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Enhancing Sustainable Social Banking Performance through Artificial Intelligence: A System Dynamics Analysis of Iranian Cooperative Banks

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ABSTRACT

With the expansion of innovative technologies, the banking industry has faced profound transformations. Artificial intelligence, as one of the most significant of these technologies, has the potential to transform the nature of banking services; however, its impact on social banking, particularly in cooperative banks, has received less attention. This research aims to investigate the impact of artificial intelligence functions on the performance of social banking in Iranian cooperative banks, utilizing a system dynamics approach. The study adopts a mixed approach (qualitative-quantitative). In the qualitative section, key variables were identified using an expert panel, and in the quantitative section, a system dynamics model was developed using Vensim software. The stock-flow model simulated the relationships between main variables, including sustainable development, bank reputation, unpredictable liquidity, non-performing loans, and artificial intelligence infrastructure, over 10 years (2021-2031). The results of the sensitivity analysis and scenario development demonstrated that strategic investments in artificial intelligence infrastructure, enhanced data protection protocols, and improved financial transparency contribute significantly to an enhanced bank reputation, substantially reduce unpredictable liquidity fluctuations, and notably decrease non-performing loans, thereby supporting sustainable banking operations. Model validation tests, including boundary conditions tests, structural tests, uncertainty tests, and integration tests, confirmed the accuracy of the relationships. This model can serve as a tool for decision-making and policy-making regarding the application of artificial intelligence in the country's social banking system.

Keywords

Social banking, Artificial intelligence, System Dynamics, Liquidity, Cooperative banks.

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1. Introduction

The banking industry has undergone remarkable transformations in recent decades. Technological advancements, particularly in the field of artificial intelligence (AI), have paved the way for new forms of banking services that respond to the diverse needs of customers and society (Jakšič and Marinč, 2019). In this context, social banking has emerged as a novel approach within the banking system, aiming to combine financial goals with social and environmental responsibilities (Ozili, 2025). Social banking seeks not only profitability but also to create sustainable value for society, the environment, and the economy (de Andreis et al., 2024).

The integration of AI technologies with social banking principles represents a transformative opportunity to enhance sustainability across all three dimensions—economic, social, and environmental. By leveraging AI's analytical capabilities, cooperative banks can achieve more efficient resource allocation, improved risk management, and enhanced customer service delivery while maintaining their commitment to social responsibility and community development (Gyau et al., 2024). This research specifically examines how AI can facilitate sustainable banking practices that strike a balance between profitability and social impact, thereby contributing to the broader goal of achieving sustainable financial systems.

In recent years, with the introduction of AI into financial services, a major transformation has occurred in the way banking services are delivered. Intelligent systems can analyze vast amounts of data, identify hidden patterns, and make more accurate credit decisions (Sadok et al., 2022). It is particularly impactful in cooperative banks, whose primary purpose is to serve their members and the local community (Venanzi and Matteucci, 2022).

Cooperative banks in many countries face multiple challenges, including resource limitations, unpredictable liquidity, and high levels of non-performing loans (Degregori et al., 2025). On the other hand, these banks, due to their social nature, have high potential for developing social banking (Korzeb et al., 2024). The use of AI can be an effective solution to overcome existing challenges and improve the performance of these banks (Rahman et al., 2021).

Studies show that implementing AI-based systems can lead to increased accuracy in credit risk assessment, improved liquidity management, and enhanced customer trust (Al-Sartawi, 2022). For example, machine-learning (ML) algorithms can analyse customer behaviour, predict loan payment patterns, and reduce default risk (Karki et al., 2025). Additionally, AI systems can analyse big data to predict liquidity fluctuations and help better manage financial resources (Iannaci and Gideon, 2020).

Despite the high potential of AI in transforming the banking industry, few studies have been conducted on the impact of this technology on social banking, particularly cooperative banks. Most existing research has focused on technical aspects of AI or commercial banks (Su and Wang, 2025). Furthermore, the lack of dynamic models to understand the complex interactions between variables affecting AI functions in social banking represents an important gap in the existing literature (Stavropoulou et al., 2023).

This research gap reflects a fundamental system-level problem: while AI technologies offer significant potential for transforming banking operations, the complex interdependencies and feedback mechanisms that determine successful AI implementation in social banking contexts remain poorly understood. The challenge is not merely technical implementation, but understanding how AI adoption creates cascading effects across multiple dimensions of bank performance—from operational efficiency and risk management to customer satisfaction and community impact—within the unique organizational and social context of cooperative banks.

In this context, the present research aims to study the impact of AI functions on social banking performance using a system dynamics approach in Iranian cooperative banks. The system dynamics method is a powerful tool for analyzing complex systems and understanding non-linear relationships between variables. This approach addresses the core research problem by examining how AI technologies create reinforcing feedback loops between infrastructure investment, service quality improvement, customer satisfaction, and resource mobilization in cooperative banks. The system-level analysis recognizes that sustainable AI-enabled transformation requires understanding not just individual technology impacts, but the dynamic interactions that either enable virtuous cycles of improvement or create implementation barriers that limit transformation potential. Using this method, we can examine the impact of changes in key variables such as AI infrastructure, unpredictable liquidity, and non-performing loans on the overall performance of the social banking system over time.

The importance of this research stems from the fact that decision-making regarding investment in AI technologies requires a deep understanding of the long-term impacts of this investment on bank performance. The dynamic model presented in this research enables the simulation of various scenarios, helping cooperative bank managers make more informed decisions about the application of AI.

The dynamic hypothesis guiding this research posits that AI implementation in social banking creates interconnected, reinforcing loops where enhanced technological capabilities improve risk assessment and service personalization, leading to increased customer satisfaction and bank reputation, which in turn enables better resource mobilization for further AI investments. However, this process is constrained by resource allocation limitations and implementation challenges that can create balancing effects, making the timing and sequencing of AI investments critical for achieving sustainable transformation.

Furthermore, the results of this research can significantly contribute to the development of social banking in Iran. Social banking, with its focus on supporting small and medium-sized businesses, empowering vulnerable groups, and promoting sustainable development, plays a crucial role in achieving the country's economic and social objectives. Combining this approach with AI capabilities can lead to innovative sustainable banking models that simultaneously improve economic efficiency, enhance social impact, and contribute to environmental sustainability through optimized operations and resource management.

Following this introduction, and after reviewing the literature and presenting the dynamic hypothesis, the research methodology is discussed. Then, the findings from modelling and simulation are introduced, and finally, conclusions and practical recommendations are provided.

2. Literature review

2.1. Social banking and sustainable development

Social banking, as defined by Pérez (2017), integrates financial objectives with social and environmental considerations. Research demonstrates that social banking plays a crucial role in directing capital toward sustainable economic activities (Andrikopoulos, 2020) and supporting the sustainability of small and medium-sized businesses through tailored financial services and collaborative networks (Stavropoulou et al., 2023).

2.2. Cooperative banks and their challenges

Cooperative banks, which focus on serving members and local communities, represent a sustainable banking model with greater stability than commercial banks during crisis conditions (Venanzi and Matteucci, 2022). However, they face challenges including credit risk management (Kil et al., 2021) and limited adoption of modern technologies and digital marketing strategies (Nethala et al., 2022).

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2.3. AI in the banking industry

AI serves as a primary driver of digital transformation in banking, enabling improved decision-making through the analysis of big data (Zamany et al., 2024). AI applications include service quality prediction (Castelli et al., 2016), strengthening bank-customer relationships through personalized services (Jakšič and Marinč, 2019), and facilitating technology adoption based on perceived usefulness and trust factors (Rahman et al., 2021).

2.4. AI-Based credit analysis

AI significantly enhances credit analysis and risk management capabilities. Research shows that AI algorithms enhance credit decision accuracy and reduce default rates (Sadok et al., 2022), facilitate effective credit scoring in microfinance (Terko et al., 2019), and support the evaluation of efficiency in cooperative banks through hybrid analytical methods (Gautam et al., 2024).

2.5. AI and liquidity management

AI technologies address liquidity management challenges through predictive capabilities. Studies demonstrate that intelligent systems optimize liquidity management by predicting cash flows (Fourie and Bennett, 2019) and enhance decision-making in capital management through market data analysis and financial trend prediction (Radhakrishna et al., 2024).

2.6. Social banking and AI: Towards a sustainable model

Limited research has explored the specific impact of AI on social banking. Recent studies have explored the relationship between social business, AI, and sustainability (de Andreis et al., 2024), AI's role in sustainable finance through improved transparency and risk reduction (Al-Sartawi et al., 2022), and the importance of social banking during crises (Thongsri and Tripak, 2024). This research gap in dynamic modeling of AI's impact on social banking, particularly in cooperative banks, motivates the present study's system dynamics approach.

2.7. Dynamic hypothesis

Building upon the literature review and drawing from expert panel insights, this research develops a comprehensive dynamic hypothesis that articulates the core feedback mechanisms driving AI adoption and performance in social banking systems.

2.7.1. Core dynamic hypothesis

The implementation of AI technologies in social banking creates interconnected reinforcing feedback loops where enhanced AI infrastructure capabilities improve risk assessment accuracy and customer service personalization, leading to increased customer satisfaction and trust. This enhanced reputation enables better resource mobilization and liquidity management, which provides additional capital for further AI investments, creating a virtuous cycle of sustainable development.

2.7.2. Key feedback mechanisms

Reinforcing loop 1 - AI Infrastructure enhancement cycle: AI infrastructure investment → Improved predictive analytics → Enhanced customer satisfaction → Increased bank reputation → Better resource access → Additional AI investment

Reinforcing loop 2 - Risk management optimization cycle: AI-powered risk assessment → Reduced non-performing loans → Improved liquidity stability → Enhanced financial performance → Resources for advanced AI systems → Superior risk management capabilities

Balancing loop 1 - Resource allocation constraints: Increased AI investment demand → Resource competition → Budget limitations → Delayed AI implementations → Temporary performance gaps

This dynamic hypothesis acknowledges that AI adoption in social banking is not a linear process, but rather involves complex interdependencies where system elements both influence and are influenced by one another over time. The hypothesis specifically addresses why some banks achieve sustainable AI-driven transformation while others struggle with implementation challenges.

The temporal dimension is crucial, as the benefits of AI investments may not be immediately apparent but unfold through cascading effects across multiple system components. Understanding these dynamics is essential for developing effective implementation strategies and managing stakeholder expectations during the transformation process.

3. Methodology

This research follows the systematic approach to system dynamics modelling established by Sterman (2000), progressing through five key stages: problem articulation, dynamic hypothesis formation, model building, testing, and policy design.

Error! Reference source not found. illustrates the comprehensive research methodology flowchart that guided this study, showing the systematic progression from problem identification through model validation and scenario analysis.

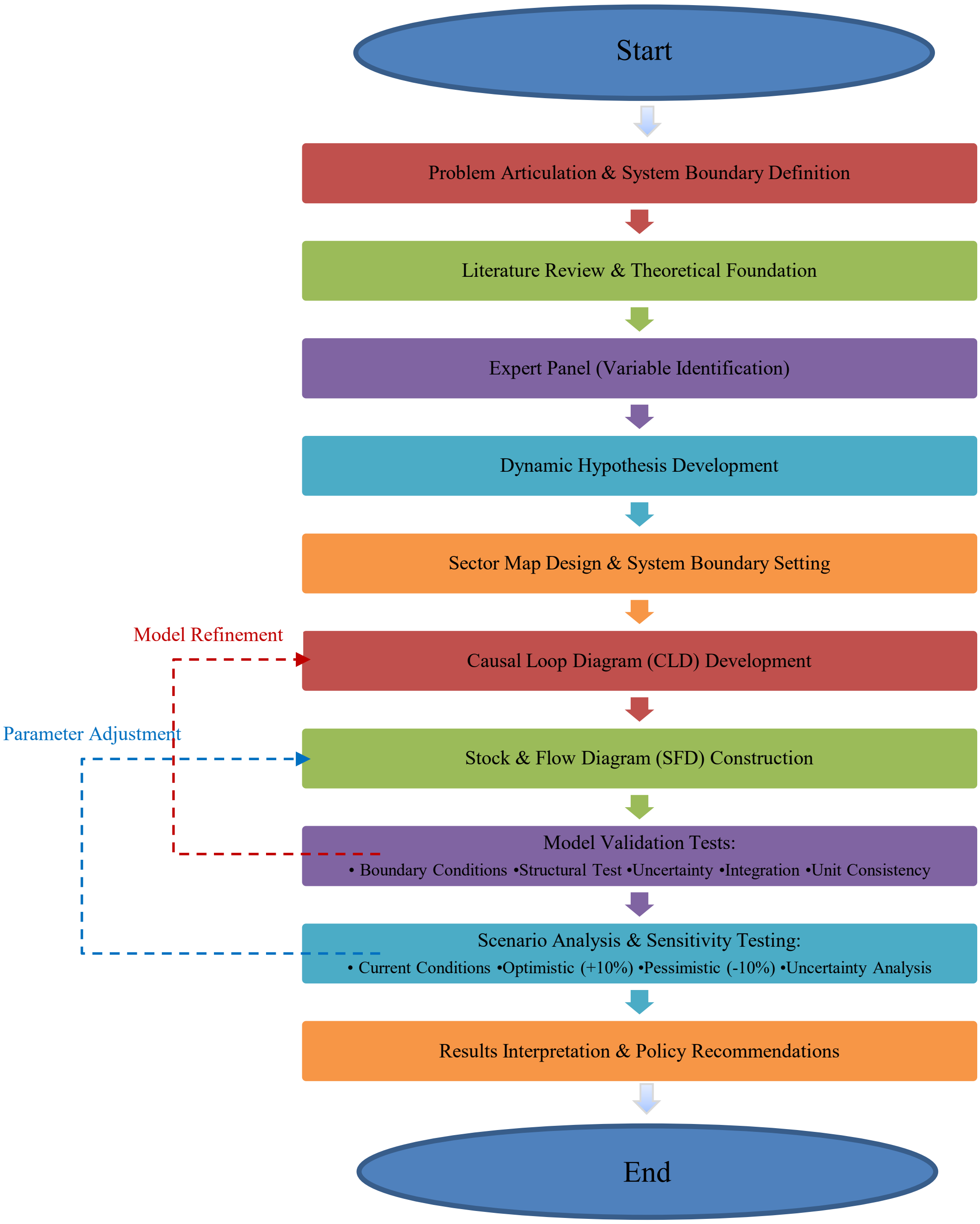

Figure 1. Research methodology flowchart

3.1. Stage 1: Problem articulation and system boundary definition

The first stage involved defining the core problem: understanding how the implementation of AI creates complex feedback effects in social banking systems, particularly within Iranian cooperative banks. System boundaries were established to include: (1) internal bank operations and AI infrastructure, (2) customer interactions and satisfaction mechanisms, (3) financial performance indicators, and (4) broader sustainability outcomes. External factors such as regulatory changes and macroeconomic conditions were treated as boundary conditions.

3.2. Stage 2: Dynamic hypothesis development

Building on a literature review and preliminary expert consultation, we formulated a dynamic hypothesis articulating three primary feedback loops that drive AI adoption in social banking: infrastructure enhancement cycles, risk management optimization cycles, and resource allocation constraint cycles (detailed in Section 2.7).

3.3. Stage 3: Model building

3.3.1. Phase 3a: Expert panel for variable identification

Using purposive sampling, 15 specialists were selected based on: mastery of cooperative banking concepts, familiarity with AI applications, a minimum master's degree, and 15+ years of senior management experience. The panel consisted of 8 doctoral and seven master's degree holders with diverse expertise (6 with 15-20 years, 5 with 21-25 years, 4 with 25+ years). Three structured panel sessions were conducted using thematic analysis.

3.3.2. Phase 3b: Model structure development

Based on expert panel results and dynamic hypothesis, we developed:

- Sector Map: Defining system boundaries and high-level structure
- Causal Loop Diagrams: Representing feedback loop structures
- Stock and Flow Diagram: Specifying accumulations and rates using Vensim software

3.3.3. Phase 3c: Model formulation

Mathematical equations were formulated for each relationship, with parameters determined through literature review, expert judgment, and available Iranian banking data (2019-2021). The model simulates system behavior over a 10-year period (2021-2031).

3.4. Stage 4: Model testing and validation

Comprehensive validation following SD best practices:

- Structure Testing: Boundary conditions, dimensional consistency, extreme conditions
- Behavior Testing: Integration test, uncertainty analysis (200 Monte Carlo runs)
- Policy Testing: Sensitivity analysis and leverage point identification

3.5. Stage 5: Scenario design and policy analysis

Three scenarios were developed following a ±10% parameter variation approach:

- Current Conditions: Baseline trajectory analysis
- Optimistic Scenario: Enhanced AI investment and improved operational parameters
- Pessimistic Scenario: Reduced capabilities and increased constraints

The ±10% range was selected based on established uncertainty analysis practices in system dynamics modeling (Sterman, 2000) and represents a conservative approach suitable for exploratory analysis in the absence of precise uncertainty distributions. This range provides sufficient sensitivity testing while avoiding extreme conditions that might not reflect realistic operational constraints in the Iranian banking context.

All analyses were performed using Vensim PLE software, with results interpreted through the lens of sustainable banking transformation and policy implications for cooperative banks.

4. Findings

4.1. Causal-Loop diagram analysis

Before presenting the detailed causal loop diagram, **Error! Reference source not found.** shows the sector map of the AI-enabled social banking model, which provides a conceptual framework identifying the main system boundaries and interactions between different sectors.

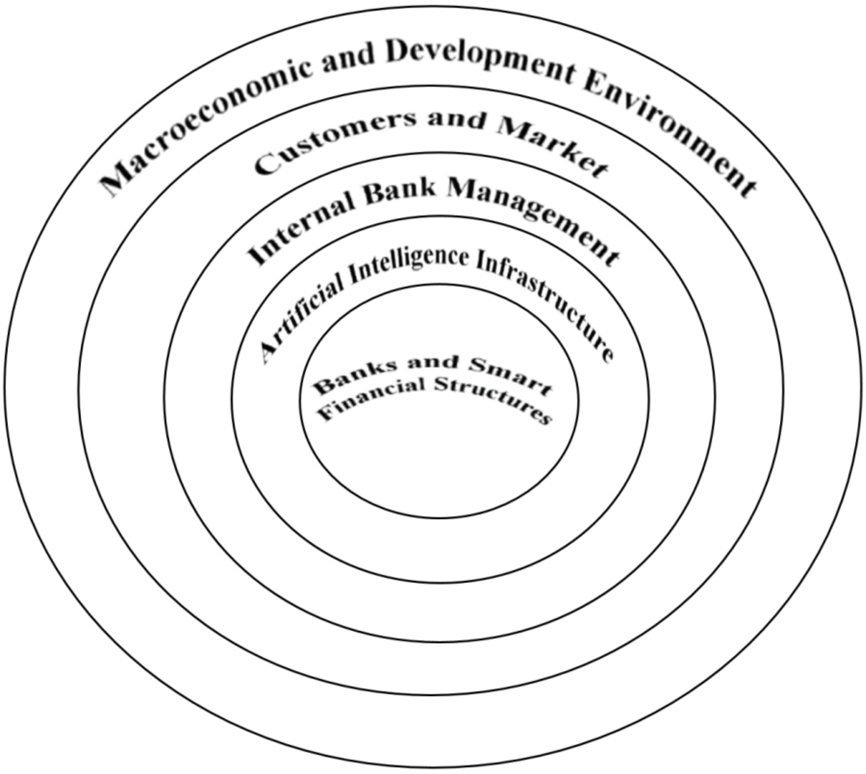

Figure 2. Sector map of AI-enabled social banking model

The sector map illustrates the layered structure of the banking system, with the intelligent banking infrastructure at its core, surrounded by an AI infrastructure layer, internal bank management, customers, and market environment, and the broader economic and development context. This mapping helps define model boundaries and focus analytical attention on key leverage points for improving bank performance.

Based on the results of the expert panel and the system boundaries identified in the sector map, three primary reinforcing feedback loops were identified that drive the behavior of AI-enabled social banking systems. These loops are presented in Figures 3, 4, and 5.

4.1.1. Loop R1: Sustainable development enhancement loop

This primary reinforcing loop demonstrates how AI infrastructure investments create a virtuous cycle of sustainable development. As shown in **Error! Reference source not found.**, enhanced AI capabilities lead to improved service quality and personalization, which increases customer satisfaction and enhances bank reputation, ultimately providing greater resources for additional AI infrastructure investment.

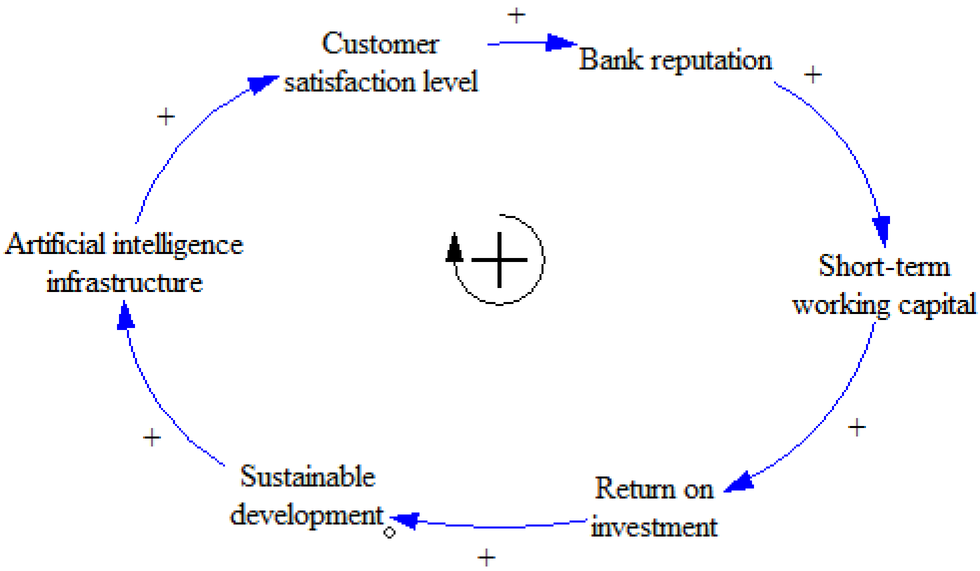

Figure 3. AI infrastructure enhancement loop in social banking

4.1.2. Loop R2: Liquidity optimization loop

Error! Reference source not found. illustrates the dynamic relationship between AI-powered predictive capabilities and liquidity management. AI-based predictive systems enhance liquidity forecasting, reduce unpredictable liquidity fluctuations, improve operational stability, and facilitate better resource allocation for the deployment of advanced AI systems.

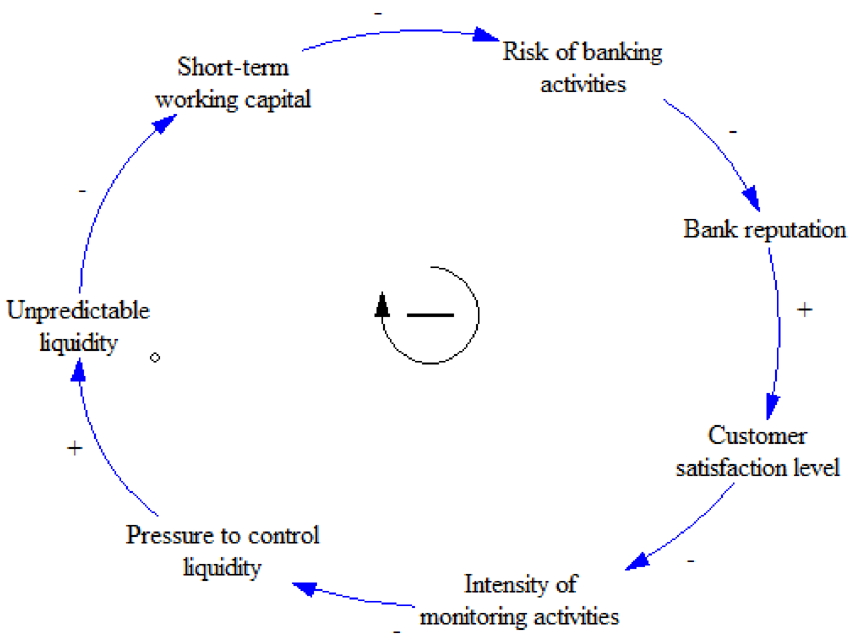

Figure 4. Liquidity management optimization loop through AI

4.1.3. Loop R3: Risk management excellence loop

As depicted in **Error! Reference source not found.**, this reinforcing loop captures how AI capabilities transform credit risk management. Advanced AI algorithms enhance credit risk assessment, reduce non-performing loans, improve financial performance, and increase investment capacity, thereby enabling more sophisticated AI risk management tools.

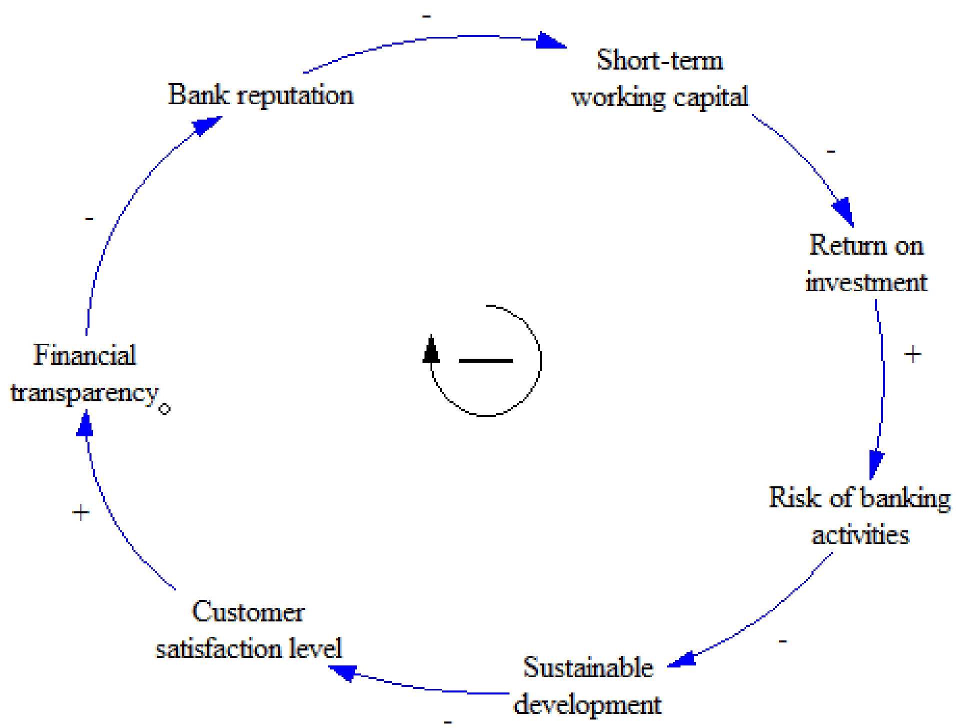

Figure 5. AI-Enabled risk management enhancement loop

These interconnected loops operate simultaneously, with their interactions determining the overall system's behavior. The visual representation in Figures 3-5 clearly demonstrates how each loop reinforces the others, creating either virtuous cycles of improvement or potential challenges when implementation faces obstacles.

4.1.4. Endogenous system dynamics

The three feedback loops presented represent the core endogenous structure of the AI-enabled social banking system. While certain boundary variables (such as regulatory complexity, financial crises, and infrastructure budget) remain exogenous to maintain realistic model boundaries, the primary system behavior emerges from internal interactions between AI infrastructure, customer satisfaction, bank reputation, and financial performance. This endogenous structure accounts for the dominant system dynamics, with exogenous variables serving as necessary boundary conditions rather than primary drivers of system behavior. The focus on these three reinforcing loops demonstrates how internal feedback mechanisms create either virtuous cycles of AI-enabled improvement or implementation challenges, independent of external forcing functions.

4.2. Stock-Flow diagram

Based on the causal-loop diagram, the stock-flow diagram of the model was designed using Vensim software. **Error! Reference source not found.** shows the diagram in which stock variables (including bank reputation, unpredictable liquidity, and non-performing loans) and flow variables (including rates of increase and decrease for each stock variable) are specified.

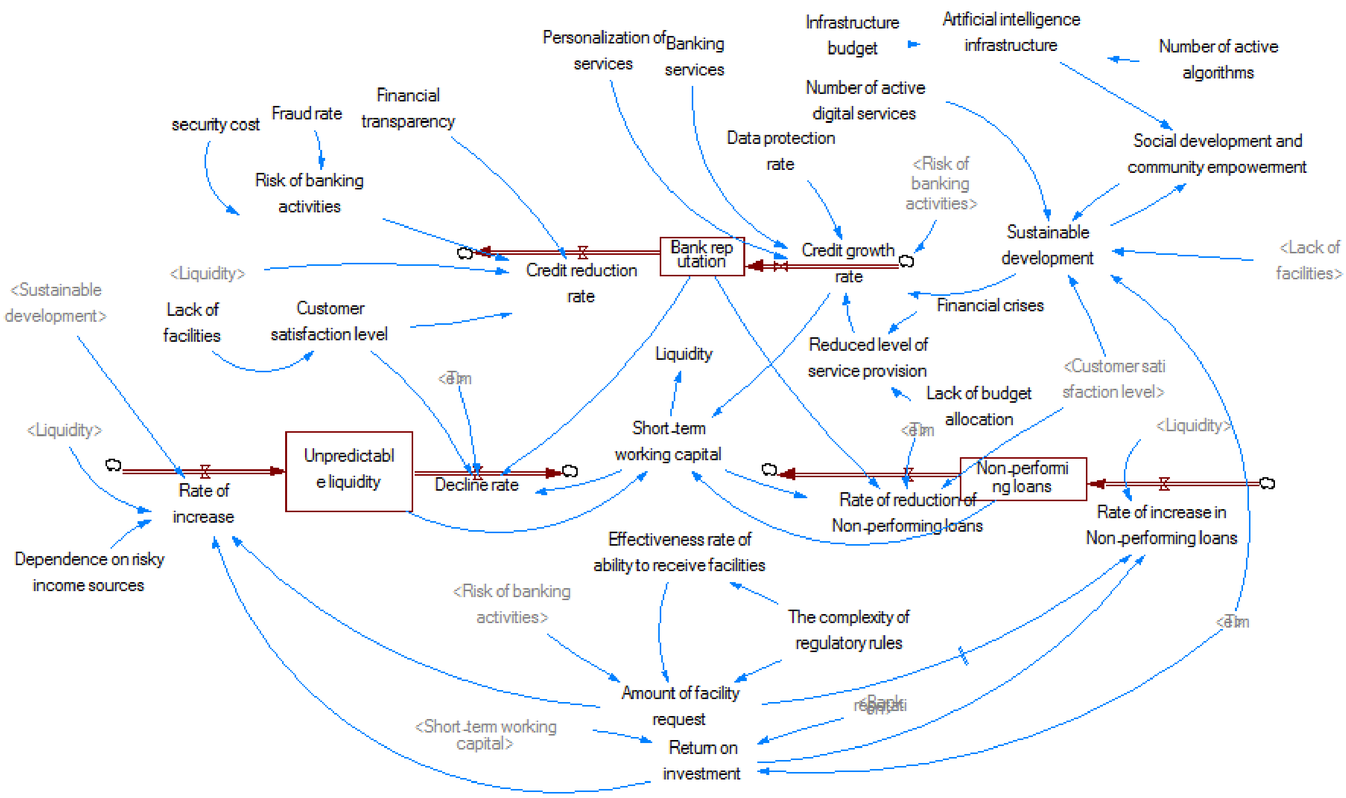

Figure 6. Stock-flow diagram of AI functions in the social banking model

The Time variable appears in the SFD for computational and integration purposes within the Vensim modeling environment, but it does not represent a substantive model component that affects system behavior. This technical variable enables proper equation processing and simulation timing without influencing the core banking dynamics analyzed in this study.

In this model, 31 key variables were identified, and mathematical relationships between them were defined. **Error! Reference source not found.** shows the components in the model.

Table 1. Components in the stock-flow model

Category	Main variables
Stock variables	Bank reputation, Unpredictable liquidity, Non-performing loans
Flow variables	Rate of reputation increase, Rate of reputation decrease, Rate of unpredictable liquidity increase, Rate of unpredictable liquidity decrease, Rate of non-performing loans increase, Rate of non-performing loans decrease
AI-related auxiliary variables	AI infrastructure, Number of active algorithms, Infrastructure budget, Service personalization, Data protection rate
Financial auxiliary variables	Short-term working capital, Return on capital, Liquidity, Financial transparency, Banking activity risk
Operational auxiliary variables	Banking services, Number of active digital services, Customer satisfaction level, Loan denial, Loan application rate
Environmental auxiliary variables	Sustainable development, Social development and community empowerment, Financial crises, Regulatory complexity, Dependency on high-risk revenue sources

Error! Reference source not found. also shows the formulas and relationships used in the model that specify how each variable is calculated.

Table 2. Mathematical equations of key model variables

	Equation	Description	Source
Core System Equations (Standardized Mathematical Notation)	**1. Reputation Enhancement Flow** $REF = (SD \times BS \times k_1 \times DPR \times SP) / (BAR \times SRL)$	SD = Sustainable development index BS = Banking services portfolio k_1 = Scaling constant (1000) DPR = Data protection rate SP = Service personalization level BAR = Banking activity risk SRL = Service reduction level	Developed through expert panel consensus and adapted from organizational reputation literature (Fombrun, 1996; Reputation Institute, 2020)
	2. Bank Reputation (Stock Variable) $BR(t) = BR(t-dt) + (REF - RDF) \times dt$	BR = Bank reputation level REF = Reputation enhancement flow RDF = Reputation deterioration flow dt = Time increment	Standard stock-flow formulation based on system dynamics methodology (Sterman, 2000)
	3. Reputation Deterioration Flow $RDF = (L/k_1) - BAR\text{^}((FT + CSL)/k_2)$	L = Liquidity indicator FT = Financial transparency index CSL = Customer satisfaction level k_2 = Normalization constant (10)	Derived from banking reputation studies and expert elicitation (Mishkin, 2019)
	4. Short-term Working Capital $STWC = NPL \times UL \times k_3 \times REF$	NPL = Non-performing loans level UL = Unpredictable liquidity k_3 = Capital efficiency factor (0.1)	Based on financial management principles (Ross et al., 2019) and Iranian banking data analysis
	5. Banking Activity Risk $BAR = SC \times FR \times k_4$	SC = Security cost index FR = Fraud rate k_4 = Risk scaling factor (1.0)	Adapted from credit risk management literature (Saunders and Allen, 2010) and expert panel validation
	6. Customer Satisfaction Level $CSL = 1 - LD$	LD = Loan denial rate	Based on SERVQUAL framework (Parasuraman et al., 1988) adapted for banking context
	7. AI Infrastructure Index $AII = (IB + AAC)/k_5$	IB = Infrastructure budget allocation AAC = Active algorithms count k_5 = Normalization factor (200)	Developed through expert panel and technology adoption literature (Davenport and Ronanki, 2018)
	8. Return on Capital $ROC = \max(0, (STWC/T - BR/T)/k_6)$	T = Time period k_6 = Performance scaling factor (1000)	Standard financial performance metrics (Gitman and Zutter, 2015) adapted for system dynamics context
	9. NPL Recovery Flow $NPLRF = (STWC/T \times CSL) + (BR/T)$	NPLRF = Non-performing loans recovery flow	Based on banking recovery models and expert judgment
	10. Liquidity Stabilization Flow $LSF = (STWC/T \times k_7 \times CSL) - (BR/T)$	LSF = Liquidity stabilization flow k_7 = Processing efficiency factor (100)	Liquidity management literature (Koch and MacDonald, 2014) and expert panel insights
Equation Development Methodology	**Literature Synthesis (40%):** Core relationships derived from established banking, AI, and system dynamics literature. **Expert Elicitation (35%):** Three rounds of structured expert panel sessions with 15 banking and AI specialists. **Empirical Calibration (25%):** Parameter values calibrated using available Iranian banking sector data (2019-2021) from Central Bank of Iran reports. **Validation:** All equations underwent dimensional analysis and behavioral testing to ensure logical consistency and realistic system behavior.		
Unit Consistency Verification	**Dimensional Analysis Results:** • All flow variables: [dimensionless units]/Time • All stock variables: [dimensionless units] • All ratios and indices: Properly normalized (0-100 scale) • All constants: Dimensionally consistent with their applications **Verification Process:** Comprehensive unit checking performed using Vensim PLE built-in dimensional analysis tools. No dimensional errors detected in the final model structure.		

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4.2.1. Parameter sources and validation

All model parameters were carefully calibrated using a combination of available banking sector data, expert judgment, and literature-based estimates. To maintain consistency and enable cross-variable comparison, all components were normalized to a 0-100 scale representing percentage values.

Table 3. Parameter constants table

Parameter	Value	Definition	Source
k_1	1000	Reputation scaling constant	Calibrated through expert panel
k_2	10	Transparency normalization factor	Based on banking disclosure standards
k_3	0.1	Capital efficiency factor	Iranian banking sector analysis
k_4	1.0	Risk scaling factor	Risk management literature
k_5	200	AI infrastructure normalization	Technology adoption studies
k_6	1000	Performance scaling factor	Financial analysis standards
k_7	100	Processing efficiency factor	Operational research literature

4.2.2. Key parameter sources

To develop the model, a set of key parameters was identified and initially calibrated. These parameters were derived from reputable academic sources, official data, and prior studies in the fields of banking and technology, as outlined below:

- Return on Capital: Based on Central Bank of Iran reports (2019-2021) and banking performance studies (Amiri et al., 2022)
- Banking Activity Risk: Derived from credit risk assessment literature (Saunders and Allen, 2010) and Iranian banking risk studies (Masoudi, 2021)
- Bank Credibility: Calibrated using customer trust surveys and reputation indices (Mishkin, 2019)
- Customer Satisfaction: Based on SERVQUAL measurement scales (Parasuraman et al., 1988) adapted for the Iranian banking context
- Financial Transparency: Derived from banking disclosure standards (Bushman and Smith, 2001)
- AI Infrastructure: Based on technology adoption frameworks in banking (Gyau et al., 2024)

4.2.3. Fixed parameter rationale

Several variables were held constant during the simulation period due to their relatively stable nature in the short to medium term or their limited direct impact on core system dynamics. This simplification approach is consistent with system dynamics modelling best practices, where the focus is on understanding behavioural patterns rather than precise numerical predictions.

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Table 4. Fixed parameter values

Variable	Value	Rationale	Variable
Active digital services	10	Based on a typical cooperative bank service portfolio	Active digital services
Active algorithms count	13	Representative of current AI implementation in Iranian banks	Active algorithms count
Infrastructure budget	12	Normalized value based on sector averages	Infrastructure budget
Security cost	400,000	Based on cybersecurity investment studies	Security cost
Financial crises impact	0.8	Historical crisis impact analysis	Financial crises impact
Loan denial rate	0.8	Iranian cooperative banking sector data	Loan denial rate
Regulatory complexity	0.25	Banking regulation complexity index	Regulatory complexity
Service personalization	25	Current personalization capability assessment	Service personalization
Data protection rate	45	Current data security implementation level	Data protection rate
Fraud rate	17	Banking fraud statistics (Central Bank of Iran)	Fraud rate
High-risk revenue dependency	1.05	Risk exposure assessment	High-risk revenue dependency

4.2.4. Qualitative variable scale definitions

All qualitative variables are normalized to a 0-100 percentage scale with the following interpretation framework:

- Bank Reputation: 0-33 (Poor reputation, limited market trust), 34-66 (Moderate reputation, average market standing), 67-100 (Strong reputation, high market confidence)
- Customer Satisfaction Level: 0-33 (Low satisfaction, frequent complaints), 34-66 (Moderate satisfaction, acceptable service), 67-100 (High satisfaction, loyal customer base)
- Financial Transparency: 0-33 (Limited disclosure, opacity in reporting), 34-66 (Standard disclosure, regulatory compliance), 67-100 (Full transparency, proactive disclosure)
- Service Personalization: 0-33 (Generic services, no customization), 34-66 (Limited personalization, basic customization), 67-100 (Highly personalized, AI-driven customization)
- Data Protection Rate: 0-33 (Basic security, minimal protection), 34-66 (Standard security, regulatory compliance), 67-100 (Advanced security, comprehensive protection)

These scales enable consistent interpretation of qualitative improvements and facilitate meaningful comparison across different model scenarios.

4.2.5. Unit consistency verification

Comprehensive unit consistency checks were performed using Vensim's built-in validation tools. All equations maintain dimensional consistency, with percentage-based variables properly scaled and normalized to prevent computational errors.

4.3. Model validation

To ensure the validity of the designed model, multiple tests were conducted. The results of these tests are as follows.

4.3.1. Boundary conditions test

In this test, system behaviour at extreme values of variables was examined. Figure 7 shows the behaviour of essential model components at extreme points.

The results show that when the "data protection rate" variable is at an extreme point, non-performing loans and unpredictable liquidity reach their minimum possible value, which improves the bank's reputation component.

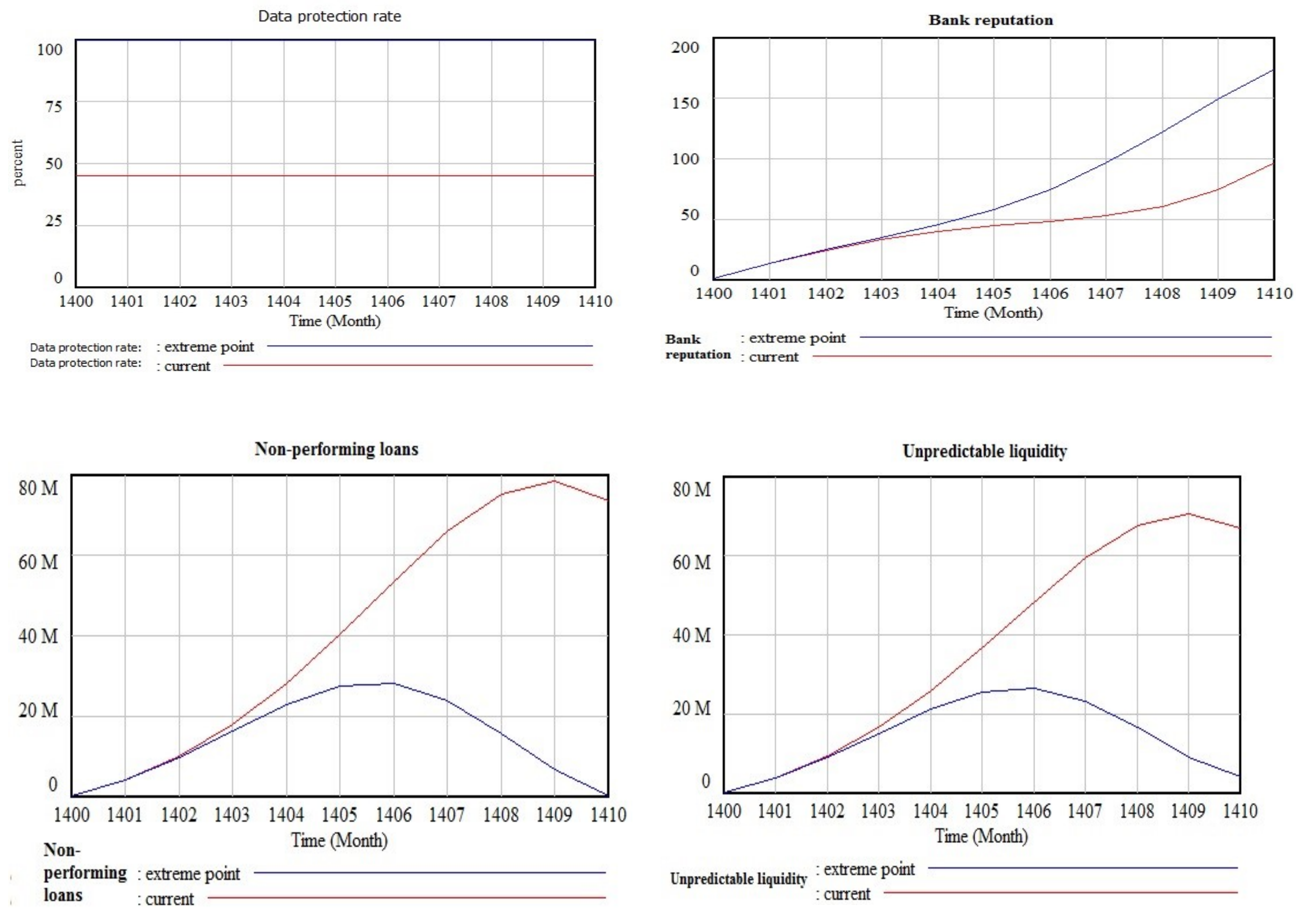

Figure 7. Reaction of main model components under boundary conditions

4.3.2. Structural test of the model

The results of the structural test show that the presented model is free of any structural errors and the defined variables are consistent with each other, as shown in Figure 8.

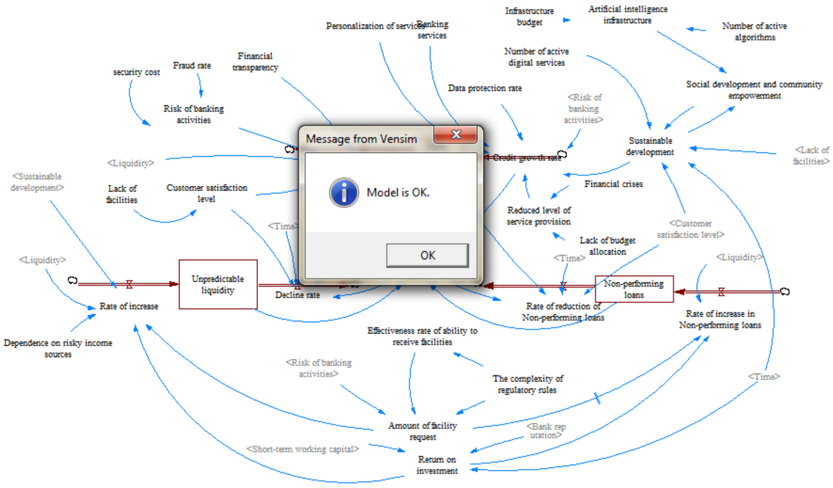

Figure 8. Confirmation of model structural correctness by Vensim software

4.3.3. Uncertainty test

In this test, the model was simulated 200 times with different input parameter values. Figure 9 shows the behaviour of the "unpredictable liquidity," "non-performing loans," and "bank reputation" components under uncertainty.

The results indicate that the yellow areas have the highest probability of occurrence, while the grey areas have the lowest probability of occurrence. Since the set of specified areas is within the approved range and no area outside the expected limit has formed, this indicates the existence of healthy relationships and behaviour among parameters and components.

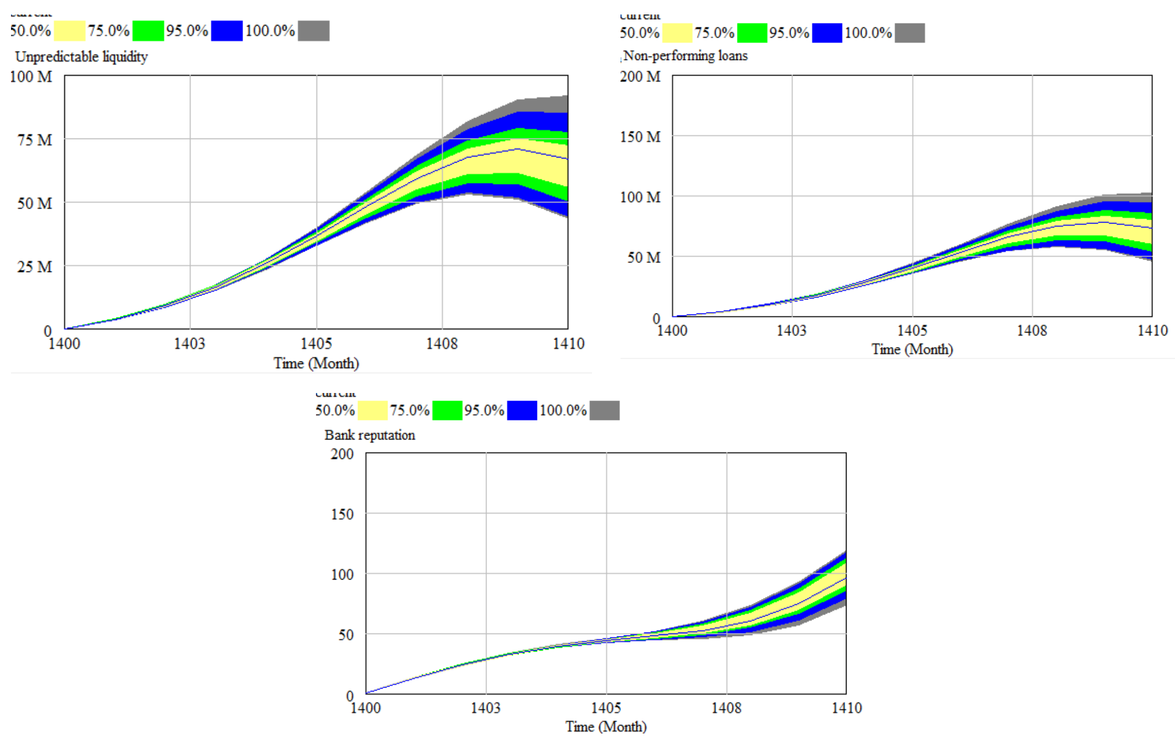

Figure 9. Uncertainty analysis of main model variables

4.3.4. Integration test

The results of the integration test, as presented in Figure 10, show that reducing the time step does not change the behavior of the graphs, and no value outside of the larger time steps is observed.

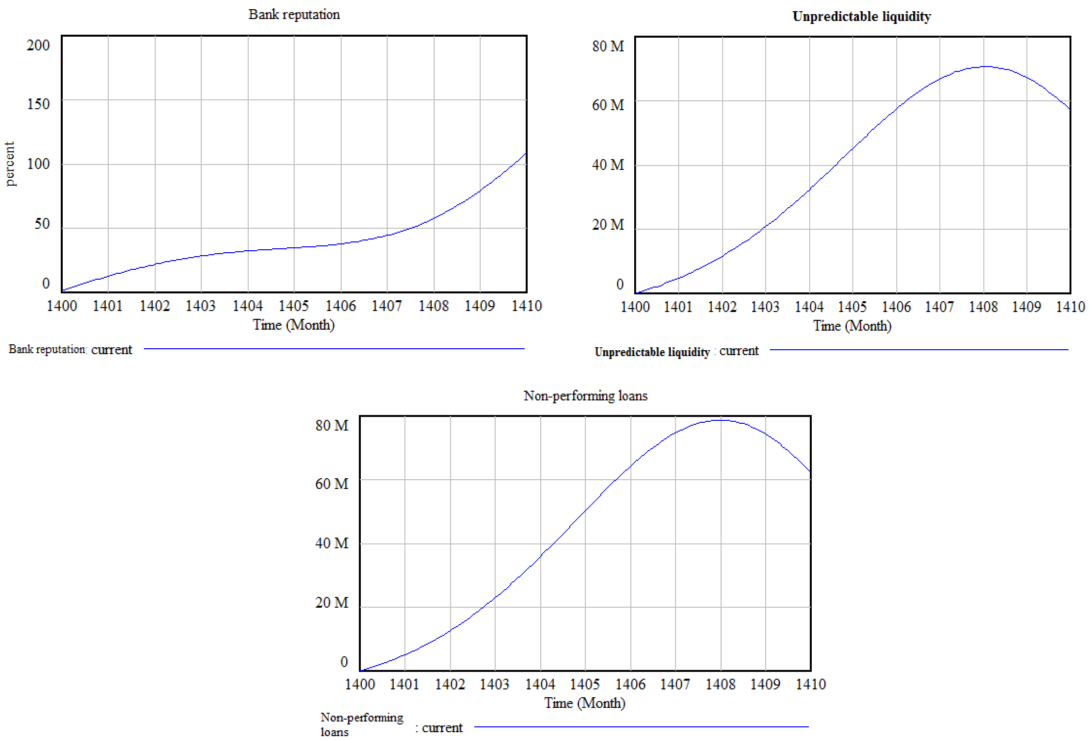

Figure 10. Model stability in different time steps

4.3.5. Leverage points test

In this test, variables that have the greatest impact on the main component were identified. The results in Figure 11 show that with a 10% increase in "service personalization," bank reputation has had a significant growth at the end of the period of interest.

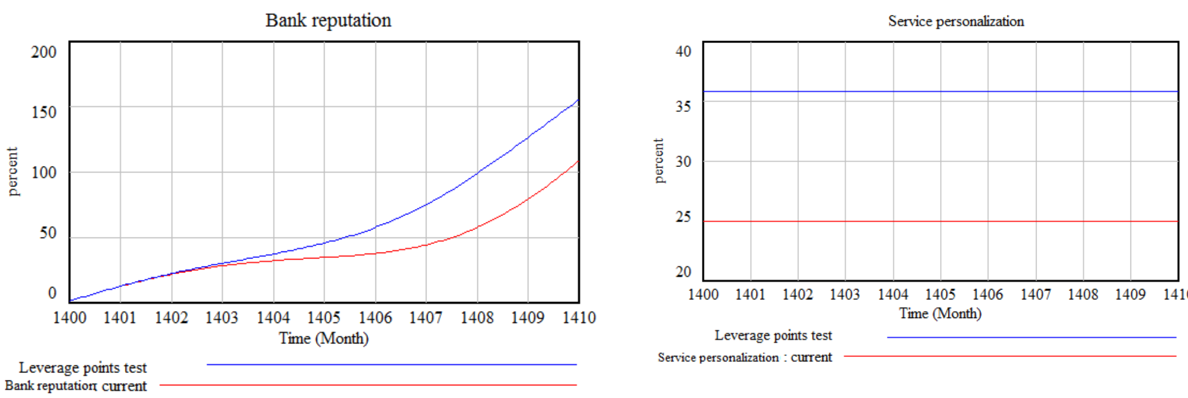

Figure 11. Effect of leverage variables on bank reputation

4.4. Scenario analysis

4.4.1. Current conditions continuation scenario

In this scenario, system behaviour was examined without changing the current trend. **Error! Reference source not found.** shows the behaviour of "unpredictable liquidity," "non-performing loans," and "bank reputation" components in normal conditions.

The results show that in this scenario:

1. Unpredictable liquidity has an upward trend from 2021 to 2028, reaching about 80 million units, and then decreases.
2. Non-performing loans also follow a trend similar to unpredictable liquidity.
3. Bank reputation has an upward trend from the beginning to the end of the period.

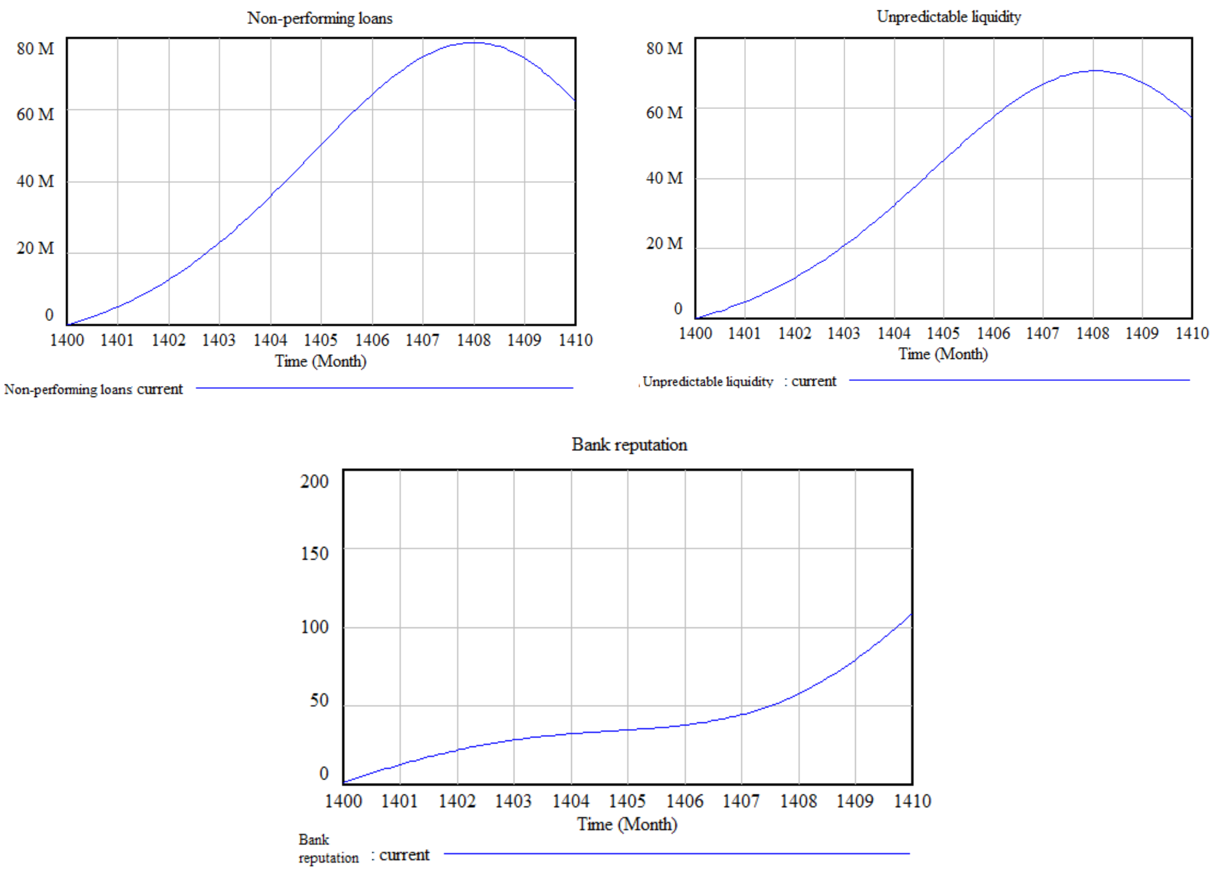

Figure 12. Trend of main model variables in the current conditions continuation scenario

4.4.2. Optimistic-Pessimistic scenario

In this scenario, model behaviour was examined with a 10% change in influencing factors. Figure 13 shows model behaviour under the optimistic-pessimistic scenario.

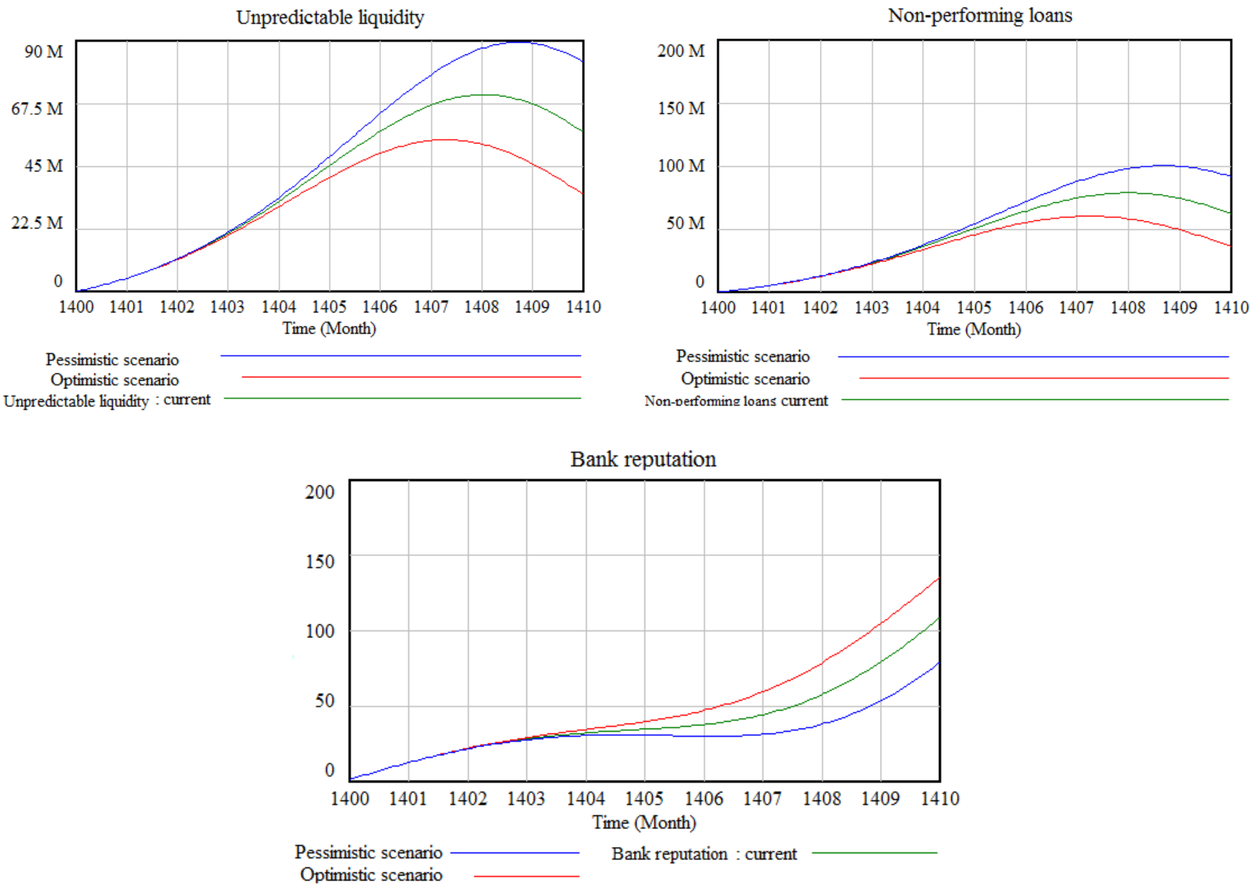

Figure 13. Comparison of optimistic and pessimistic scenarios for key variables

Tables 5, 6, and 7 present parameter changes related to the variables of "unpredictable liquidity," "non-performing loans," and "bank reputation" under the influence of the optimistic-pessimistic scenario.

Table 5. Parameter changes related to "unpredictable liquidity" under the influence of an optimistic-pessimistic scenario

Unpredictable liquidity	Optimistic state	Pessimistic state
Dependency on high-risk revenue sources	10% decrease	10% increase
Loan denial	10% decrease	10% increase

Table 6. Parameter changes related to "non-performing loans" under the influence of an optimistic-pessimistic scenario

Non-performing loans	Optimistic state	Pessimistic state
Budget non-allocation	10% decrease	10% increase
Financial crises	10% decrease	10% increase

Table 7. Parameter changes related to "bank reputation" under the influence of an optimistic-pessimistic scenario

Bank reputation	Optimistic state	Pessimistic state
Data protection rate	10% increase	10% decrease
Financial transparency	10% increase	10% decrease

Scenario design and interpretation framework:

For qualitative variables in this study, the ±10% changes represent realistic operational adjustments rather than precise quantitative shifts:

- **Data protection rate (±10%):** Represents implementation of enhanced/reduced cybersecurity protocols and data governance measures
- **Financial transparency (±10%):** Reflects increased/decreased disclosure practices and reporting frequency
- **Loan denial rate (±10%):** Indicates tightened/relaxed credit approval criteria
- **Service personalization (±10%):** Represents enhanced/reduced AI-driven customer service customization

Outcome interpretability:

Given the normalized 0-100 scale for all variables, outcomes should be interpreted as relative performance indicators rather than absolute measures. For instance, "bank reputation increase" indicates improved relative standing compared to baseline conditions, while the magnitude reflects the strength of improvement within the modelled system constraints.

The results show that:

(1) In the optimistic scenario, unpredictable liquidity decreases to 34 million (compared to 57 million in the baseline scenario), while in the pessimistic scenario, it increases to 82 million.
(1) In the optimistic scenario, non-performing loans reach 32 million (compared to 60 million in the baseline state), while in the pessimistic scenario, they increase to 90 million.
(2) In the optimistic scenario, bank reputation increases by 20%, while in the pessimistic scenario, it decreases by 20%.

4.4.3. Optimistic-Pessimistic scenario under uncertainty

Figure 14 shows the behaviour of the bank reputation component under uncertainty.

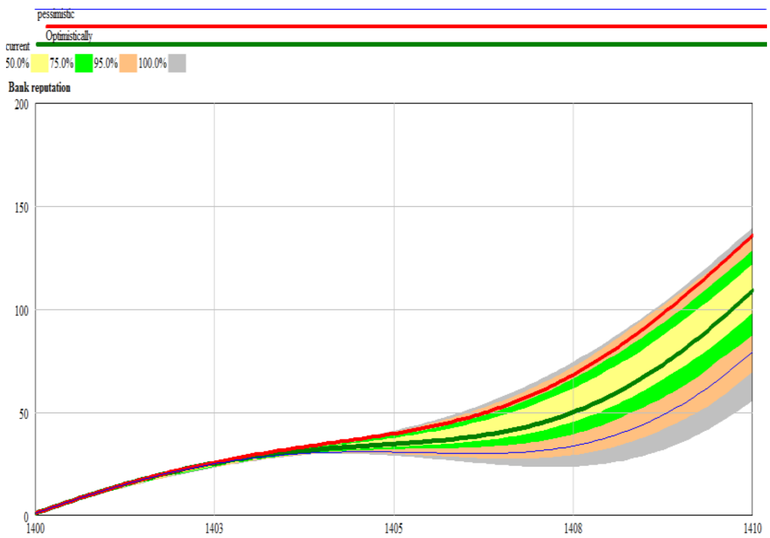

Figure 14. Probability of occurrence of different scenarios for bank reputation

The results show that the likelihood of the bank reputation component being in the pessimistic state is higher than in the optimistic state, which indicates insufficient attention to this topic and the need for addressing it to prevent a decrease and taking measures to increase the value of this component. Table 8 shows the level of uncertainty in different states of the bank reputation component.

Table 8. Confidence levels for different scenarios of bank reputation

Capital lockup	Uncertainty: 100	Uncertainty: 95	Uncertainty: 75	Uncertainty: 50
Optimistic state	✓			
Normal state				✓
Pessimistic state		✓		

5. Discussion and conclusion

This research was conducted to study the impact of AI functions on social banking performance using a system dynamics approach in Iranian cooperative banks. The results from modelling and simulation indicate the significant impact of AI infrastructure on key variables of the social banking system. In this section, the research findings are discussed and compared with the results of previous studies. Next, the practical and theoretical applications of the research, its limitations, and suggestions for future studies are presented.

The research results demonstrated that strategic investments in AI infrastructure, coupled with enhanced data protection protocols and improved financial transparency, generate substantial improvements across key performance indicators. The modelling analysis revealed significant positive impacts on bank reputation, marked reductions in unpredictable liquidity fluctuations, and notable decreases in non-performing loans, supporting the hypothesis that AI-enabled social banking can achieve sustainable operational excellence. These findings are consistent with previous studies on the impact of AI on improving risk management and liquidity (Fourie and Bennett, 2019; Sadok et al., 2022).

Analysis of the causal-loop diagram showed that three main cycles could be identified in the AI functions in social banking model: the cycle of relationship between sustainable development, bank reputation, liquidity, and short-term working capital; the cycle of interaction between liquidity, unpredictable liquidity, and short-term working capital; and the cycle of relationship between liquidity, non-performing loans, and short-term working capital. These cycles demonstrate the complexity of relationships between key system variables and are consistent with previous studies on banking system dynamics (Al-Sartawi et al., 2022).

Scenario analysis indicated that if current conditions persist, unpredictable liquidity and non-performing loans will exhibit an upward trend, but after reaching a peak, they are expected to decline. This behavioural pattern could be due to corrective actions and control policies that are adopted after experiencing crisis conditions. This finding is consistent with the results of Thongsri and Tripak's (2024) study, which showed that social banks take effective measures for liquidity and risk management in crisis conditions.

A comparison of optimistic and pessimistic scenarios revealed that relatively small changes (10%) in key parameters can have a significant impact on system behavior. This finding demonstrates the system's sensitivity to changes and the importance of strategic decisions regarding the application of AI. Venanzi and Matteucci (2022) also highlighted the importance of strategic decisions in the sustainability of cooperative banks in their study.

Uncertainty analysis showed that the probability of the bank reputation component being in the pessimistic state is higher than in the optimistic state. This finding highlights the need for increased attention to factors influencing bank reputation and the adoption of effective policies for risk management in this area. Korzeb et al.'s (2024) study also emphasized the importance of risk management and maintaining reputation in cooperative banks.

From a theoretical perspective, this research adds to the existing literature on social banking and applications of AI in banking. The presented dynamic model provides a conceptual framework for understanding complex interactions between key variables of the AI functions in the social banking system. This model can serve as a basis for future research in this field.

From a practical perspective, the results of this research can serve as a useful guide for cooperative bank managers when considering investment in AI technologies. The presented model enables simulation of different scenarios and helps managers predict the consequences of various decisions.

Based on the research findings, several strategies are proposed for improving AI functions in social banking performance. Investment in AI infrastructure is a fundamental priority that includes developing the necessary infrastructure for implementing intelligent systems, encompassing hardware, software, and specialized human resources. Additionally, enhancing data security by implementing advanced security protocols to safeguard customer data and mitigate cyber threats is crucial.

Developing data analysis systems using ML algorithms to analyse customer behaviour and provide personalized services is another strategy that can help improve the quality of banking services. Optimizing lending processes through the use of AI models for credit risk assessment and improving the loan-granting process is also of high importance. Finally, increasing financial transparency using modern technologies to enhance transparency in financial transactions can lead to improved customer trust and strengthen the position of cooperative banks in the country's banking system.

While this study primarily focuses on the economic and social dimensions of AI-enabled banking, we also recognize that comprehensive sustainability requires environmental considerations. Future research should explore how AI technologies in banking can contribute to environmental sustainability through paperless operations, optimized energy consumption in banking facilities, and support for green financing initiatives. The current model provides a foundation that can be extended to incorporate environmental indicators as data availability and measurement frameworks improve in the Iranian banking context.

This research, like any other research, has faced limitations. First, the presented model has been developed based on available data and expert opinions, and may not fully reflect the complexities of the real system. Second, model parameters have been determined based on expert estimates and may require revision as conditions change. Third, this research has focused only on Iranian cooperative banks, and its results may not be generalizable to other types of banks or other countries. The current model does not explicitly incorporate time delays between cause-and-effect relationships, which could provide additional realism in representing the temporal dynamics of AI implementation impacts. Future model iterations should consider incorporating appropriate delay structures based on empirical evidence of AI adoption timelines in banking operations.

To complement and build upon the achievements of this research, several potential research paths for future studies are proposed. Developing the model with real data, using actual bank data for model calibration, can significantly help increase prediction accuracy. Comparing different banks to explore the impact of AI on the performance of various kinds of banks (commercial, specialized, and cooperative) can provide a more comprehensive perspective on the topic.

Examining the role of organizational culture in the successful implementation of AI systems in banks is another important study area that can help better understand human factors affecting this process. Conducting a more detailed analysis of the costs and benefits of investing in AI technologies in cooperative banks can also lead to more effective economic decisions in this area. Finally, developing models with longer time horizons to examine the long-term impacts of AI on bank sustainability and competitiveness can provide a clearer vision of the future of the banking industry.

This research demonstrates that AI can play a significant role in enhancing social banking performance in cooperative banks. Investing in AI infrastructure, enhancing data protection, and improving financial transparency can increase a bank's reputation, reduce unpredictable liquidity, and lower non-performing loans. The system dynamics model presented in this research provides a framework for understanding complex interactions between key system variables and can be used as a tool for decision-making and policy-making regarding the application of AI in the country's social banking system.

Given the growing trend of digitalization in banking services and the increasing importance of banks' social responsibilities, implementing AI functions in a social banking model can be an important step toward sustainable development, improving financial performance, and increasing customer satisfaction. It requires a commitment from senior management, appropriate investment, and the development of long-term strategies.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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