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Providing a Model for Assessing the Implementation and Deployment of Artificial Intelligence in the Banking Industry

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ABSTRACT

Artificial intelligence (AI) technology, through its self-learning algorithms, has played a significant role in enhancing banking processes. By reducing human resource costs, analyzing data, and identifying patterns, this technology has assisted policymakers in achieving organizational objectives. Despite these advantages, a precise evaluation and the provision of adequate infrastructure prior to its implementation in banks, particularly in developing countries, is essential. In Iranian banks, due to infrastructural weaknesses, the successful execution of AI has been challenging, necessitating technological and organizational preparations to minimize issues of incompatibility and rising costs. This study employs a mixed-methods (quantitative and qualitative) research design. The expert community for the qualitative phase consisted of 18 individuals selected via purposive snowball sampling. For the quantitative phase, involving factor analysis, a sample of 342 specialists was selected using Cochran's sampling formula. Questionnaire reliability for the factor analysis was assessed using Cronbach's alpha coefficient and SPSS software. In the qualitative phase, 34 factors were initially extracted from prior literature using a content analysis approach. These were then refined to 27 factors through a three-round Fuzzy Delphi process based on expert opinion. Subsequently, these confirmed factors were structured into indicators and sub-indicators using Exploratory Factor Analysis (EFA) with specialist input. Finally, Confirmatory Factor Analysis (CFA) was applied to formulate structural equations and validate the final model. The indicators, ranked by order of importance based on standardized coefficients, are: Data Management and Infrastructure (0.90), AI Systems and Algorithms (0.84), Customer Experience and Interaction (0.76), Security and Risk Management (0.73), and Business Process and Optimization (0.53).

Keywords: Artificial Intelligence, Assessment, Implementation, Banking Industry

Introduction

The banking industry is undergoing a profound transformation driven by the rapid integration of Artificial Intelligence (AI). AI's unprecedented ability to process vast volumes of structured and unstructured financial data with speed and precision is reshaping the way banks design services, manage risks, and compete in increasingly digital markets [1, 2]. Traditional banking operations that relied heavily on human expertise and rule-based systems are no longer sufficient to address the complexity and scale of digital transactions [3]. Instead, AI-powered analytics, predictive modeling, and automation enable banks to reduce human error, accelerate decision-making, improve personalization, and strengthen fraud detection [4, 5]. These developments are not merely incremental improvements but strategic enablers of competitiveness and sustainable growth.

AI lies at the heart of the ongoing digital transformation by moving beyond basic automation toward intelligence-driven services [6, 7]. Through machine learning, deep learning, and natural language processing, banks can anticipate customer needs, evaluate creditworthiness in real time, and redesign workflows for greater efficiency [8, 9]. Digital touchpoints such as chatbots, voice assistants, and virtual financial advisors are redefining customer interaction, offering personalized financial recommendations and 24/7 support [10, 11]. These technologies not only enhance customer satisfaction but also increase operational agility and cost efficiency [12, 13]. At the same time, the convergence of AI with complementary technologies such as blockchain and big data analytics is fostering secure and transparent transactions, improving fraud detection, and reinforcing trust in financial services [1, 6]. This integration creates new digital ecosystems and strengthens regulatory compliance while mitigating cyber risks [4, 14-16].

A major frontier of AI adoption is customer-centric innovation. By analyzing diverse data streams—from purchase histories to behavioral signals—AI-driven systems support dynamic credit scoring, personalized loan offers, investment guidance, and predictive default management [17, 18]. These capabilities help banks cultivate stronger customer loyalty and retention in competitive environments [19]. AI-powered customer relationship management integrates multi-source data to deliver context-aware recommendations and seamless onboarding [12, 13]. Such personalization enhances trust and digital engagement, making financial services more intuitive and responsive [10, 11]. In parallel, user interface redesign and automated service channels reduce complexity for consumers and operational burden for banks [20, 21].

Operational efficiency is another major value driver of AI. Intelligent systems enhance decision-making across credit risk analysis, liquidity planning, asset allocation, and compliance monitoring [2, 9]. Predictive fraud detection algorithms can rapidly identify anomalies in transactional data, preventing losses and safeguarding reputation [4, 14]. Simultaneously, robotic process automation reduces manual workloads in repetitive tasks such as data entry and regulatory reporting [5, 20]. By redirecting human resources toward complex, strategic decision-making, banks improve agility and cost-effectiveness [16, 22]. These transformations are vital in emerging markets where resource constraints and competitive pressures require lean yet innovative operating models [23, 24].

Alongside efficiency gains, AI is reshaping security and risk management in banking. As digital banking expands, cyberattacks and fraud have become increasingly sophisticated. AI-based systems detect anomalies, predict potential threats, and secure sensitive financial data through advanced encryption and behavioral analytics [4, 14]. AI also enables more dynamic compliance management, automating reporting and risk evaluation while adapting to evolving regulations [6, 18]. However, the adoption of AI-driven security measures raises new challenges, particularly regarding algorithmic fairness and transparency [1, 9]. Ethical and explainable AI models are needed to maintain trust and regulatory approval [15, 24], while strong governance frameworks must ensure compliance and data privacy [7, 19].

Despite the global momentum, the adoption of AI is uneven across contexts. Developed economies benefit from mature digital infrastructures and clear regulatory guidance, but many emerging economies face significant barriers [6, 23]. Inadequate data governance, high implementation costs, legacy IT systems, and a shortage of AI talent impede adoption [5, 20]. Banks in these environments often encounter integration problems, escalating costs, and cultural resistance to technological change [18, 23]. Concerns about workforce displacement and organizational readiness further slow transformation [5, 10]. In addition, smaller institutions struggle with the financial burden of building AI-capable infrastructure and risk falling behind in competitiveness [15-17, 19]. These disparities underscore the need for tailored strategies and structured frameworks to guide AI deployment.

Current scholarship recognizes the necessity of comprehensive AI implementation models that address the interplay of technology, organizational capacity, and governance [23, 24]. Many existing studies focus narrowly on technological readiness or user adoption but fail to integrate the full spectrum of requirements for sustainable and safe AI-driven transformation [1, 2]. The absence of holistic frameworks leads to fragmented adoption efforts, inefficiencies, and increased exposure to operational and regulatory risks [15, 18]. Scholars increasingly call for models that combine robust data management, adaptable AI algorithms, secure infrastructure, regulatory alignment, and cultural readiness [4, 6, 11, 20]. Additionally, ethical AI practices and capacity-building initiatives are crucial to prepare both employees and customers for these technologies [10, 19].

Addressing these gaps is particularly urgent for emerging banking systems seeking to modernize without exposing themselves to systemic risk or excessive costs [23, 24]. A structured and validated framework can help banks assess readiness, align data and infrastructure with AI requirements, adapt algorithms to local challenges, optimize customer interaction, and strengthen cybersecurity [1, 15]. It also supports policymakers in designing adaptive regulations that promote innovation while ensuring fairness and stability [7, 16]. By providing actionable guidance, such a model can reduce fragmentation, improve cost-effectiveness, and accelerate sustainable digital transformation [20, 21].

Therefore, the aim of this study is to develop and empirically validate a comprehensive, multi-dimensional model for assessing and guiding the implementation of artificial intelligence in the banking industry to support sustainable, secure, and value-driven digital transformation.

Methodology

This study employed a mixed-methods research design, integrating qualitative and quantitative approaches to develop and validate a comprehensive model for AI implementation in the banking sector.

The qualitative phase utilized content analysis to identify and extract pertinent factors from the existing body of literature. As a established qualitative method in scientific research, content analysis enables the systematic and structured examination of qualitative data, facilitating the identification of core patterns and themes. A comprehensive review of scientific articles and reports was conducted, from which factors with a direct or indirect influence on the research subject were extracted and systematically analyzed. Table 1 presents the list of key factors identified from the literature, which served as the foundational input for the subsequent quantitative phase.

Table 1

Extracted Factors from Previous Studies (Qualitative Method)

No.	Extracted Factor (Aligned with Research Objective)	Source
1	Degree of compatibility of AI with banking processes	Tang S. M. et al., 2020
2	Existence of systems for collecting customer experience information	Tang S. M. et al., 2020
3	Degree of alignment of database structure with AI needs	Deshpande R. S., 2020
4	Existence of mechanisms for collecting employee performance information	Deshpande R. S., 2020
5	Proper orientation of service delivery processes in the IT environment as much as possible	Deshpande R. S., 2020
6	Mechanization of financial flows in the IT environment	Giltikyn O. J. et al., 2020
7	Proper implementation of algorithms required to optimize AI performance in e-banking	Giltikyn O. J. et al., 2020
8	Existence of comprehensive and effective market sensitivity analysis structures	Carpenter T., 2020
9	Existence of mechanisms for collecting positive customer experience information	Carpenter T., 2020
10	Existence of appropriate infrastructure for providing electronic financial services	Mihata J., 2020
11	Use of customized and dedicated databases tailored to system needs	Mihata J., 2020
12	Existence of mechanisms to evaluate the quality of information in the system	Smith A. et al., 2020
13	Formulation of mechanisms to ensure information security	Smith A. et al., 2020

14	Use of structures ensuring the speed of information transfer	Smith A. et al., 2020
15	Application of risk analysis mechanisms in the system for evaluation and measurement	Almeyotairi M. et al., 2020
16	Designing mechanisms to prevent cyber fraud	Almeyotairi M. et al., 2020
17	Existence of suitable infrastructure for maximum digitization of banking services and processes	Kayur N. et al., 2020
18	Designing processes considering machine learning infrastructure needs	Di L., 2020
19	Existence of a comprehensive structure for identifying cyber threats	Khimka P. et al., 2020
20	Existence of mechanisms facilitating digital processes in the bank	Zain N. R. M. et al., 2020
21	Digital comprehensiveness of interactions between employees and customers	Raisio E., 2019
22	Existence of mechanisms for sentiment and opinion analysis of customers and converting it to digital data	Kaya O. et al., 2019
23	Proper adaptation of neural networks and support vector machines with the target system	Dagieu O. H. N., 2019
24	Implementation of communication channels with customers to collect AI system data	Foyori L. et al., 2019
25	Proper alignment between hardware required for data collection and system needs	Crossman P., 2018
26	Implementation of infrastructure for chatbots, voice assistants, auto-verification, and biometric technology	Crossman P., 2018
27	Proper infrastructure to ensure successful performance of learning models in the system	Li A., 2017
28	Meeting banking service orientation needs in the AI environment	Castilli M. et al., 2016
29	Providing necessary infrastructure for calculating banking profits in AI environment	Sonmalz F. et al., 2015
30	Use of suitable, comprehensive, and inclusive databases	Sonmalz F. et al., 2015
31	Explainability and acceptance of technology by employees and banking processes	Li J. C. et al., 2022
32	Secure and reliable data management for successful AI integration	Almeyotairi M. et al., 2020
33	Existence of trust-building mechanisms for customer technology adoption	Noreen U. et al., 2023
34	Proper implementation of prediction models based on artificial neural networks in AI environment	Aydin E. D. et al., 2015

The quantitative phase employed factor analysis techniques to structure and validate the conceptual model. Specifically, Exploratory Factor Analysis (EFA) was used to develop the initial model and classify the identified factors into coherent categories. Subsequently, Confirmatory Factor Analysis (CFA) was applied to test the robustness and validate the fit of the developed model. This phase relied on the input of two distinct groups of specialists, as detailed below.

Two panels were defined for this research:

1- Expert Panel: This panel consisted of 18 individuals selected through a purposive snowball sampling technique. These experts were engaged in multiple stages of the research: defining the characteristics for the specialist pool, naming the factors and indicators during the EFA process, and validating the methodological steps. The selection criteria for experts were as follows:

- Possession of a Master's degree or higher.
- A minimum of five years of executive experience in banking automation and related technologies.
- Demonstrable knowledge and expertise in AI approaches, processes, and mechanisms.
- Holding a senior-level organizational or executive position relevant to the research objectives.

2. Specialist Panel: The broader specialist population comprised 342 individuals, selected based on the criteria established by the expert panel and the researcher's accessibility. From this population, a sample size of 181 specialists was determined using Cochran's sampling formula. This group was utilized for data collection via the EFA and CFA questionnaires. The characteristics of the specialists were:

- Possession of a Bachelor's degree or higher.
- Knowledge and awareness of Artificial Intelligence concepts.
- Familiarity with the fundamentals of using AI technology in the banking industry.

Holding mid-level management or operational positions within banks

Findings and Results

The factors extracted from the literature were refined using the Fuzzy Delphi technique, incorporating the input of 18 research experts over three rounds. This process resulted in the reduction of the initial 34 factors to a final set of 27 key factors. Subsequently, a conceptual model was developed using Exploratory Factor Analysis (EFA). This analysis was performed on data collected through a questionnaire based on the effective factors identified from prior studies. The data analysis for the EFA was conducted using SPSS software. The resulting factor groupings were then reviewed, confirmed, and named by the expert panel, leading to the establishment of the study's conceptual model.

In the second stage, to validate this model, Confirmatory Factor Analysis (CFA) was employed to formulate structural equations and verify the integrity of the conceptual model. A new questionnaire, designed with reflective items based on the established model, was distributed to the panel of specialists. The final model was then analyzed using LISREL software.

The computational procedure for the Fuzzy Delphi technique was as follows: After converting the linguistic variables from expert responses into their corresponding triangular fuzzy numbers (each defined by a lower limit, a middle point, and an upper limit), the average of all corresponding upper, middle, and lower limits was calculated for each factor (defuzzified mean) . This step produced a consolidated view of all expert opinions which is shown in Table 2.

Table 2

Screening with Fuzzy Delphi Method (First Round)

No.	Factors	Fuzzy Bounds of Factors (L, M, U)			defuzzified mean
		L	M	U	
1	Alignment of AI with banking processes	0.605	0.855	0.895	0.803
2	Development of mechanisms to guarantee information security	0.605	0.855	0.895	0.803
3	Design of mechanisms to prevent cyber fraud	0.697	0.947	0.947	0.885
4	Synchronization of database structures with AI requirements	0.632	0.868	0.882	0.813
5	Creating a suitable foundation to ensure the successful operation of learning models in the system	0.566	0.816	0.842	0.76
6	Mechanization of financial flows on an IT platform	0.566	0.816	0.842	0.76
7	Existence of a comprehensive structure for identifying cyber threats	0.526	0.776	0.829	0.727
8	Proper adaptation of neural networks and support vector machines to the target system	0.553	0.789	0.829	0.74
9	Accurate implementation of prediction models based on artificial neural networks within the AI framework	0.553	0.789	0.829	0.74
10	Secure and reliable data management for AI integration	0.461	0.697	0.789	0.661
11	Existence of comprehensive and effective market sensitivity analysis	0.539	0.789	0.842	0.74
12	Presence of information quality assessment mechanisms within the system	0.539	0.776	0.816	0.727
13	Suitable foundations for successful learning patterns	0.513	0.75	0.803	0.704
14	Use of structures guaranteeing data transfer speed	0.474	0.711	0.776	0.668
15	Implementation of risk analysis mechanisms in the system for assessment and measurement	0.618	0.868	0.895	0.813
16	Correct implementation of algorithms for optimizing AI performance in e-banking	0.566	0.816	0.868	0.766
17	Existence of mechanisms for collecting employee performance information	0.539	0.789	0.842	0.74
18	Existence of a platform for maximizing the digitization of banking services and processes	0.553	0.789	0.842	0.743
19	Integration of employee and customer data into AI	0.447	0.684	0.776	0.648
20	Trust-building mechanisms for customer technology adoption	0.553	0.803	0.855	0.753
21	Effective orientation of service delivery processes through information technology	0.513	0.75	0.803	0.704
22	Process design considering the needs of machine learning infrastructure	0.605	0.855	0.868	0.796
23	Use of appropriate, comprehensive, and inclusive databases	0.487	0.724	0.789	0.681
24	Existence of suitable infrastructure for providing e-financial services	0.526	0.776	0.842	0.73
25	Use of customized proprietary databases tailored to system needs	0.526	0.776	0.829	0.727
26	Presence of systems for collecting information from customer experiences	0.539	0.776	0.829	0.73
27	Structural design for effective cultural preparation for successful AI implementation	0.605	0.855	0.895	0.803

28	Providing the necessary infrastructure for calculating bank interest in an AI environment	0.553	0.803	0.855	0.753
29	Implementation of communication channels with customers to gather data for the AI system	0.553	0.803	0.842	0.75
30	Existence of mechanisms for sentiment/opinion analysis of customers	0.618	0.868	0.882	0.809
31	Comprehensiveness of digital interactions between employees and customers	0.487	0.737	0.789	0.688
32	Meeting the requirements of banking service orientation in the context of artificial intelligence	0.408	0.645	0.75	0.612
33	Implementation of infrastructure for chatbots, voice assistants, auto-verification, and biometrics	0.539	0.789	0.842	0.74
34	Degree of explainability and technology acceptance by employees and banking processes	0.487	0.724	0.776	0.678

Note: The defuzzified mean was calculated using the centroid method: (L + M + U) / 3. A common acceptance threshold is a defuzzified mean ≥ 0.70. Factors below this threshold (e.g., items 10, 14, 19, 23, 31, 32, 34) are typically considered for removal in subsequent rounds.

Next, the fuzzy mean for each factor was computed using the formula: (Lower Limit + [2 × Middle Point] + Upper Limit) / 4. A factor was deemed acceptable and retained if this calculated value was greater than or equal to the threshold of 0.7; otherwise, it was rejected. This entire procedure was repeated in a second round to assess the reliability of the Fuzzy Delphi process as shown in Table 3.

Table 3

Screening with Fuzzy Delphi Method (Second Round)

No.	Factors	Fuzzy Bounds of Factors (L, M, U)			Fuzzy Mean	Abs. Diff.	Reliability	Accept/Reject
		L	M	U				
1	Alignment of AI with banking processes	0.579	0.829	0.882	0.78	0.023	Reliable	Accept
2	Development of mechanisms to guarantee information security	0.632	0.882	0.921	0.829	0.026	Reliable	Accept
3	Design of mechanisms to prevent cyber fraud	0.684	0.934	0.947	0.875	0.01	Reliable	Accept
4	Synchronization of database structures with AI requirements	0.579	0.816	0.855	0.766	0.046	Reliable	Accept
5	Creating a suitable foundation to ensure the successful operation of learning models	0.566	0.816	0.855	0.763	0.003	Reliable	Accept
6	Mechanization of financial flows on an IT platform	0.645	0.895	0.895	0.832	0.072	Reliable	Accept
7	Existence of a comprehensive structure for identifying cyber threats	0.579	0.829	0.855	0.773	0.046	Reliable	Accept
8	Proper adaptation of neural networks and support vector machines	0.513	0.763	0.816	0.714	0.026	Reliable	Accept
9	Accurate implementation of prediction models based on artificial neural networks	0.566	0.816	0.842	0.76	0.02	Reliable	Accept
10	Secure and reliable data management for AI integration	0.316	0.539	0.697	0.523	0.138	Unreliable	Reject
11	Existence of comprehensive and effective market sensitivity analysis structures	0.526	0.776	0.842	0.73	0.01	Reliable	Accept
12	Presence of information quality assessment mechanisms	0.592	0.842	0.868	0.786	0.059	Reliable	Accept
13	Suitable foundations for successful learning patterns	0.645	0.895	0.895	0.832	0.128	Unreliable	Accept
14	Use of structures guaranteeing data transfer speed	0.553	0.803	0.829	0.747	0.079	Reliable	Accept
15	Implementation of risk analysis mechanisms for assessment and measurement	0.592	0.842	0.855	0.783	0.03	Reliable	Accept
16	Correct implementation of algorithms for optimizing AI performance in e-banking	0.579	0.829	0.855	0.773	0.007	Reliable	Accept
17	Existence of mechanisms for collecting employee performance data	0.579	0.829	0.868	0.776	0.036	Reliable	Accept

18	Existence of a platform for maximizing the digitization of banking services and processes	0.513	0.75	0.816	0.707	0.036	Reliable	Accept
19	Integration of employee and customer data into AI	0.474	0.697	0.789	0.664	0.016	Reliable	Reject
20	Trust-building mechanisms for customer technology adoption	0.408	0.632	0.737	0.602	0.151	Unreliable	Accept
21	Effective orientation of service delivery processes through IT	0.579	0.829	0.855	0.773	0.069	Reliable	Accept
22	Process design considering the needs of machine learning infrastructure	0.553	0.803	0.842	0.75	0.046	Reliable	Accept
23	Use of appropriate, comprehensive, and inclusive databases	0.592	0.842	0.868	0.786	0.105	Unreliable	Accept
24	Existence of a suitable platform for providing electronic financial services	0.579	0.829	0.882	0.78	0.049	Reliable	Accept
25	Use of customized proprietary databases tailored to system needs	0.5	0.75	0.803	0.701	0.026	Reliable	Accept
26	Presence of systems for collecting information from customer experiences	0.592	0.829	0.868	0.78	0.049	Reliable	Accept
27	Structural design for effective cultural preparation for AI implementation	0.513	0.763	0.829	0.717	0.086	Reliable	Accept
28	Providing the necessary infrastructure for calculating bank interest in an AI environment	0.5	0.737	0.803	0.694	0.059	Reliable	Reject
29	Implementation of customer communication channels for AI data collection	0.566	0.816	0.855	0.763	0.013	Reliable	Accept
30	Existence of mechanisms for analyzing customer sentiments and opinions	0.566	0.816	0.855	0.763	0.046	Reliable	Accept
31	Comprehensiveness of digital interactions between employees and customers	0.526	0.763	0.816	0.717	0.03	Reliable	Accept
32	Meeting the requirements of banking service orientation in an AI context	0.566	0.816	0.855	0.763	0.151	Unreliable	Accept
33	Implementation of infrastructure for chatbots, voice assistants, and biometrics	0.553	0.803	0.842	0.75	0.01	Reliable	Accept
34	*Degree of explainability and technology acceptance by employees and banking processes*	*0.447*	*0.697*	*0.789*	*0.658*	*0.02*	*Reliable*	*Reject*

Note: *The acceptance criteria were: (1) Defuzzified Mean ≥ 0.70, and (2) Absolute Difference ≤ 0.10 for reliability. Factors were rejected if they failed to meet the defuzzified mean threshold (e.g., items 10, 19, 20, 28, 34) regardless of reliability status*.

To ensure the reliability of the Fuzzy Delphi questionnaire, this calculation was performed for at least two rounds. If the absolute difference between the fuzzy means of two consecutive rounds for any factor exceeded 0.15, that factor was presented to the experts for a third round of evaluation. At this stage, the deviation of each expert's opinion from the mean of the panel's responses was calculated. A subsequent questionnaire was then distributed to the experts, which included both their initial individual responses and the calculated deviation from the panel's mean.

The iterative polling process was governed by a termination criterion. By comparing the responses from the first and second rounds, the process was halted if the discrepancy between the experts' opinions in these two rounds fell below the threshold of 0.2. Given that the calculated discrepancy between the first and second rounds of the Delphi procedure was indeed less than this pre-defined threshold of 0.2, the polling was concluded after the second round for the majority of factors.

According to Table 3, five factors (10, 19, 20, 28, 34) underwent a third round of questionnaire administration using the Fuzzy Delphi approach, as the absolute difference between their fuzzy means from the first and second rounds exceeded the acceptable threshold. The results of this third round for these five factors are presented in Table 4. Following the third Fuzzy

Delphi round, the discrepancy between the Defuzzified means of the second and third rounds was deemed acceptable, allowing for the final consolidation of the results.

Table 4

Screening with the Fuzzy Delphi Method in the Third Stage

No	Acceptance Threshold (0.7)**				Defuzzified Mean	Absolute Difference (2nd & 3rd Stages)	Reliability Result	Accept/Reject
	Item	Fuzzy Mean						
		L	M	U				
1	Secure and reliable data management for the successful integration of artificial intelligence	0.342	0.553	0.684	0.533	0.010	Reliable	Reject
2	Appropriate infrastructures for successful learning patterns	0.500	0.750	0.855	0.714	0.118	Reliable	Accept
3	Trust-building mechanisms for customer acceptance of technology	0.395	0.618	0.737	0.592	0.010	Reliable	Reject
4	Use of appropriate, comprehensive, and inclusive databases	0.500	0.737	0.803	0.694	0.092	Reliable	Reject
5	Meeting the requirements of banking service orientation in the context of artificial intelligence	0.487	0.724	0.789	0.681	0.082	Reliable	Reject

Note: *The acceptance threshold was set at Defuzzified Mean ≥ 0.70. Only factors meeting this threshold were accepted for the final model. The absolute difference between the second and third rounds indicates the stability of expert opinions, with values ≤ 0.20 generally considered acceptable for convergence.*

EFA was employed to identify the underlying dimensions, explain the proportion of variance, and establish the relative priority of the factors. The reliability of the EFA questionnaire was assessed using Cronbach's alpha, which was calculated to be 0.795, indicating suitable internal consistency. Preliminary analysis led to the removal of factors (5, 6, 10, 12, 14) due to significant skewness and non-normal distribution. Following this, Cronbach's alpha was recalculated to confirm the reliability of the refined instrument for the EFA.

Table 5

Reliability and Sampling Adequacy Metrics

Number of Items		Cronbach's Alpha (α)
22		0.813
0.727		Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy
3083.717	Approx. Chi-Square (χ^2)	Bartlett's Test of Sphericity
231	Degrees of Freedom (df)	
< 0.001	Significance (p-value)	

The suitability of the data for factor analysis was then evaluated. The Kaiser-Meyer-Olkin (KMO) measure was computed. Furthermore, Bartlett’s Test of Sphericity was significant (Sig. = 0.018), as shown in Table 5, confirming that the correlation matrix is factorable. As indicated in Table 6, all extracted communalities were required to exceed 0.50. This criterion ensures that the factors sufficiently contribute to forming an integrated model. Consequently, any factor with an extracted communality below 0.50 was excluded from further analysis.

Table 6

Extracted Communalities of Research Factors

No.	Research Factor	Extracted Communality
1	Compatibility of AI with banking processes	0.809
2	Development of mechanisms to guarantee information security	0.759
3	Design of protocols to prevent the possibility of cyber fraud	0.866
4	Alignment of database structure with AI requirements	0.675
5	Existence of a comprehensive structure for identifying cyber threats	0.945
6	Correct adaptation of neural networks and support vector machines to the target system	0.890

7	Accurate implementation of prediction models based on artificial neural networks in the AI platform	0.860
8	Existence of mechanisms for assessing data quality within the system	0.789
9	Utilization of structures guaranteeing data transfer speed	0.678
10	Proper implementation of algorithms required for optimizing AI performance in e-banking systems	0.862
11	Existence of mechanisms for collecting employee performance data	0.669
12	Existence of a suitable infrastructure for maximizing the digitization of banking services and processes	0.797
13	Effective orientation of service delivery processes within the IT infrastructure to the greatest extent possible	0.842
14	Process design considering the requirements of machine learning infrastructure	0.758
15	Existence of a suitable platform for providing electronic financial services	0.936
16	Utilization of customized and tailored proprietary databases aligned with system needs	0.706
17	Existence of systems for collecting information from customer experiences	0.775
18	Designing a framework for appropriate cultural development to ensure the successful implementation of AI technology	0.884
19	Implementation of customer communication channels for data collection for the AI system	0.861
20	Existence of mechanisms for analyzing customer sentiments and feedback and converting them into digital data	0.744
21	Comprehensiveness of digital interactions between employees and customers	0.655
22	Implementation of infrastructure for utilizing chatbot technologies, voice assistants, automated verification, and biometrics	

Table 7 displays the results for the 22 potential factors initially considered. For each factor, the table provides:

- The total variance explained (eigenvalue),
- The percentage of total variance explained,
- The cumulative percentage of variance explained.

Table 7

Total Variance Explained by Factor Analysis Solution in the Research Sample

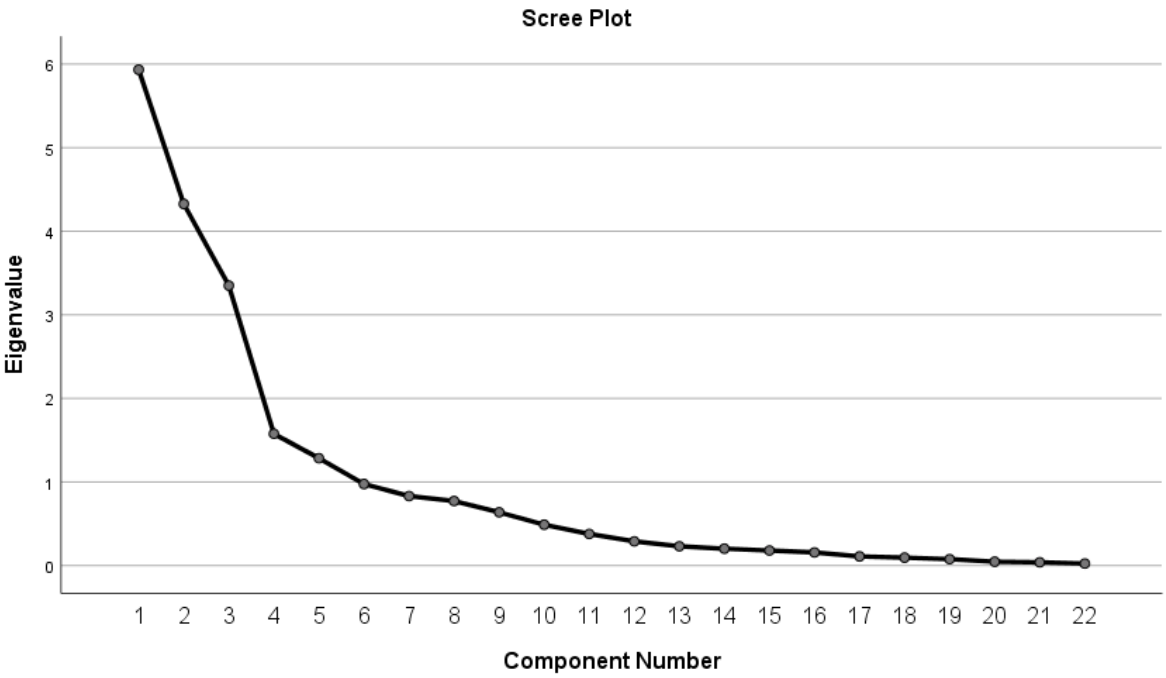
	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.933	26.966	26.966	5.933	26.966	26.966	4.153	17.732	17.732
2	4.327	19.669	46.635	4.327	19.669	46.635	3.029	14.323	34.929
3	3.350	15.227	61.862	3.350	15.227	61.862	2.345	11.278	51.809
4	1.577	7.166	69.029	1.577	7.166	69.029	1.104	5.381	63.573
5	1.284	5.837	74.866	1.284	5.837	74.866	0.899	3.563	72.928
6	0.975	4.434	79.300	0.975	4.434	79.300	0.682	2.174	83.772
7	0.831	3.779	83.079	-	-	-	-	-	-
8	0.772	3.508	86.586	-	-	-	-	-	-
9	0.638	2.898	89.485	-	-	-	-	-	-
10	0.488	2.220	91.705	-	-	-	-	-	-
11	0.378	1.717	93.422	-	-	-	-	-	-
12	0.289	1.314	94.736	-	-	-	-	-	-
13	0.231	1.049	95.785	-	-	-	-	-	-
14	0.202	0.917	96.702	-	-	-	-	-	-
15	0.180	0.816	97.518	-	-	-	-	-	-
16	0.157	0.714	98.232	-	-	-	-	-	-
17	0.109	0.498	98.730	-	-	-	-	-	-
18	0.095	0.430	99.160	-	-	-	-	-	-
19	0.076	0.347	99.507	-	-	-	-	-	-
20	0.046	0.210	99.717	-	-	-	-	-	-
21	0.039	0.175	99.892	-	-	-	-	-	-
22	0.024	0.108	100.000	-	-	-	-	-	-

*Note : **Extraction Method:** Principal Axis Factoring . **Rotation Method:** Varimax with Kaiser Normalization*

The middle section of Table 7 specifically highlights the factors with an eigenvalue greater than 1.0—a standard criterion for factor retention (Kaiser's rule). Based on this, four key factors were retained for the final model.

Figure 1

Scree Plot



However, the scree plot indicated a clear point of inflection, suggesting a six-factor structure was more appropriate. Following as shown in Table 8 multiple factor rotations in SPSS 22, factors were assigned to groups based on the magnitude of their factor loadings. Variables with significant loadings on multiple factors were assigned to the group with the highest loading. The solution was iteratively refined to eliminate negative factor loadings and any group containing only one or two factors, which led to the removal of one factor ("Frequent Changes in Design or Project Scope (X13)").

Table 8

Rotated Factor Matrix of the Research Constructs

Item Code	Research Factor / Variable Description	Factors				
		1	2	3	4	5
x1	Alignment of AI with banking processes	0.684	0.113	0.534	0.526	0.287
x4	Synchronization of database structures with AI requirements	0.699	0.129	0.298	0.514	0.169
x15	Correct implementation of algorithms for optimizing AI performance in e-banking	0.843	0.118	0.226	0.327	0.319
x8	Proper adaptation of neural networks and support vector machines to the target system	0.833	0.151	0.253	0.210	0.311
x9	Accurate implementation of prediction models based on artificial neural networks within the AI framework	0.850	0.240	0.167	0.305	0.217
x27	Implementation of infrastructure for utilizing technologies like chatbots, voice assistants, auto-verification, and biometrics	0.173	0.816	0.270	0.346	0.168
x18	Effective orientation of service delivery processes through information technology	0.122	0.907	0.272	0.094	0.172
x19	Process design considering the needs of machine learning infrastructure	0.155	0.866	0.315	0.319	0.136
x20	Existence of a suitable platform for providing electronic financial services	0.152	0.945	0.111	0.198	0.750
x22	Presence of systems for collecting information from customer experiences	0.438	0.320	0.736	0.252	0.146
x16	Existence of mechanisms for collecting data on employee performance	0.242	0.546	0.733	0.355	0.331
x21	Use of customized proprietary databases tailored to system needs	0.468	0.124	0.737	0.317	0.140
x11	Presence of information quality assessment mechanisms within the system	0.699	0.188	0.882	0.351	0.366
x17	Existence of a suitable platform for maximizing the digitization of banking services and processes	0.282	0.634	0.833	0.259	0.098

x26	Comprehensiveness of digital interactions between employees and customers	0.201	0.572	0.177	0.709	0.384
x25	Existence of mechanisms for analyzing customer sentiments and feedback, converting them into digital data	0.121	0.271	0.478	0.699	0.216
x24	Implementation of communication channels with customers to gather data for the AI system	0.400	0.146	0.582	0.724	0.136
x23	Structural design for effective cultural preparation for successful AI technology implementation	0.401	0.159	0.398	0.813	0.106
x2	Development of mechanisms to guarantee information security	0.500	0.150	0.490	0.583	0.780
x3	Design of mechanisms to prevent the possibility of cyber fraud	0.466	0.240	0.303	0.046	0.712
x7	Existence of a comprehensive structure for identifying cyber threats	0.530	0.126	0.299	0.036	0.791

Note: Extraction Method: Principal Axis Factoring. Rotation Method: Varimax with Kaiser Normalization. Factor loadings above 0.70 are in bold to indicate strong associations with a specific factor, aiding in the interpretation of the factor structure.

The final factor groupings were presented to the expert panel for naming. An iterative process was used where experts were informed of previous suggestions and asked to refine them, culminating in a final consensus on the names for the latent constructs, thus finalizing the conceptual model. The resulting factors and their loadings are presented in **Table 9**.

Table 9

Factors and Factor Loadings for AI Implementation Indices in the Banking Sector.

Row	Index	Symbol	Factors	Factor Loading
1	AI Systems and Algorithms	x1	Compatibility of AI with banking processes	0.684
2		x4	Alignment of database structure with AI requirements	0.699
3		x15	Proper implementation of algorithms required for optimizing AI performance in e-banking systems	0.843
4		x8	Correct adaptation of neural networks and support vector machines to the target system	0.833
5		x9	Accurate implementation of prediction models based on artificial neural networks in the AI platform	0.850
6	Business Process and Optimization	x27	Implementation of infrastructure for utilizing chatbot technologies, voice assistants, automated verification, and biometrics	0.816
7		x18	Effective orientation of service delivery processes within the IT infrastructure to the greatest extent possible	0.907
8		x19	Process design considering the requirements of machine learning infrastructure	0.866
9		x20	Existence of a suitable platform for providing electronic financial services	0.945
10	Data Management and Infrastructure	x22	Existence of systems for collecting information from customer experiences	0.736
11		x16	Existence of mechanisms for collecting employee performance data	0.733
12		x21	Utilization of customized and tailored proprietary databases aligned with system needs	0.737
13		x11	Existence of mechanisms for assessing data quality within the system	0.882
14		x17	Existence of a suitable infrastructure for maximizing the digitization of banking services and processes	0.833
15	Customer Experience and Interaction	x26	Comprehensiveness of digital interactions between employees and customers	0.709
16		x25	Existence of mechanisms for analyzing customer sentiments and feedback and converting them into digital data	0.699
17		x24	Implementation of customer communication channels for data collection for the AI system	0.724
18		x23	Designing a framework for appropriate cultural development to ensure the successful implementation of AI technology	0.813
19	Security and Risk Management	x2	Development of mechanisms to guarantee information security	0.780
20		x3	Design of protocols to prevent the possibility of cyber fraud	0.712
21		x7	Existence of a comprehensive structure for identifying cyber threats	

To proceed with parametric tests, the normality of the data distribution for the identified constructs was assessed using the Kolmogorov-Smirnov test. As shown in Table10, the significance levels for all constructs were greater than 0.05, confirming a normal distribution.

Table 10

Normality Test of the Statistical Population Using the Kolmogorov-Smirnov Test

No.	Research Indicators and Sub-indicators	K-S Statistic	Sig. (p-value)	Result
1	AI Systems and Algorithms Index	0.077	0.308	Normal
2	Business Process and Optimization Index	0.092	0.289	Normal
3	Data Management and Infrastructure Index	0.082	0.451	Normal
4	Customer Experience and Interaction Index	0.075	0.298	Normal
5	Security and Risk Management Index	0.096	0.422	Normal
6	Overall Model Pattern	0.061	0.141	Normal

Note: The Kolmogorov-Smirnov (K-S) test was used to assess the normality of the data distribution. A non-significant p-value (Sig. > 0.05) indicates that the data for each index do not significantly deviate from a normal distribution

The reliability of each construct and the overall model was re-assessed using Cronbach's Alpha, with all values exceeding 0.7, confirming internal consistency as shown in Table 11.

Table 11

Cronbach's Alpha Coefficients for Research Dimension

Research Dimensions and Sub-dimensions	Cronbach's Alpha (α)	Reliability Status
AI Systems and Algorithms	0.811	Reliable
Business Processes and Optimization	0.866	Reliable
Data Management and Infrastructure	0.856	Reliable
Customer Experience and Interaction	0.922	Reliable
Security and Risk Management	0.833	Reliable
Overall Model Framework	0.711	Reliable

Note: *Cronbach's Alpha was used to assess the internal consistency reliability of the research instrument. All coefficients exceed the acceptable threshold of 0.70, indicating satisfactory reliability for all research dimensions and the overall model.*

The CFA was conducted on the final conceptual model, which comprised 21 items. The path diagram (**Figure 2**) shows the standardized coefficients for the model. The t-values for all measured variables in this construct were greater than 1.96, indicating that all paths were significant and no items needed to be removed from the model.

Figure 2

Standardized coefficients of the model for the construct

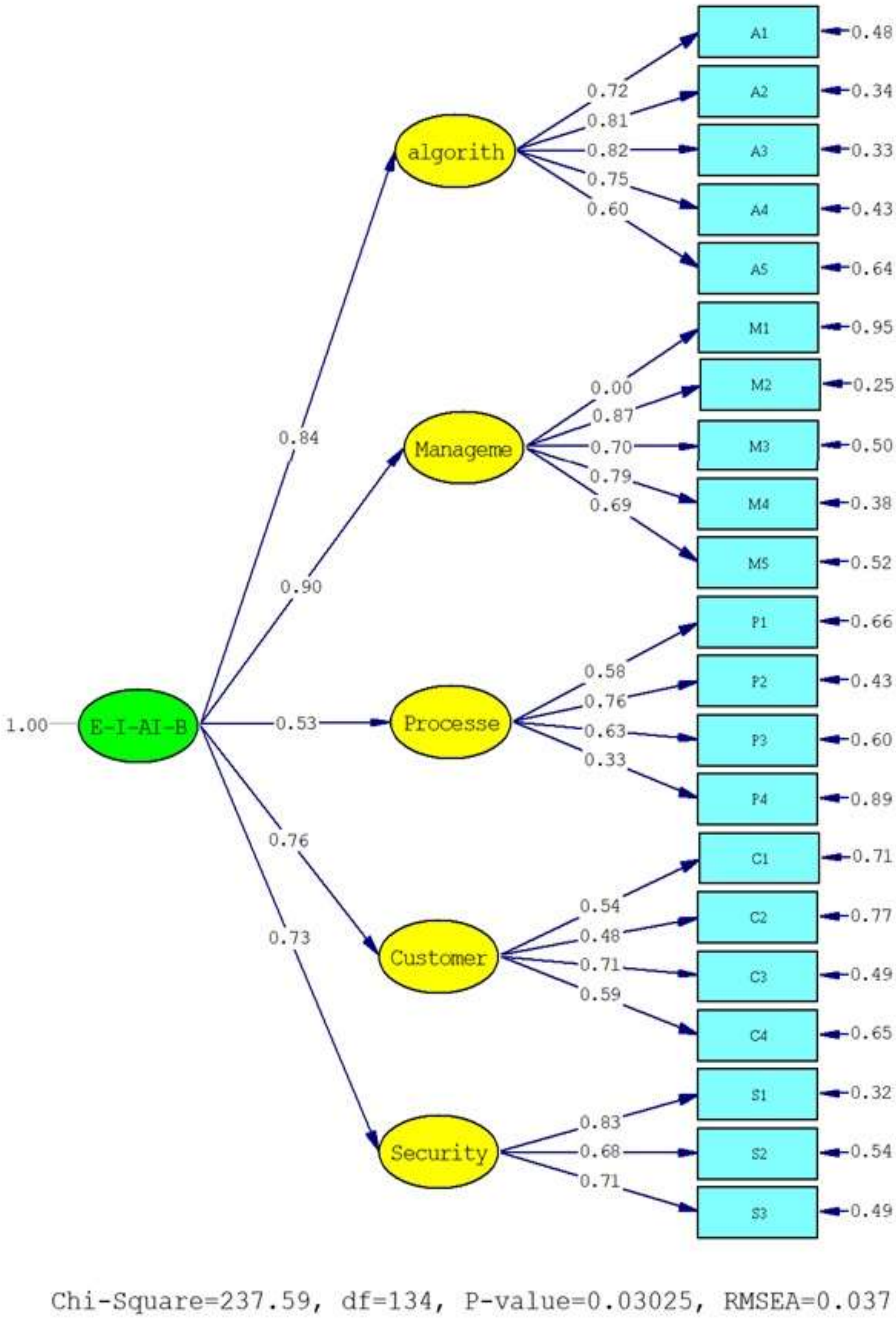
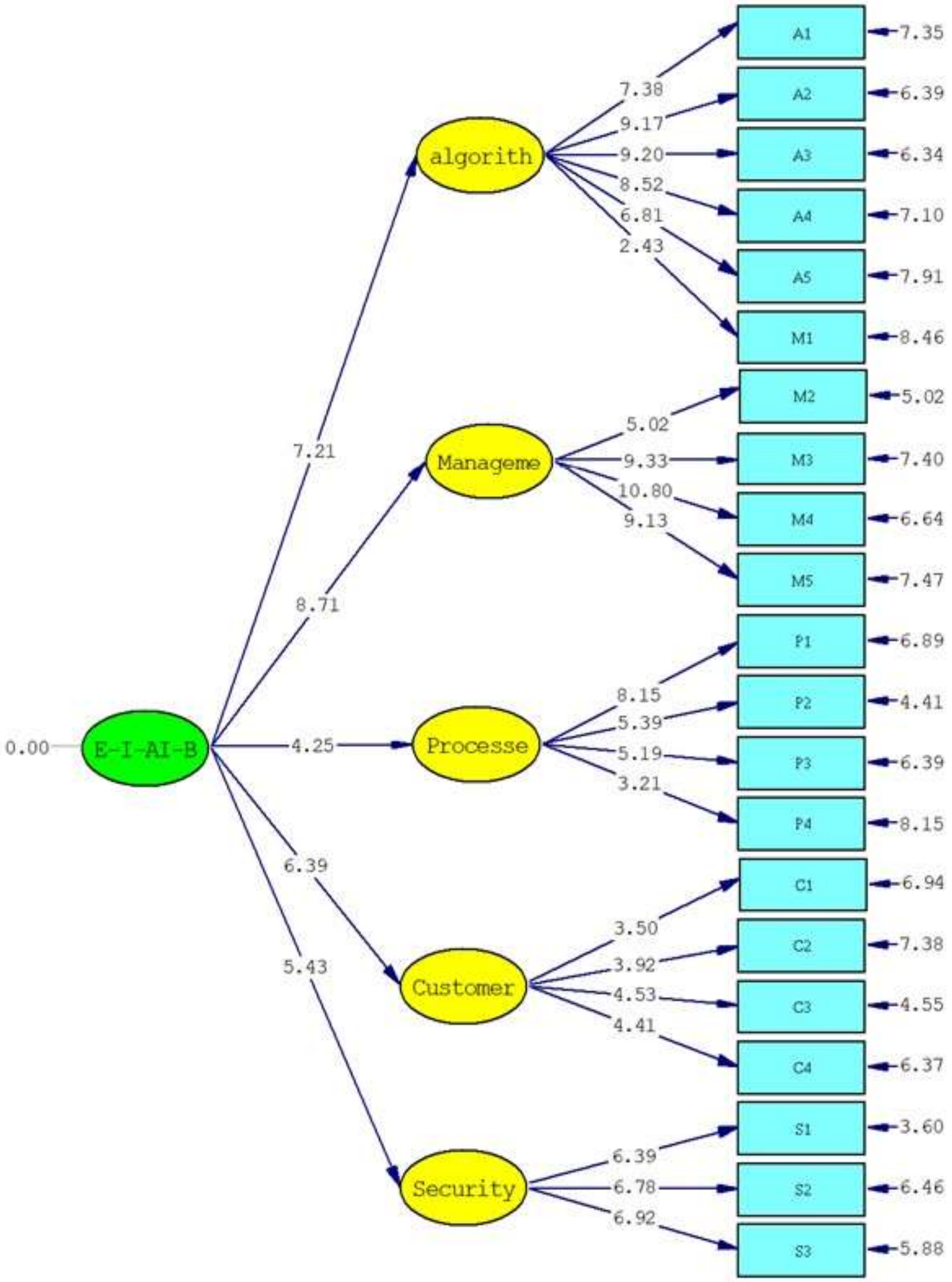


Figure 3

t-values and significance of relationships in the construct



Chi-Square=237.59, df=134, P-value=0.03025, RMSEA=0.037

Figure 3 presents the standardized coefficients for the structural model.

The goodness-of-fit indices for the "Developed Conceptual Model" (Table 12) were all at acceptable levels, confirming that the model has a good fit.

Table 12

Goodness-of-Fit Indices for the Structural Model

Fit Index	Calculated Value	Acceptance Threshold	Result
χ^2/df	1.77	< 3.00	Confirmed
RMSEA	0.037	< 0.08	Confirmed
SRMR	0.049	< 0.10	Confirmed
NFI	0.98	> 0.90	Confirmed
AGFI	0.96	> 0.90	Confirmed
GFI	0.97	> 0.90	Confirmed
CFI	0.97	> 0.90	Confirmed
NNFI (TLI)	0.95	> 0.90	Confirmed

***Note**: χ^2/df = Normed Chi-Square; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual; NFI = Normed Fit Index; AGFI = Adjusted Goodness-of-Fit Index; GFI = Goodness-of-Fit Index; CFI = Comparative Fit Index; NNFI/TLI = Non-Normed Fit Index / Tucker-Lewis Index. All indices meet their respective acceptance thresholds, indicating a good fit of the model to the data.*

Table 13

Summary of Structural Equation Modeling (SEM) Results

No.	Research Variables and Components	Standardized Coefficients (β)	T-Values
1	AI Systems and Algorithms	0.84	7.21
2	Business Processes and Optimization	0.53	4.25
3	Data Management and Infrastructure	0.90	8.71
4	Customer Experience and Interaction	0.76	6.39
5	Security and Risk Management	0.73	5.43

***Note:** All path coefficients (β) and T-values are statistically significant ($p < 0.001$), indicating that all hypothesized relationships are supported. T-values > |1.96| are typically considered significant at $p < 0.05$.*

Discussion and Conclusion

The findings of this research led to the development and empirical validation of a comprehensive multi-dimensional model for assessing and guiding the implementation of artificial intelligence (AI) in the banking industry. The results indicated that five interrelated dimensions—Data Management and Infrastructure, AI Systems and Algorithms, Customer Experience and Interaction, Security and Risk Management, and Business Process and Optimization—collectively provide the necessary foundation for effective and sustainable AI deployment. Among these, Data Management and Infrastructure emerged with the highest standardized coefficient (0.90), underscoring its pivotal role as the backbone of AI adoption. Without reliable, accessible, and well-structured data systems, other elements such as advanced algorithms, intelligent customer engagement, and robust security cannot perform effectively [1, 2]. This result aligns with prior studies emphasizing that data quality and integration are essential preconditions for successful AI-driven transformation in banking [4, 20]. Banks require clean, interoperable, and scalable data infrastructures to support predictive analytics, machine learning, and real-time decision-making [5, 8].

The second most influential dimension, AI Systems and Algorithms (β = 0.84), highlights the centrality of advanced computational methods in enabling the banking industry to move beyond traditional automation toward predictive and prescriptive intelligence. Sophisticated neural networks, ensemble models, and decision trees are essential for analyzing complex customer behavior, forecasting credit risk, and enhancing operational strategies [7, 9]. These findings echo earlier work emphasizing that algorithmic adaptability to banking contexts—particularly real-time data processing and high reliability in financial decision-making—is crucial [2, 15]. By validating this dimension empirically, the present study reinforces the argument that algorithms and models cannot be deployed in isolation but must be tightly integrated with underlying data and system capabilities [11, 17].

Customer Experience and Interaction, with a strong yet comparatively lower weight (β = 0.76), reflects AI's capacity to redefine customer journeys through personalization, conversational interfaces, and predictive engagement. Chatbots, voice assistants, and recommendation engines offer seamless and tailored services while enhancing satisfaction and loyalty [10, 11]. These results support recent findings that AI-enabled personalization significantly improves digital banking adoption and continued use intention [12, 13]. Moreover, studies show that customer-facing AI fosters stronger trust and long-term engagement when paired with ethical data practices and transparent decision-making [1, 18]. Our model positions customer interaction as a downstream effect of robust data infrastructures and algorithmic sophistication, consistent with the notion that personalization quality is constrained by data richness and analytical capability [19].

Security and Risk Management (β = 0.73) emerged as another critical but data- and algorithm-dependent domain. The findings confirm that AI-driven security systems—including fraud detection, anomaly recognition, and cyber threat analysis—are essential in digital banking environments prone to advanced cyberattacks and financial crime [4, 14]. Prior literature consistently reports that AI-enhanced threat intelligence and intrusion detection significantly reduce fraud losses and increase resilience against cyber threats [6, 16]. However, our study also highlights that these systems are only as robust as the data pipelines and model reliability that support them, echoing concerns over algorithmic bias and data-driven vulnerabilities [1, 9]. Furthermore, regulatory compliance is deeply intertwined with this dimension; AI-powered risk analytics must adhere to local and international frameworks to maintain consumer trust and system stability [18, 24].

Finally, Business Process and Optimization held the lowest relative weight (β = 0.53), indicating that while process improvement is a key outcome of AI deployment, it depends on the maturity of other components. This observation aligns with recent studies describing operational efficiency and cost reduction as downstream benefits once data governance and algorithmic infrastructure are solidified [17, 23]. Through automating repetitive tasks, optimizing workflow, and enhancing regulatory reporting, AI improves cost-effectiveness and responsiveness [5, 20]. However, our findings caution against seeing process optimization as a starting point; instead, it should be approached as an integrated outcome of strategic AI planning, which is consistent with strategic frameworks proposed in emerging literature [6, 15].

An important implication of these results is the hierarchical interdependence among the dimensions. Data Management and Infrastructure act as a foundation enabling algorithmic intelligence, which in turn drives customer-facing capabilities, security mechanisms, and operational optimization. This layered perspective enriches previous models that considered these factors separately [1, 2]. Our validated model also integrates organizational and cultural readiness into customer interaction and process dimensions, acknowledging the human element in digital transformation [10, 24]. Cultural acceptance, employee training, and user trust emerge as subtle but powerful enablers of AI success, echoing recommendations that technological change in banking must be socially and institutionally embedded [5, 18].

Another noteworthy contribution is the model's applicability to emerging economies. Prior studies have noted significant barriers to AI adoption in such contexts, including legacy systems, regulatory uncertainty, and resource constraints [20, 23].

By identifying readiness factors and linking them to measurable outcomes, this research provides a practical roadmap for banks facing these structural challenges. It also supports calls for strategic investment in data infrastructure and algorithmic capability before pursuing large-scale AI initiatives [8, 15]. In addition, our findings reinforce that robust security frameworks and transparent data governance must evolve concurrently with AI adoption to avoid unintended regulatory and reputational risks [1, 6].

This work advances the literature by merging technical, organizational, and cultural dimensions into a single empirically validated framework. Unlike previous models that focused narrowly on technology or customer factors [11, 13], our approach links back-end readiness with front-end service quality and risk resilience. It also bridges the often-separate discussions of operational research and strategic AI adoption by demonstrating how foundational layers support advanced banking innovation [1, 2]. Consequently, the study offers both theoretical and practical insight for institutions striving for sustainable and secure AI integration.

While the study provides a robust, multi-dimensional model for AI implementation in banking, several limitations should be acknowledged. First, although the sample size was substantial and included experts and specialists, the data were primarily drawn from a single national banking environment. This may limit the model's external validity across different regulatory systems, market maturities, and cultural contexts. Second, the study employed cross-sectional data; as AI technology evolves rapidly, the results capture a moment in time and may require future recalibration as tools and strategies advance. Third, while the model integrates organizational and cultural readiness, it may not fully account for emerging ethical, legal, and socio-technical complexities, such as evolving global AI governance or unintended consequences of algorithmic decision-making. Finally, resource constraints and geopolitical factors affecting technology adoption in certain markets were not deeply analyzed, which could influence model applicability under highly unstable economic or regulatory conditions.

Future investigations could expand this model by testing it across diverse international contexts to explore how regulatory stringency, cultural attitudes toward technology, and digital maturity influence AI adoption pathways. Longitudinal studies would provide valuable insights into the temporal dynamics of AI readiness and performance impact, capturing how iterative investments and cultural adaptation shape success over time. Further research could also examine ethical AI governance in greater depth, integrating fairness, explainability, and consumer protection as explicit components of implementation frameworks. Another promising avenue is exploring the interaction between AI and other disruptive technologies such as quantum computing, edge AI, and advanced blockchain protocols to understand compound effects on banking resilience and innovation. Lastly, qualitative explorations of organizational change management and employee skill transformation could complement this model by illuminating the human factors that sustain AI-driven transformation.

Bank leaders can use this validated model as a strategic roadmap for responsible AI integration. Prioritizing investment in data infrastructure and robust governance mechanisms will ensure the reliability of downstream applications, while fostering organizational readiness through training and cultural adaptation will reduce resistance and increase adoption success. Regulators and policymakers can leverage these findings to design balanced frameworks that encourage AI-driven financial innovation while safeguarding consumer rights and systemic stability. Technology developers and service providers may also use the model to better align their AI solutions with banking realities, ensuring their systems address the sector's nuanced security, data, and customer experience demands.

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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.

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