuzzy linguistic scale for Delphi analysis

Linguistic Term	Triangular Fuzzy Number
Very Low	(0.0, 0.0, 0.1)
Low	(0.0, 0.1, 0.3)
Moderately Low	(0.1, 0.3, 0.5)
Medium	(0.3, 0.5, 0.7)
Moderately High	(0.5, 0.7, 0.9)
High	(0.7, 0.9, 1.0)
Very High	(0.9, 1.0, 1.0)

To analyze the conceptual structure of the indicators, we employed the Self-Structured Interaction Matrix (SSIM) and the Initial Reachability Matrix within the framework of Interpretive Structural Modeling (ISM). Additionally, to examine the causal relationships among the indicators, we utilized a Fuzzy Direct Relationship Matrix based on the Fuzzy DEMATEL technique. In the final stage, to measure the impact of the identified factors from the perspective of end-users (customers of both public and private banks in Iraq), a structured questionnaire was designed and distributed. The questionnaire was developed using a 5-point Likert scale, as presented in Table 2.

Table 2: 5-point Likert scale for variable measurement

Response Option	Score
Strongly Disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Figure (1) presents the step-by-step implementation process of the Interpretive Structural Modeling (ISM) and MICMAC analysis, beginning with literature review and expert interviews, followed by identification of research indicators and sub-criteria and data collection, subsequently constructing the Structured Self-Interaction Matrix (SSIM) based on expert opinions which is then transformed into an Initial Reachability Matrix, followed by consistency evaluation and potential revision cycles to achieve required consistency levels, leading to development of the Final Reachability Matrix and structural level classification of indicators, ultimately resulting in conceptual model development based on inter-indicator relationships and execution of MICMAC analysis to examine variable influence and dependence patterns, thereby enabling identification of key, dependent, and linking variables within the system.

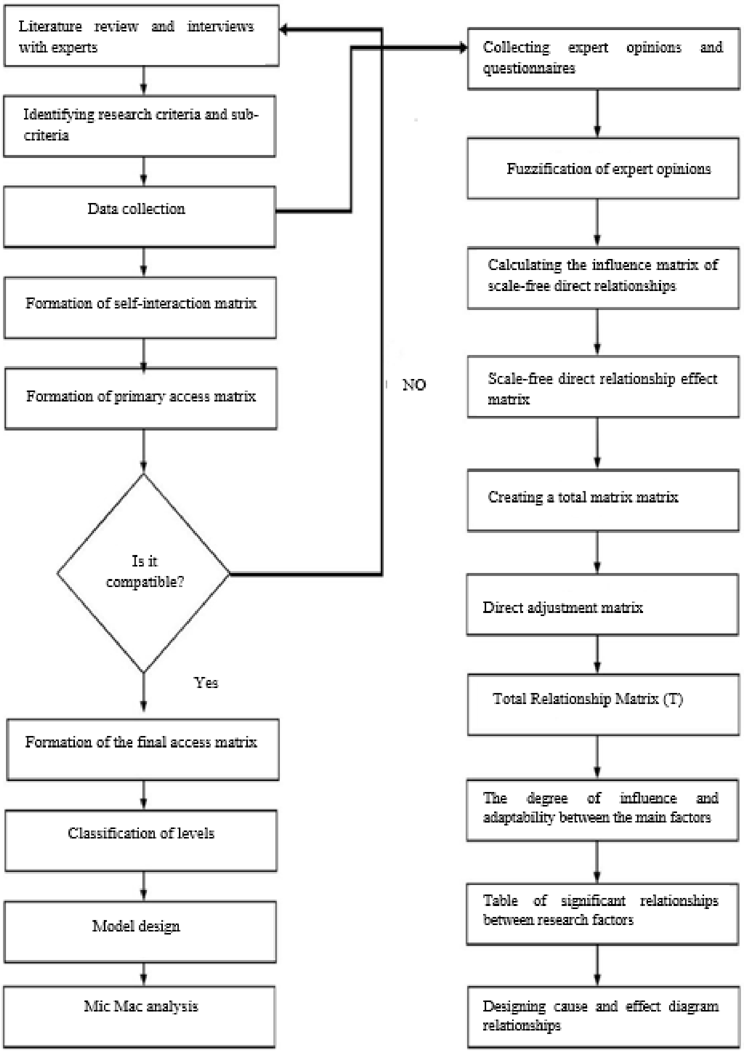

Figure 1: Implementation Stages of the Hybrid Research Method

The subsequent section illustrates the combined execution phases of the Fuzzy Delphi Method and Fuzzy DEMATEL causal relationship analysis. The process begins with outputs from expert interviews and questionnaire data collected in previous stages. The linguistic data obtained from experts are then encoded and fuzzified using fuzzy set theory to reduce ambiguity and uncertainty inherent in human judgments. Next, based on the fuzzy data, a direct influence relation matrix is extracted and normalized to derive the final direct influence matrix. These data are used to compute the total relation matrix, encompassing both direct and indirect effects among the indicators. In the final steps, the influence degree and dependence degree of each indicator are calculated, determining their causal strength and interdependence. The process concludes by plotting a causal relationship diagram to analyze the position and role of each research indicator within the overall model structure.

3. Findings and Results

This section examines the relationship between electronic banking services (as the independent variable) and the development of the financial system in (as the dependent variable), along with a set of influential factors, as reported in Table (3):

Table 3: Criteria and sub-criteria of the impact of electronic banking services on the development of the financial

Main Criteria	Code	Sub-criteria	Code	References
ICT Infrastructure	A	High-speed internet access	A1	[24,25,26,27]
		Network stability and quality	A2	
		Bank investments in IT	A3	
		Mobile/internet banking usability	A4	
E-banking Service Quality	B	Transaction processing speed	B1	[25,28,29,40,41]
		Service variety (payments, transfers, inquiries)	B2	
		24/7 service availability	B3	
		Application ease-of-use	B4	
Trust & Security	C	Strong authentication systems	C1	[30,31,32,33,42]
		Cybersecurity protection	C2	
User Adoption	D	Digital banking usage rate	D1	[7,28,34,41,42]
		User digital literacy	D2	
		Willingness to replace in-person services	D3	
		Customer satisfaction	D4	
Market Development Impact	E	Increased financial transaction volume	E1	[29,26,40,46,47]
		Reduced operational costs	E2	
		Accelerated money circulation	E3	
Regulatory Framework	F	Clear digital banking regulations	F1	[26,33,43]
		Government support for digital transformation	F2	
		Central Bank's supervisory role	F3	
Financial Inclusion	G	Improved access for underserved populations	G1	[33,35,44,45]
		Online account opening	G2	
		Mobile services for low-income customers	G3	
Digital Innovation	H	Service innovation level	H1	[36,37,25,7,9]
		Emerging tech adoption (blockchain, AI, biometrics)	H2	
		Digital wallet development	H3	
		Digital culture promotion	H4	

The implementation of the fuzzy Delphi technique was conducted in this phase. Following questionnaire collection, expert opinions were aggregated and analyzed through frequency analysis of responses and repetition of viewpoints. Indicators achieving the highest consensus among respondents were selected as the final research criteria. The methodological workflow of the interpretive structural model is illustrated in Figure (1). The finalized indicators, utilized in designing the ISM (Interpretive Structural Modeling) questionnaire, are systematically presented in Table (4) as a Structured Self-Interaction Matrix (SSIM). This matrix formulation enables the hierarchical structuring of interdependencies among identified factors through pairwise comparison of expert judgments, where directional relationships between variables (V, A, X, O notations) establish the foundational logic for subsequent reachability matrix development and cross-impact matrix multiplication (MICMAC analysis).

Table 4: Self-Structured Interaction Matrix (SSIM)

	A	B	C	D	E	F	G	H
A		V	V	V	V	O	V	V
B			V	X	V	O	V	V
C				A	A	O	O	O
D					A	O	O	O
E						A	A	V
F							V	V
G								O
H								

Following the principles of Interpretive Structural Modeling (ISM), after constructing the Self-Structured Interaction Matrix (SSIM), it is essential to convert this matrix into an Initial Reachability Matrix. This conversion involves transforming the qualitative relationships between indicators (represented by the letters V, A, X, and O) into equivalent numerical values according to the following coding rules:

- If indicator i influences indicator j, a value of 1 (denoted by V) is assigned
- If indicator j influences indicator i, a value of -1 (denoted by A) is recorded
- When a bidirectional relationship exists between i and j, a value of 2 (denoted by X) is allocated
- In cases where no relationship exists between i and j, a value of 0 (denoted by O) is applied

The consensus of expert opinions regarding inter-indicator relationships and the resulting numerical transformation of the SSIM are presented in Table (5). This matrix conversion represents a critical methodological step that enables subsequent reachability analysis and hierarchical partitioning within the ISM framework, ultimately facilitating the identification of key driving factors and dependence relationships within the complex system under investigation.

Table 5: Expert Consensus on Indicator Relationships

	A	B	C	D	E	F	G	H
A	1	1	1	1	1	0	1	1
B	1-	1	1	2	1	0	1	1
C	1-	1-	1	1-	1-	0	0	0
D	1-	2	1	1	1-	0	0	0
E	1-	1-	1	1	1	1-	1-	1
F	0	0	0	0	1	1	1	1
G	1-	1-	0	0	1	1-	1	0
H	1-	1-	0	0	1-	1-	0	1

Formation of Initial Reachability Matrix: Following the numerical transformation of the Self-Structured Interaction Matrix (SSIM) and application of ISM modeling rules, the Initial Reachability Matrix was constructed, which captures expert-validated direct relationships between indicators through binary coding (1 indicating a direct causal influence where row affects column, and 0 denoting no direct relationship), thereby establishing the foundation for subsequent structural analyses including hierarchical partitioning and influence-dependence assessment through MICMAC methodology, with the complete matrix presented in Table (6) following standard ISM conventions for system structure modeling.

Table 6: Development of the Reachability Matrix

	A	B	C	D	E	F	G	H
A	1	1	1	1	1	0	1	1
B	0	1	1	1	1	0	1	1
C	0	0	1	0	0	0	0	0
D	0	1	1	1	0	0	0	0
E	0	0	1	1	1	0	0	1
F	0	0	0	0	1	1	1	1
G	0	0	0	0	1	0	1	0
H	0	0	0	0	0	0	0	1

The matrix presented in Table (7) systematically quantifies influence-dependence relationships among indicators through binary coding, where each row summation represents the driving power (total influence exerted by an indicator) and each column summation reflects the dependence power (total influence received by an indicator). This computational approach enables:

Table 7: Final Reachability Matrix Formation

	A	B	C	D	E	F	G	H	Convergence
A	1	1	1	1	1	0	1	1	7
B	0	1	1	1	1	0	1	1	6
C	0	0	0	0	0	0	0	0	1
D	0	1	1	1	1	0	1	1	6
E	0	1	1	1	1	0	0	1	5
F	0	0	1	1	1	1	1	1	6
G	0	0	1	1	1	0	1	1	5
H	0	0	0	0	0	0	0	1	1
Dependency	1	4	7	6	6	1	5	7	

The results presented in Table (8) quantify the driving power (influence) and dependence (vulnerability) of each indicator, calculated from the final reachability matrix. This analysis enables the classification of indicators into four distinct clusters through MICMAC (Matrice d'Impacts Croisés-Multiplication Appliquée à un Classement) methodology:

Table 8: Analysis of Driving Power and Dependence of Indicators Using MICMAC Technique

Indicator	Dependence	Driving Power
A	1	7
B	4	6
C	7	1
D	6	6
E	6	5
F	1	6
G	5	5
H	7	1

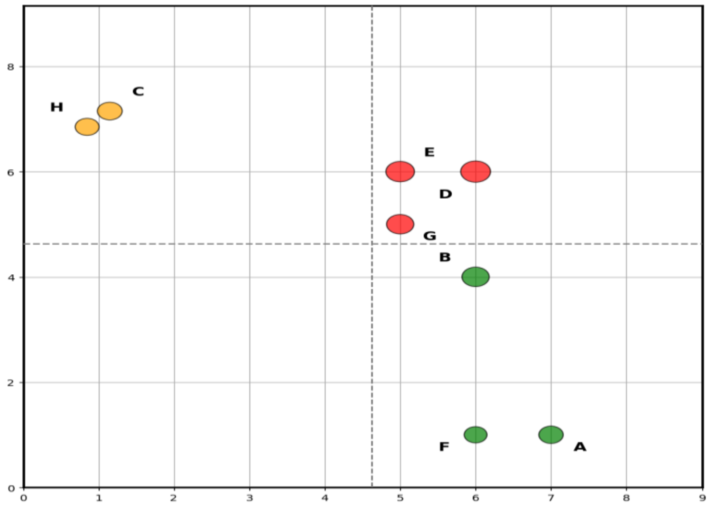

Figure 2: Influence-Dependence Power Analysis

Figure (2) illustrates the positioning of each indicator based on its driving power (horizontal axis) and dependence level (vertical axis), providing a visual representation of their systemic influence and interdependence through quadrant analysis. This graphical representation facilitates the identification of four distinct indicator clusters: autonomous (low driving power/low dependence), dependent (low driving power/high dependence), linkage (high driving power/high dependence), and independent (high driving power/low dependence) variables, which are critical for understanding the system's structural dynamics.

Following the development of the initial reachability matrix, the subsequent phase in Interpretive Structural Modeling (ISM) involves rigorous consistency verification of the matrix's internal logic. Any identified inconsistencies are resolved through systematic relationship analysis, yielding the final reachability matrix that serves as the foundation for hierarchical decomposition. The level partitioning process then commences, involving the iterative computation of three fundamental sets for each indicator: (1) the reachability set (elements influenced by the indicator), (2) the antecedent set (elements influencing the indicator), and (3) the intersection set (common elements between both sets). An indicator is assigned to a specific hierarchical level when its reachability set perfectly matches its intersection set, after which it is removed from subsequent iterations to enable progressive level identification. This methodical process, documented step-by-step in Tables (9) through (14), ultimately produces a complete hierarchical structure of the system's indicators.

Table 9: Identification of Level 1 Factors

Iteration	Indicator	Reachability Set	Antecedent Set	Intersection Set
Exit > Level 1	3	C	A, B, C, D, E, F, G	C
Exit > Level 1	8	H	A, B, D, E, F, G, H	H

Table 10: Identification of Level 2 Factors

Iteration	Indicator	Reachability Set	Antecedent Set	Intersection Set
Exit > Level 2	4	B, D, E, G	A, B, D, E, F, G	B, D, E, G
Exit > Level 2	5	B, D, E	A, B, D, E, F, G	B, D, E

Table 11: Identification of Level 3 Factors

Iteration	Indicator	Reachability Set	Antecedent Set	Intersection Set
Exit > Level 3	7	G	A, B, F, G	G

Table 12: Identification of Level 4 Factors

Iteration	Indicator	Reachability Set	Antecedent Set	Intersection Set
Exit > Level 4	2 (B)	B	A, B	B
Exit > Level 4	6 (F)	F	F	F

Table 13: Identification of Level 5 Factor

Iteration	Indicator	Reachability Set	Antecedent Set	Intersection Set
Fifth	1	A	A	A

Table 14: Final ISM Hierarchical Structure

Level	Primary Factor	Secondary Factor
1	C	H
2	D	E
3	G	-
4	B	F
5	A	-

In this phase, the fuzzy DEMATEL technique was employed to examine causal relationships and mutual influences among the identified factors. DEMATEL questionnaires were used to collect necessary data from expert panels, assessing the degree of influence each factor exerts on others based on fuzzy linguistic scales. Following data collection, expert opinions were analyzed through standard fuzzy DEMATEL procedures, including:

- Fuzzification of collected responses.
- Calculation of the normalized direct influence matrix.
- Computation of the total relation matrix.
- Extraction of influence (D) and receptivity (R) values for each factor.
- Drawing a cause-and-effect diagram.

Formation of the Average Matrix (Matrix A): The initial step after collecting questionnaires on main criteria was to construct the average matrix. In this study, assessments from 20 experts regarding the influence of each main factor on others were compiled to derive the average matrix. Table (15) presents the average expert opinion matrix (Matrix A).

Table 15: Average Expert Opinion Matrix (Direct Relation Matrix or Matrix A)

	A	B	C	D	E	F	G	H
A	0	3.52	3.15	2.91	2.49	3.66	2.81	3.14
B	2.71	0	2.16	2.74	2.72	2.92	2.29	2.21
C	1.35	1.24	0	1.93	2.8	1.16	2.18	2.74
D	2.94	2.98	2.29	0	2.82	2.66	2.8	2.79
E	2.25	2.78	2.88	2.85	0	2.42	2.74	2.9
F	3.59	3.27	1.97	2.81	2.31	0	2.78	2.37
G	2.83	2.15	2.66	2.83	2.59	2.81	0	2.68
H	1.53	2.26	2.74	2.67	2.81	2.37	2.69	0

Calculation of the Normalized Direct Influence Matrix (Matrix D): The normalized direct influence matrix was derived by normalizing the average expert opinion matrix (Matrix A) through multiplication with a normalization factor. This factor was determined by: (1) calculating row and column sums of Matrix A, (2) identifying the maximum sum value, (3) taking its inverse, and (4) selecting the smallest resultant value as the normalization factor (Formula (1)). The computational results are presented in Tables 16 and 17.

$$k = \max\left\{\max\left(\sum_{j=1}^{n} x_{ij}\right), \sum_{i=1}^{n} x_{ij}\right\} = 21.68$$

Table 16: Calculation of the Normalization Coefficient

	A	B	C	D	E	F	G	H
A	0	0.16	0.15	0.13	0.11	0.17	0.13	0.14
B	0.13	0	0.1	0.13	0.13	0.13	0.11	0.1
C	0.06	0.06	0	0.09	0.13	0.05	0.1	0.13
D	0.14	0.14	0.11	0	0.13	0.12	0.13	0.13
E	0.1	0.13	0.13	0.13	0	0.11	0.13	0.13
F	0.17	0.15	0.09	0.13	0.11	0	0.13	0.11
G	0.13	10	0.12	0.13	0.12	0.13	0	0.12
H	0.07	0.1	0.13	0.12	0.13	0.11	0.12	0

Table 17: Normalized Direct Influence Matrix (Matrix D)

	A	B	C	D	E	F	G	H
A	1	0.16-	0.15-	0.13-	0.11-	0.17-	0.13-	0.14-
B	0.13-	1	0.10-	0.13-	0.13-	0.13-	0.11-	0.10-
C	0.06-	0.06-	1	0.09-	0.13-	0.05-	0.10-	0.13-
D	0.14-	0.14-	0.11-	1	0.13-	0.12-	0.13-	0.13-
E	0.10-	0.13-	0.13-	0.13-	1	0.11-	0.13-	0.13-
F	0.17-	0.15-	0.09-	0.13-	0.11-	1	0.13-	0.11-
G	0.13-	010-	0.12-	0.13-	0.12-	0.13-	1	0.12-
H	0.07-	0.10-	0.13-	0.12-	0.13-	0.11-	0.12-	1

Computing the Total Relation Matrix (T): Following derivation of the normalized direct influence matrix (D), the fuzzy DEMATEL methodology proceeds to calculate the total relation matrix (T), which captures both direct and indirect inter-factor influences within the system. The computation involves three sequential operations: (1) subtracting D from the identity matrix (I) to obtain (I-D), (2) inverting the resultant (I-D) matrix, and (3) multiplying D by this inverse matrix, as formalized in Equation 2:

$$T=D\times(I-D)^{-1}$$

In this matrix, the rows represent the degree of influence each factor exerts on other factors, while the columns indicate the degree to which each factor is influenced by others. Thus, computing this matrix enables in-depth analysis of causal relationships between the indicators. The results of these calculations, including matrix D, matrix $(I - D)^{-1}$, and ultimately the total relation matrix, are presented in subsequent research tables (Tables 18 to 20).

Table 18: Values of Matrix (I - D)

	A	B	C	D	E	F	G	H
A	1.6211	0.7926	0.7669	0.7882	0.7669	0.7908	0.7701	0.7982
B	0.6368	1.5526	0.6318	0.6787	0.672	0.6652	0.6499	0.6606
C	0.4559	0.4732	1.4141	0.513	0.5429	0.4662	0.5137	0.5461
D	0.683	0.7136	0.6774	1.6085	0.7175	0.6962	0.7095	0.724
E	0.6379	0.6849	0.6801	0.7043	1.5836	0.6661	0.6878	0.7085
F	0.7084	0.7259	0.6653	0.7236	0.6983	1.589	0.7088	0.7085
G	0.6576	0.6606	0.6696	0.701	0.6868	0.6787	1.5733	0.698
H	0.5642	0.6156	0.6261	0.6467	0.648	0.6141	0.6362	1.5393

Table 19: Inverse Matrix $(I - D)^{-1}$

	A	B	C	D	E	F	G	H
A	1.6211	0.7926	0.7669	0.7882	0.7669	0.7908	0.7701	0.7982
B	0.6368	1.5526	0.6318	0.6787	0.672	0.6652	0.6499	0.6606
C	0.4559	0.4732	1.4141	0.513	0.5429	0.4662	0.5137	0.5461
D	0.683	0.7136	0.6774	1.6085	0.7175	0.6962	0.7095	0.724
E	0.6379	0.6849	0.6801	0.7043	1.5836	0.6661	0.6878	0.7085
F	0.7084	0.7259	0.6653	0.7236	0.6983	1.589	0.7088	0.7085
G	0.6576	0.6606	0.6696	0.701	0.6868	0.6787	1.5733	0.698
H	0.5642	0.6156	0.6261	0.6467	0.648	0.6141	0.6362	1.5393

Table 20: Total Relation Matrix (T) (Matrix of Total Direct and Indirect Influences)

	A	B	C	D	E	F	G	H
A	0.6211	0.7926	0.7669	0.7882	0.7669	0.7908	0.7701	0.7982
B	0.6368	0.5526	0.6318	0.6787	0.672	0.6652	0.6499	0.6606
C	0.4559	0.4732	0.4141	0.513	0.5429	0.4662	0.5137	0.5461
D	0.683	0.7136	0.6774	0.6085	0.7175	0.6962	0.7095	0.724
E	0.6379	0.6849	0.6801	0.7043	0.5836	0.6661	0.6878	0.7085
F	0.7084	0.7259	0.6653	0.7236	0.6983	0.589	0.7088	0.7085
G	0.6576	0.6606	0.6696	0.701	0.6868	0.6787	0.5733	0.698
H	0.5642	0.6156	0.6261	0.6467	0.648	0.6141	0.6362	0.5393

The index (D + R) represents the sum of each factor's influence (D) and receptivity (R), indicating its overall interaction intensity within the system. Higher values denote greater structural importance. The index (D - R) reflects the net causal role: positive values classify factors as causes (influential), while negative values categorize them as effects (receptive). Table (21) presents the calculated values of influence (D), receptivity (R), prominence (D + R), and causal role (D - R) for all factors.

Table 21: Influence and Receptivity Measures Among Key Factors

Factor	Influence (D)	Receptivity (R)	Net Cause/Effect (D-R)	Prominence (D+R)
A	4.9649	6.0948	-1.1299	11.0597
B	5.219	5.1476	0.0714	10.3666
C	5.1313	3.925	1.2063	9.0562
D	5.3638	5.5296	-0.1658	10.8934
E	5.3159	5.3532	-0.0373	10.6691
F	5.1663	5.5279	-0.3616	10.6941
G	5.2494	5.3256	-0.0762	10.5749
H	5.3832	4.8901	0.4931	10.2732

The causal diagram developed through the DEMATEL technique positions the horizontal axis (D+R) to indicate each indicator's overall importance (combining influence and receptivity), while the vertical axis (D-R) determines its causal role. Indicators on the right side of the horizontal axis are classified as causal factors (drivers), with higher D+R values indicating stronger systemic influence. Conversely, indicators on the left side are effect factors (receivers), where lower D+R values denote greater receptivity. Although the total relation matrix suggests nearly universal inter-factor influences, many such relationships are weak and analytically insignificant. Therefore, applying a threshold value is essential to focus on meaningful relationships. In this study, following standard DEMATEL practice and banking expert consensus, the mean value of all entries in the total relation matrix was adopted as the threshold. Only relationships exceeding this threshold were retained as significant. The final screened relationships are presented in Table (22).

Table 22: Research Threshold Value

Threshold (τ)	0.653

The study employed a threshold-based approach to identify meaningful causal relationships in the DEMATEL model by analyzing the total relation matrix. First, the arithmetic mean of all matrix values was calculated and established as the significance threshold (τ=0.653). Each matrix value was then compared against this threshold: values ≥τ were coded as 1 (indicating significant causal relationships), while values <τ were coded as 0 (non-significant relationships). This process generated a binary matrix containing only statistically significant interactions, which served as the foundation for constructing the network relationship map and conducting the final model analysis. The complete results of this thresholding procedure are presented in Table (23), providing a clear distinction between meaningful and negligible causal connections in the system.

Table 23: Significant Relationships Among Research Factors

	A	B	C	D	E	F	G	H
A	0	1	1	1	1	1	1	1
B	0	0	0	1	1	1	0	1
C	0	0	0	0	0	0	0	0
D	1	1	1	0	1	1	1	1
E	0	1	1	1	0	1	1	1
F	1	1	1	1	1	0	1	1
G	1	1	1	1	1	1	0	1
H	0	0	0	0	0	0	0	0

Table 23's threshold application revealed key causal relationships among factors, identifying influential elements and receptive ones. These relationships form the basis for the final conceptual model analysis. Figure 3 presents them as a directed network, where arrows indicate influence paths, clarifying each factor's relative position and role in the model structure.

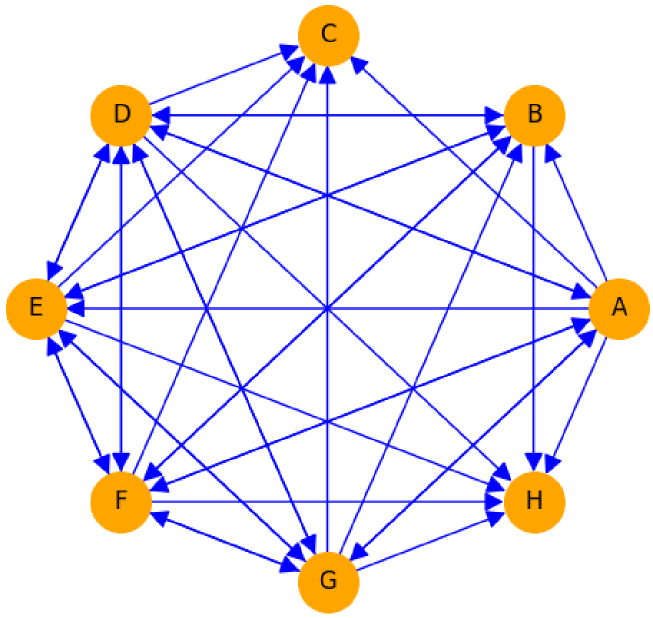

Figure 3: Causal Diagram of Factors Influencing Electronic Banking Services on Iraq's Financial System Development

Figure (3) Analysis: The causal diagram reveals the mutual influence patterns among factors affecting electronic banking's impact on Iraq's financial system development, demonstrating how identified elements interact as either drivers or receivers within the network structure.

4. Discussion and Conclusion

The findings of this study provide a coherent and multi-layered explanation of how electronic banking services contribute to the development of Iraq's financial system by operating through an interdependent set of technological, behavioral, organizational, and institutional mechanisms. The integrated application of the fuzzy Delphi method, Interpretive Structural Modeling (ISM), and fuzzy DEMATEL allowed the study to move beyond isolated factor analysis and instead reveal a structured causal architecture in which certain dimensions function as primary drivers while others operate as mediators or outcome-oriented components. In line with the proposed model, the results demonstrate that electronic banking does not exert a direct and uniform effect on financial system development; rather, its impact is transmitted through a network of reinforcing relationships among infrastructure readiness, service quality, trust and security, user adoption, regulatory support, financial inclusion, and digital innovation.

One of the most salient findings of the ISM and DEMATEL analyses is the dominant causal role of trust and security, digital innovation, and ICT infrastructure as key driving forces within the system. These factors exhibit high driving power and relatively lower dependence, positioning them as foundational enablers of other dimensions. This result is consistent with prior research emphasizing that security, privacy, and reliability are prerequisite conditions for customer engagement and loyalty in electronic banking environments [11, 17]. In contexts characterized by heightened sensitivity to financial risk and institutional fragility, such as Iraq, trust-related concerns appear to exert a disproportionate influence on user behavior. The present findings reinforce evidence that perceived security and privacy protection significantly enhance customer confidence, which in turn facilitates adoption, satisfaction, and continued usage of digital banking services [4, 8]. Accordingly, trust and security function not merely as service attributes but as systemic stabilizers that condition the effectiveness of all other e-banking investments.

The structural positioning of ICT infrastructure as a high-level driver further highlights the importance of technological readiness in shaping the success of electronic banking initiatives. Robust internet connectivity, reliable transaction platforms, and scalable IT systems enable banks to deliver consistent and efficient digital services, which then support higher levels of user adoption and service quality. This finding aligns with regional and cross-provincial assessments showing that disparities in electronic banking performance are closely linked to infrastructural differences [14]. Similarly, frameworks for technology transfer in electronic banking emphasize that without effective infrastructural absorption capacity, digital innovations remain underutilized or fragmented [15]. In the Iraqi context, the results suggest that infrastructure investment is not a peripheral concern but a central lever for financial system modernization, as deficiencies at this level propagate constraints throughout the entire system.

Digital innovation also emerged as a critical causal factor influencing multiple downstream variables, including service quality, user adoption, and financial inclusion. The DEMATEL results indicate that innovation-related dimensions—such as the adoption of advanced digital tools and the diversification of electronic service offerings—strengthen the system's adaptive capacity and expand the functional scope of banking services. This is consistent with empirical evidence showing that innovativeness enhances organizational performance and productivity by enabling banks to redesign processes and improve service delivery efficiency [13]. Moreover, customer-facing innovations, including interactive and experience-enhancing technologies, have been shown to increase engagement and perceived value in digital banking environments [3]. The present study extends these insights by demonstrating that innovation also plays a system-level role, indirectly supporting financial inclusion and transparency by lowering access barriers and facilitating continuous service availability.

User adoption and service quality occupy an intermediate position in the model, functioning as both influenced and influencing variables. The ISM hierarchy and DEMATEL causal mapping indicate that while adoption and service quality are shaped by infrastructure, trust, and innovation, they also exert feedback effects on financial system outcomes. This mediating role is strongly supported by prior research demonstrating that customer satisfaction and perceived service quality are central pathways through which e-banking dimensions translate into loyalty, sustained usage, and broader financial participation [1, 9, 10]. In particular, studies adopting structural equation modeling approaches consistently show that service quality influences financial outcomes indirectly via satisfaction and attitudinal loyalty, rather than through immediate transactional effects [7, 8]. The current findings corroborate this mechanism by situating adoption and quality as critical transmission channels between technological drivers and system-level development.

Financial inclusion appears in the model as a predominantly dependent variable, reflecting its sensitivity to upstream improvements in service accessibility, affordability, and usability. The results suggest that electronic banking contributes to financial inclusion by enabling remote account access, reducing transaction costs, and offering services tailored to diverse user groups. This aligns with evidence that digital banking expansion broadens participation by lowering entry barriers for underserved populations, particularly when supported by reliable service quality and trust mechanisms [2, 4]. Furthermore, research on the diffusion of e-banking among younger and digitally educated segments indicates that early adoption can create long-term inclusion effects by establishing digital-first financial habits [19]. The present study integrates these perspectives by demonstrating that inclusion outcomes are not automatic but contingent upon coordinated progress across infrastructure, innovation, regulation, and user acceptance.

The regulatory framework is identified as a supportive yet indirectly influential factor within the system. While not the most dominant driver in terms of direct causal power, regulation plays a crucial enabling role by reinforcing trust, mitigating cyber risks, and ensuring compliance. This finding is consistent with arguments that effective governance and legal clarity enhance the credibility of electronic banking systems, thereby amplifying the benefits of technological investments [5]. In environments where regulatory oversight is weak or ambiguous, even technically advanced systems may fail to gain user confidence. The present results thus underscore that regulation functions as an institutional backbone that stabilizes interactions among technological and behavioral components.

At the aggregate level, the model supports the view that electronic banking contributes to financial system development through a cumulative and synergistic process rather than through isolated interventions. Profitability-focused studies in different regions have shown that the financial impact of e-banking is mediated by institutional and contextual determinants [16]. Similarly, analyses of service quality in commercial banks emphasize that improvements in one dimension often require complementary changes elsewhere to achieve sustainable outcomes [18]. The current study advances this literature by offering an empirically grounded causal structure that explains how such complementarities operate in a transitional financial system. By integrating expert judgment with causal modeling and user-level data, the findings provide a nuanced explanation of why partial or uncoordinated digital initiatives may yield limited developmental returns.

Overall, the discussion highlights that electronic banking serves as a strategic infrastructure for financial system development in Iraq, but its effectiveness depends on the alignment of technological capability, institutional trust, service performance, and regulatory support. The results are broadly consistent with international evidence while also reflecting context-specific sensitivities related to security, adoption, and institutional maturity. By clarifying the causal hierarchy among key factors, the study offers both theoretical and practical insights into how digital banking can be leveraged as a driver of systemic financial transformation.

Despite its contributions, this study has several limitations that should be acknowledged. First, the expert-based components of the fuzzy Delphi, ISM, and DEMATEL analyses rely on subjective judgments, which, although systematically aggregated, may still reflect contextual biases or experiential limitations of the selected panel. Second, the empirical validation focuses on customers of public and private banks within Iraq, which may limit the generalizability of the findings to other countries or financial systems with different institutional structures. Third, the cross-sectional nature of the survey data restricts the ability to capture dynamic changes in adoption behavior and system development over time.

Future research could extend this work by employing longitudinal designs to examine how the causal relationships among electronic banking factors evolve as digital maturity increases. Comparative studies across countries with similar post-conflict or transitional financial systems would also help assess the external validity of the proposed model. In addition, future studies could integrate objective performance indicators, such as transaction volumes or cost-efficiency metrics, with perceptual measures to strengthen causal inference. Finally, exploring the role of emerging technologies, such as artificial intelligence-driven personalization or blockchain-based settlement systems, could further enrich understanding of digital banking's developmental impact.

From a practical perspective, policymakers and bank managers should prioritize coordinated investments rather than isolated digital initiatives. Strengthening cybersecurity and privacy protection should be treated as a foundational requirement for building user trust. Simultaneously, sustained investment in ICT infrastructure and service innovation is essential to ensure reliable and inclusive access. Regulatory authorities should focus on clarifying digital banking rules and enhancing supervisory capacity to support innovation while mitigating risk. Finally, banks should adopt a user-centered approach to service design, emphasizing simplicity, reliability, and continuous engagement to translate technological capability into meaningful financial system development.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

References

[1] S. M. Minhaj and M. A. Khan, "Dimensions of E-Banking and the Mediating Role of Customer Satisfaction: A Structural Equation Model Approach," *International Journal of Business Innovation and Research*, vol. 36, no. 1, pp. 42-57, 2025, doi: 10.1504/IJBIR.2025.143944.

[2] R. Mintah, G. M. Y. Owusu, R. Amoah-Bekoe, and G. Obro-Adibo, "Banking without limits: a bibliometric analysis of scholarly works on electronic banking," *International Journal of Bank Marketing*, vol. ahead-of-print, no. ahead-of-print, 2023, doi: 10.1108/IJBM-02-2023-0086.

[3] K. Mukerjee, "Augmented reality and customer engagement in the context of e-banking," *Journal of Financial Services Marketing*, vol. 29, no. 4, pp. 1559-1571, 2024, doi: 10.1057/s41264-024-00284-6 10.1057/s41264-024-00290-8.

[4] A. Tahtamouni, "E-banking services and the satisfaction of customers in the Jordanian banks," *Journal of Science and Technology Policy Management*, vol. 14, no. 6, pp. 1037-1054, 2023, doi: 10.1108/JSTPM-06-2021-0082.

[5] F. Kalibri, "The Impact of Electronic Banking on Financial Transparency, Resource Allocation, and Combating Money Laundering and Banking Crimes," 2022. [Online]. Available: https://civilica.com/doc/1738016.

[6] L. Abdollahzadeh Ramhormozi, A. H. Azh, and M. Khaki, "Evaluation and ranking service quality in the banking system and its impact on CRM Rishi Kant from the model (Case study: Melli Bank of Iran)," (in en), *Transactions on Data Analysis in Social Science*, vol. 5, no. 1, pp. 11-24, 2023, doi: 10.47176/TDASS/2023.11.

[7] M. Nourizadeh, K. Nourbakhsh, and F. Haqshenas, "Designing a Dual-Dimensional Model of Customer Loyalty for Electronic Banking Services," *Consumer Behavior Studies*, vol. 10, no. 2, pp. 113-137, 2023. [Online]. Available: https://cbs.uok.ac.ir/article_62705.html?lang=en.

[8] S. G. Ayinaddis, B. A. Taye, and B. G. Yirsaw, "Examining the effect of electronic banking service quality on customer satisfaction and loyalty: an implication for technological innovation," *Journal of Innovation and Entrepreneurship*, vol. 12, no. 1, p. 22, 2023, doi: 10.1186/s13731-023-00287-y.

[9] A. Widayanti and I. A. Alam, "The Influence of E-Banking and Service Quality on Loyalty in Customers of Bank Bri Unit Bukit Kemuning Lampung Utara," *Formosa Journal of Multidisciplinary Research*, vol. 3, no. 2, pp. 305-316, 2024, doi: 10.55927/fjmr.v3i2.8262.

[10] S. Yousefi Chermehini, M. R. Pasand, and M. Yousefi Chermehini, "Investigating the Impact of Electronic Banking Service Quality on Customer Satisfaction and Electronic Loyalty at Bank Mellat Branches in Ahvaz," in *Ninth International and*

National Conference on Management, Accounting, and Law, Tehran, 2023. [Online]. Available: https://elmnet.ir/doc/11229296-81261.

[11] B. Kaulu, G. Kaulu, and P. Chilongo, "Factors influencing customers' intention to adopt e-banking: a TAM and cybercrime perspective using structural equation modelling," *Journal of Money and Business,* vol. 4, no. 1, pp. 38-53, 2024, doi: 10.1108/JMB-01-2024-0007.

[12] Y. K. Liao, H. L. T. Nguyen, T. C. Dao, P. T. T. Nguyen, and H. Sophea, "The antecedents of customers' attitude and behavioral intention of using e-banking: The moderating roles of social influence and customers' traits," *Journal of Financial Services Marketing,* vol. 29, no. 3, pp. 1037-1061, 2024, doi: 10.1057/s41264-023-00254-4.

[13] D. A. O. Apendi, K. Li, J. B. B. Pea-Assounga, and P. D. R. Bambi, "Investigating the impact of e-banking, employee job security, innovativeness, and productivity on organizational performance: Perspectives from South Africa," *Sustainable Futures,* vol. 9, p. 100605, 2025, doi: 10.1016/j.sftr.2025.100605.

[14] A. Farhang, S. Kianpour, and S. Hosseinnia Chafjiri, "Assessment of Electronic Banking Indicators in Provinces Using Principal Component and Cluster Analysis Approaches," *Islamic Economics and Banking Journal,* vol. 14, no. 51, pp. 359-384, 2022.

[15] M. Dehbid, A. Shah Mansouri, and S. A. Derakhshan, "Presenting a Technology Transfer Framework in Electronic Banking," *Business Management,* 2023.

[16] K. Adalessossi, "Impact of E-Banking on the Islamic bank profitability in Sub-Saharan Africa: What are the financial determinants?," *Finance Research Letters,* vol. 57, p. 104188, 2023, doi: 10.1016/j.frl.2023.104188.

[17] B. Vojdani, "Investigating the Impact of Privacy and Security of Electronic Banking Services on Customer Loyalty with Emphasis on Reliability," in *1st International Conference on Management, Industrial Engineering, Accounting, and Economics in Humanities*, 2024. [Online]. Available: https://civilica.com/doc/2025680.

[18] K. Traore and O. K. Loang, "The Factors That Influence E-Banking Service Quality In Guinea's Commercial Banks," *International Journal of Accounting,* vol. 8, no. 46, pp. 153-167, 2023.

[19] M. M. Nirmala and N. S. Kumar, "A Study on E-Banking Services and Its Growth Among the Educated Teenagers in Bangalore," in *Information and Communication Technology in Technical and Vocational Education and Training for Sustainable and Equal Opportunity: Education, Sustainability and Women Empowerment*: Springer Nature Singapore, 2024, pp. 481-493.