Design and Validation of a Social Banking Model Based on Artificial Intelligence in Iranian Cooperative Banks

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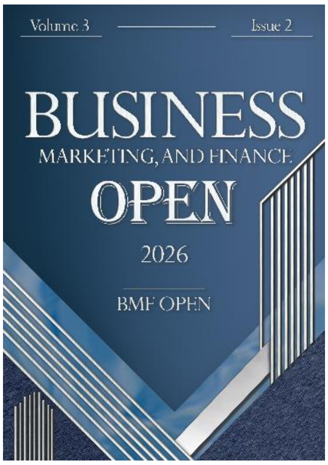

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Abstract: In today's banking landscape, artificial intelligence (AI) is recognized as a key tool for transforming processes and enhancing banking services. However, the adoption of AI in cooperative banks, which are inherently social and customer-centric, still requires appropriate and practical modeling. This study aims to design and validate a social banking model leveraging AI functionalities in cooperative banks. The research is applied in nature and employs a mixed-method approach (qualitative-quantitative). In the qualitative phase, thematic analysis was conducted on 298 scientific articles published between 2014 and 2024, identifying the dimensions and components of the model. In the quantitative phase, the extracted model was validated through confirmatory factor analysis (CFA) and surveys with 82 banking industry experts. The findings revealed that the final model consists of nine dimensions and 54 components, with "AI technology and infrastructure," "legal and regulatory aspects," and "risk and security" being the most influential factors for the model's success. Additionally, the analysis demonstrated that the proposed model exhibits acceptable reliability and validity, explaining 88% of the variance in the dependent variable. The results suggest that implementing AI in cooperative banks can not only improve operational performance but also contribute to sustainable development and enhance their social responsibility. It is recommended that cooperative banks invest in technological infrastructure and address legal and security requirements to take practical steps toward implementing this model.

Keywords: Social Banking, Artificial Intelligence, Sustainable Banking, Innovative Financial Technologies, Social Responsibility, Digital Transformation

1. Introduction

The global banking industry is currently experiencing a profound transformation driven by digitalization, financial innovation, and increasing societal expectations regarding sustainability and social responsibility. In this evolving landscape, the convergence of artificial intelligence (AI), social finance, and cooperative banking models represents a critical frontier for both theory and practice. Social finance has been conceptualized as a financial paradigm that integrates economic objectives with social and environmental value creation [1], while Islamic and socially oriented financial systems further emphasize ethical commitments and inclusive development [2]. Within this broader framework, social banking has emerged as a model that prioritizes stakeholder welfare, community empowerment, and responsible investment alongside profitability [3, 4]. In parallel, cooperative banks—characterized by democratic governance, member ownership, and local embeddedness—have been recognized as inherently aligned with sustainable and socially responsible banking principles [5, 6]. However, the accelerating integration of AI technologies into financial services is redefining operational, strategic, and governance structures in banking systems worldwide [7, 8]. This technological shift raises a fundamental question: how can cooperative banks leverage AI not merely for efficiency gains, but for advancing a comprehensive social banking model that strengthens sustainability, inclusion, and long-term resilience?

Artificial intelligence has been widely acknowledged as a transformative force in financial services, enhancing predictive analytics, credit scoring, fraud detection, service quality, and strategic decision-making [9, 10]. Empirical evidence suggests that AI adoption improves operational efficiency, customer satisfaction, and risk management capabilities in banking institutions [8, 11]. Advanced scoring models and neural-network-based systems have been implemented in cooperative and microfinance contexts to refine credit assessment and portfolio management [12, 13]. Moreover, AI-driven relationship banking and fintech integration have strengthened personalized service delivery and information asymmetry reduction [14]. The emergence of super-intelligent financial services, integrating big data analytics and autonomous decision systems, further underscores the strategic importance of AI in contemporary banking ecosystems [7]. Beyond operational optimization, AI applications in earnings prediction and financial reporting enhance transparency and financial stability [15]. Nonetheless, while the technical benefits of AI are increasingly documented, its integration within socially oriented and cooperative banking models requires deeper conceptual and structural examination.

The concept of social banking extends beyond conventional corporate social responsibility, encompassing sustainable financial intermediation, inclusive credit allocation, and stakeholder-centric governance [16, 17]. Social banking institutions emphasize financial inclusion, support for small and medium-sized enterprises (SMEs), and community development initiatives [18, 19]. In contexts such as post-crisis and post-pandemic environments, social banking has demonstrated resilience by maintaining credit flows to vulnerable sectors and strengthening local economies [20, 21]. Studies on cooperative and rural banking systems indicate that social capital and community engagement significantly enhance institutional performance and sustainability [22]. Marketing strategies in cooperative banks increasingly emphasize community value creation rather than pure profit maximization [23]. Additionally, social banking contributes to reducing financial conflicts between banks and production enterprises by aligning financial intermediation with developmental objectives [24]. The evolution from development banking toward digital financial inclusion reflects a broader structural transformation in which technological innovation and social missions must coexist [25]. However, despite this rich literature, limited research has systematically integrated AI capabilities into a structured social banking model tailored specifically to cooperative banks.

Digital transformation introduces both opportunities and barriers in cooperative banking environments. While AI and fintech integration can enhance service personalization, operational agility, and knowledge management [26, 27], several obstacles impede seamless digital adoption. Technical infrastructure deficiencies, cybersecurity vulnerabilities, regulatory ambiguities, and user resistance are among the most frequently cited challenges [28, 29]. Digital banking transformation requires strategic alignment, organizational culture adaptation, and intelligent governance systems [30, 31]. In cooperative banking contexts, scoring models and credit risk systems must be calibrated to preserve social objectives while ensuring financial prudence [11]. Furthermore, risk management frameworks must incorporate AI-driven fraud monitoring and secure transaction systems to safeguard customer trust [10]. The integration of AI into sustainable finance is particularly critical, as responsible investment and environmental risk assessment increasingly rely on advanced analytics [32]. Thus, the challenge is not merely technological adoption, but the strategic orchestration of AI infrastructure, governance mechanisms, and social development priorities within cooperative banking systems.

Sustainability and social responsibility represent central pillars of contemporary banking models. Corporate social liability frameworks in banking emphasize stakeholder rights, brand attachment, and citizenship-oriented financial practices [33]. ESG performance in cooperative banks has become a benchmark for long-term competitiveness and legitimacy [6]. Social entrepreneurship transformation initiatives illustrate how banking institutions can catalyze community empowerment through responsible financial intermediation [34]. The SEBI index provides quantitative measurement of banks' adherence to social banking principles, highlighting the need for standardized assessment tools [3]. Moreover, alternative social banking system evaluations underscore the importance of multi-criteria decision-making approaches in aligning financial strategies with societal outcomes [35]. Emerging research on comprehensive customer experience models rooted in social responsibility indicates that digital transformation must be accompanied by ethical design and inclusive service architecture [36, 37]. Social media usage and knowledge dissemination further influence customer engagement and trust in digital banking ecosystems [38]. Therefore, an AI-based social banking model must holistically integrate technological sophistication with sustainability, governance, customer-centricity, and inclusive growth objectives.

Despite extensive research on AI adoption, cooperative banking sustainability, digital transformation, and social finance, a significant theoretical and empirical gap persists in synthesizing these domains into a unified structural model. Existing studies have either concentrated on AI technical applications [9, 10], sustainable financial frameworks [17, 32], cooperative governance [5], or digital inclusion trajectories [25]. More recent works emphasize the need for integrated approaches combining AI, sustainability, and social business ecosystems [39, 40]. However, a validated, multidimensional model specifically designed for AI-based social banking within cooperative banks—particularly in emerging economies—remains underdeveloped. Addressing this research lacuna is critical, given the increasing regulatory pressures, competitive dynamics, and technological acceleration confronting cooperative banking institutions. Therefore, the aim of this study is to design and validate a comprehensive AI-based social banking model for cooperative banks that systematically integrates technological infrastructure, governance, risk management, sustainability, financial performance, and social development dimensions.

2. Methodology

This study employs a mixed-method approach, combining qualitative and quantitative techniques. The qualitative phase uses thematic analysis, while the quantitative phase involves CFA.

In the qualitative phase, thematic analysis based on Braun & Clarke's [41] framework was employed. The target population comprised all scientific studies and reputable articles on social banking, AI in the banking industry, and cooperative banks published between 2014 and 2024. A comprehensive search was conducted across major international databases, including Elsevier, Wiley, Springer, Taylor & Francis, and Emerald, as well as local databases such as SID, Civilica, and Magiran. This search identified 298 relevant articles within the specified timeframe.

The thematic analysis followed six distinct steps:

1. **Familiarization with the Data:** All identified articles were carefully reviewed to gain a comprehensive understanding of the content.
2. **Generating Initial Codes:** Titles and abstracts were examined, and 185 irrelevant articles were excluded. Initial coding was performed on the remaining articles.

3. **Searching for Themes:** Similar codes were grouped into broader categories to identify potential themes.
4. **Reviewing Themes:** Articles were evaluated using the CASP (Critical Appraisal Skills Programme) tool, which assesses the quality of research across 10 criteria. Articles scoring below 30 out of 50 were excluded, resulting in the removal of 77 additional articles.
5. **Defining and Naming Themes:** Themes were refined, defined, and named for clarity and relevance to the research objectives.
6. **Producing the Report:** The remaining 36 articles underwent in-depth analysis to extract meaningful insights.

The quality and validity of the research were ensured through collaboration with academic experts in banking and AI. Validity was addressed at three levels:

- **Descriptive Validity**: Regular review sessions and reference management using Endnote.
- **Interpretive Validity**: Ongoing evaluation of findings by the research team.
- **Practical Validity**: Incorporation of expert feedback to enhance applicability.

Reliability was assessed using the CASP tool and evaluated by two independent reviewers. Only articles that passed this rigorous evaluation were included in the final analysis.

The quantitative phase of the study targeted a population of 82 employees working in the cooperative banking sector. Participants were selected to ensure diversity in educational qualifications and professional experience. Among the respondents, 28 were heads of provincial branch credit departments, 23 were credit experts in branch management, 21 held the position of deputy credit and legal managers, 8 served as deputy financial and foreign exchange managers, and 2 were provincial deputies. The geographic distribution of participants was balanced across 31 provinces and their associated cities to ensure comprehensive representation.

To analyze the collected data, preliminary tests were conducted to assess the suitability of the dataset for factor analysis. The Kaiser-Meyer-Olkin (KMO) test was applied to evaluate sample adequacy, while Bartlett's test of sphericity confirmed the appropriateness of the dataset for further analysis. Subsequently, the measurement model was examined using SMART-PLS software, which assessed the model in terms of standardized coefficients and the significance of these coefficients. Retention of each item in the model was contingent upon achieving a p-value less than 0.05 or a t-value greater than 1.96 [42]. Indicators with factor loadings below 0.7 were excluded to ensure the model's robustness.

The reliability of the model was evaluated using Cronbach's alpha (CA) and composite reliability (CR) indices, ensuring internal consistency and reliability of the constructs. For validity assessment, convergent and discriminant validity were examined. Convergent validity was confirmed through significant factor loadings and an average variance extracted (AVE) value exceeding 0.5. Discriminant validity was assessed using the Fornell-Larcker criterion to establish the distinctiveness of each construct.

To evaluate the overall quality of the measurement model, the Goodness of Fit (GOF) index was employed, providing a holistic measure of how well the model represented the observed data. This rigorous validation process ensured the reliability, validity, and overall suitability of the proposed social banking model for practical application in the cooperative banking context.

3. Findings and Results

This section presents the research findings in two parts: qualitative and quantitative. First, the results of thematic analysis conducted on the reviewed literature to identify the dimensions and components of the AI-based social banking model are discussed. Then, the results of CFA validating the extracted model are examined.

During the first stage of thematic analysis, a detailed review of the final 36 articles led to the extraction and coding of sentences and phrases related to social banking and AI applications. In the second stage, 245 initial codes were identified. These codes were categorized into 56 basic themes in the third stage. Subsequently, these basic themes were grouped into nine organizing themes (main dimensions) in the fourth stage. In the fifth stage, the organizing themes were refined, and final titles were assigned. Finally, in the sixth stage, the thematic network was developed, as shown in Table 1.

The thematic analysis results reveal that the AI-based social banking model encompasses nine main dimensions: AI Technology and Infrastructure, Social Development and Community Empowerment, Financial and Economic, Management and Strategic, Legal and Regulatory, Banking Products and Services, Customer-Centricity and User Experience, Risk and Security, Sustainability and Sustainable Development

Table 1. Thematic Network of the AI-Based Social Banking Model

Organizing Themes (Dimensions)	Abb.	Basic Themes (Components)	Ref.
AI Technology and Infrastructure (AITI)	AITI1	Machine Learning and Advanced Algorithms	[8-10, 12-14, 39]
	AITI2	Natural Language Processing	[14, 32, 43]
	AITI3	Expert and Decision Support Systems	[9, 11, 12, 15, 26]
	AITI4	Big Data and Data Analytics	[8, 10, 13, 31]
	AITI5	Localization of AI Technologies	[20, 29, 30]
	AITI6	Integration of Banking Systems	[14, 27, 35]
Social Development and Community Empowerment (SDCE)	SDCE1	Empowering Local Communities	[4, 22, 25]
	SDCE2	Support for Small Businesses	[17, 18, 23]
	SDCE3	Participation in Social Projects	[1, 2, 16, 34]
	SDCE4	Financial Inclusion	[18, 21]
	SDCE5	Job Creation and Entrepreneurship	[4, 31, 34]
	SDCE6	Support for Domestic Production	[1, 6, 17, 32]
	SDCE7	Local Economic Development	[1, 6, 17, 32]
	SDCE8	Empowerment of Female-Headed Households	[1, 6, 17, 32]
Financial and Economic (FE)	FE1	Sustainable Profitability	[3, 5, 17]
	FE2	Cost Optimization	[11, 24, 29]
	FE3	Management of Resources and Expenditures	[13, 18, 25, 27]
	FE4	Microfinance	[2, 12, 30]
	FE5	Liquidity Management in Inflationary Conditions	[1, 6, 17, 32]
	FE6	Supply Chain Financing	[1, 6, 17, 32]
Management and Strategic (MS)	MS1	Strategic Planning	[3, 5, 31]
	MS2	Change Management	[14, 20, 27]
	MS3	Human Resource Development	[23, 33, 35]
	MS4	Organizational Innovation	[14, 16, 21, 39]
	MS5	Corporate Governance	[1, 3, 5, 33]
	MS6	Knowledge Management	[8, 20, 26, 31]
	MS7	Organizational Culture	[22, 33]
	MS8	Sanctions Management	[1, 6, 17, 32]
	MS9	Development of Domestic Brokerage Networks	[1, 6, 17, 32]
Legal and Regulatory (LR)	LR1	Compliance with Banking Regulations	[11, 24, 32]
	LR2	Data Protection	[10, 14, 29]

	LR3	Anti-Money Laundering	[11, 27, 32]
	LR4	Financial Transparency	[1, 3, 6, 33]
	LR5	Customer Rights	[18, 21, 25]
	LR6	Compliance with Sharia Laws	[1, 6, 17, 32]
	LR7	Management of Sanctions Risk	[1, 6, 17, 32]
Banking Products and Services (BPS)	BPS1	Digital Banking	[20, 27, 28, 30, 35]
	BPS2	Intelligent Advisory Services	[10, 14, 15, 26]
	BPS3	Customized Products	[14, 21, 23]
	BPS4	Modern Payment Solutions	[20, 29]
	BPS5	Social Loans	[2, 4]
	BPS6	Cooperative Services	[5, 6, 22]
	BPS7	Alternative Foreign Exchange Services to SWIFT	[8, 20]
	BPS8	Products Aligned with a Resilient Economy	[3, 6, 27]
Customer-Centricity and User Experience (CCUE)	CCUE1	Personalization of Services	[14, 21, 23]
	CCUE2	Ease of Access	[20, 25, 28, 30]
	CCUE3	Smart Responsiveness	[9, 27-29]
	CCUE4	Customer Satisfaction	[16, 18, 23]
Risk and Security (RS)	RS1	Cyber Risk Management	[10, 14, 32]
	RS2	Transaction Security	[28, 29, 35]
	RS3	Fraud Monitoring	[10, 11, 15]
	RS4	Crisis Management	[5, 20, 31]
Sustainability and Sustainable Development (SSD)	SSD1	Environmental Responsibility	[1, 3, 32, 39]
	SSD2	Sustainable Economic Development	[5, 17, 18, 39]
	SSD3	Social Justice	[25, 33, 34]
	SSD4	Responsible Investment	[1-3, 6, 16]

To quantitatively evaluate the extracted model, CFA was employed. Initially, the KMO test and Bartlett's test of sphericity were conducted to assess sampling adequacy. The KMO value was found to be 0.734, and the significance level of Bartlett's test was less than 0.05, indicating that the data was suitable for factor analysis.

In the evaluation of the measurement model, factor loadings and the significance of coefficients were examined. The indicators MS3 and BPS2 were removed from the model due to their factor loadings being below 0.7. After refining the model, as illustrated in Figures 1 and 2, all remaining indicators demonstrated factor loadings above 0.7 and significance coefficients exceeding 1.96.

The revised model ensures robust reliability and validity, confirming its suitability for further application in the context of AI-based social banking.

The results of reliability and validity analysis, as presented in Table 2, indicate the suitability of the measurement tool. Examination of CA and CR values for all variables shows values exceeding 0.7, confirming adequate reliability. Furthermore, AVE for all variables is greater than 0.5, and the CR surpasses the AVE, indicating strong convergent validity for the model.

The Fornell-Larcker matrix presented in Table 3 confirms that the correlations between variables are positive and significant. Additionally, as the square root of the AVE for each variable is greater than its correlation with other variables, the model's discriminant validity is also verified.

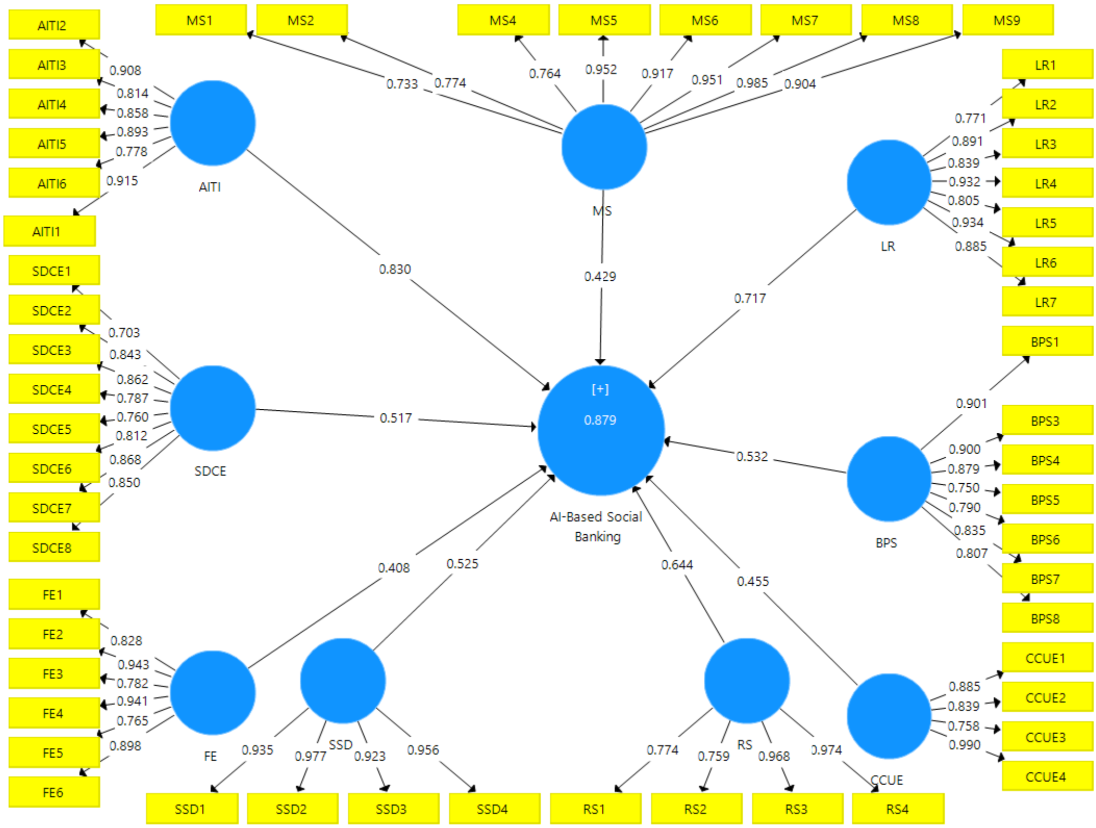

Figure 1. Measurement Model in Standardized Coefficients

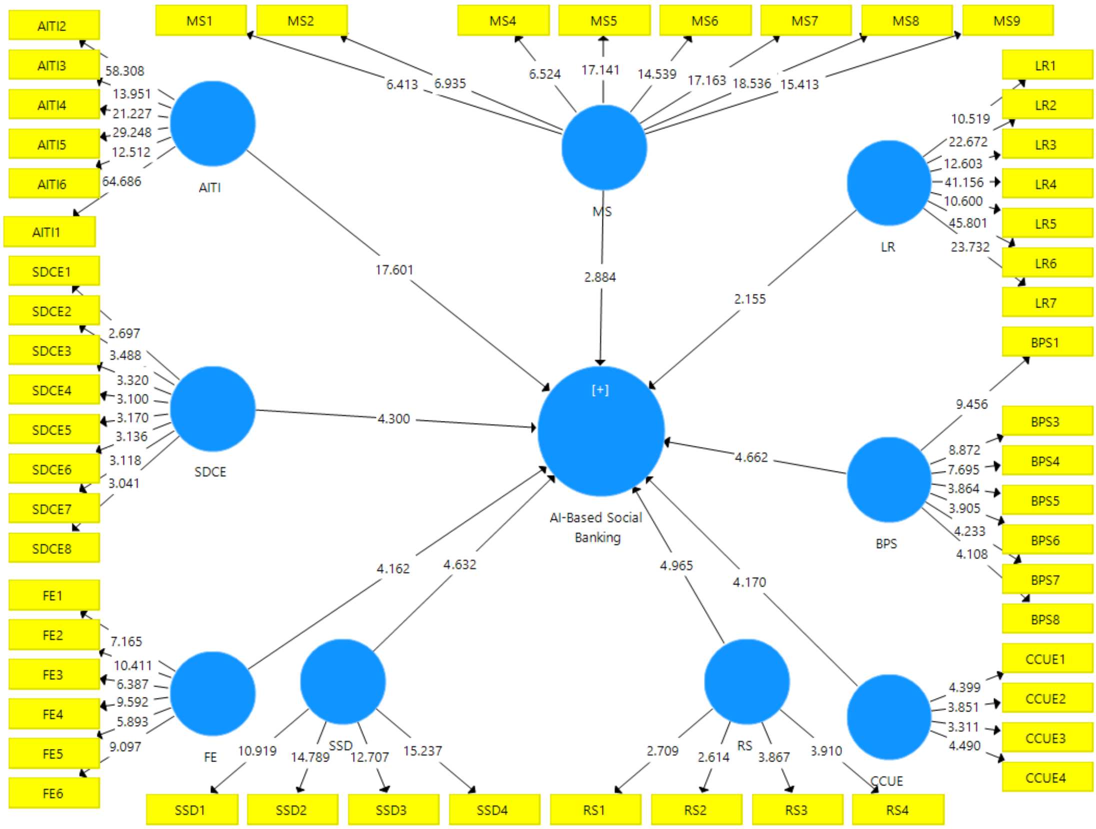

Figure 2. Measurement Model in Coefficient Significance

Table 2. Indices of the Final Model

Dimensions	CA	CR	AVE
AITI	0.933	0.945	0.744
BPS	0.937	0.943	0.704
CCUE	0.921	0.926	0.761
FE	0.931	0.945	0.744
LR	0.945	0.955	0.752
MS	0.957	0.964	0.770
RS	0.915	0.928	0.765
SDCE	0.937	0.939	0.660
SSD	0.962	0.973	0.899

Table 3. The Fornell-Larcker Matrix

	AITI	BPS	CCUE	FE	LR	MS	RS	SDCE	SSD
AITI	0.862								
BPS	0.238	0.839							
CCUE	0.146	0.045	0.872						
FE	0.217	0.234	0.012	0.863					
LR	0.420	0.169	0.000	0.215	0.867				
MS	0.160	0.239	0.185	0.108	0.339	0.877			
RS	0.040	0.064	0.148	0.329	0.186	0.216	0.875		
SDCE	0.153	0.030	0.017	0.375	0.043	0.227	0.368	0.813	
SSD	0.255	0.024	0.091	0.169	0.109	0.085	0.014	0.236	0.948

These findings collectively validate the reliability and validity of the proposed model, making it robust for practical application in AI-based social banking. The structural model of the research, developed using PLS software, is presented in Figure 3 for standardized coefficients and Figure 4 for coefficient significance.

The evaluation of the structural model, as shown in Table 4, indicates that the significance coefficients (t-values) for all relationships exceed 1.96, confirming their statistical significance. Furthermore, the GOF index, calculated using Equation (1) as 0.815, demonstrates that the model exhibits excellent fit. These results collectively validate the credibility of the extracted model.

$$GOF = \sqrt{\overline{AVE} \times \overline{R^2}} \quad (1)$$

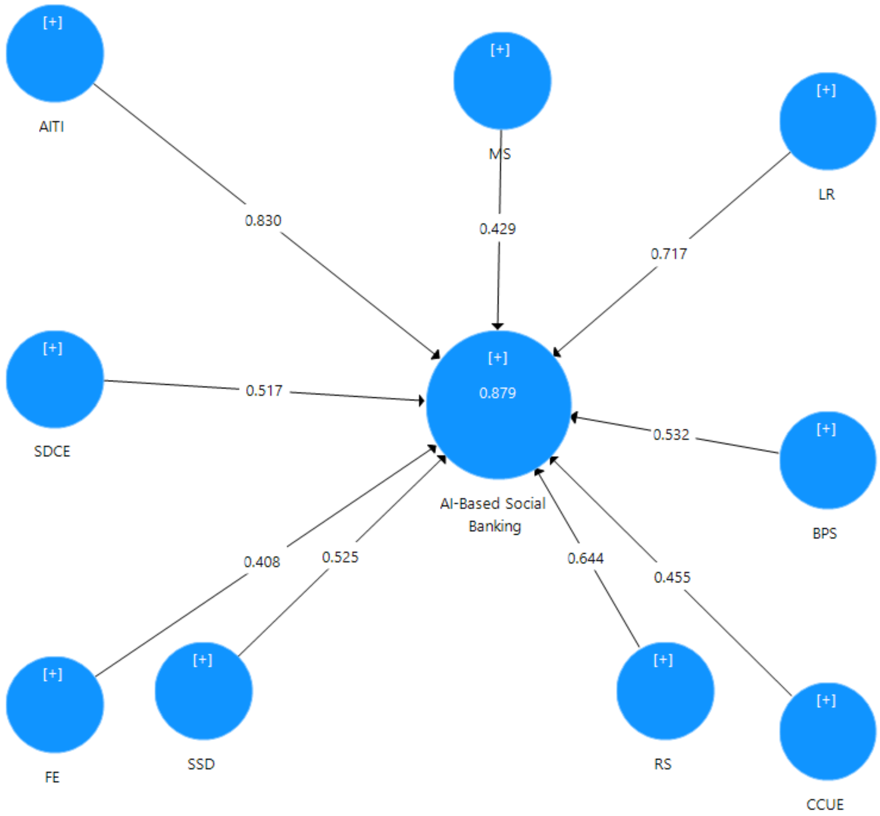

Figure 3. Structural Model with Standardized Coefficients

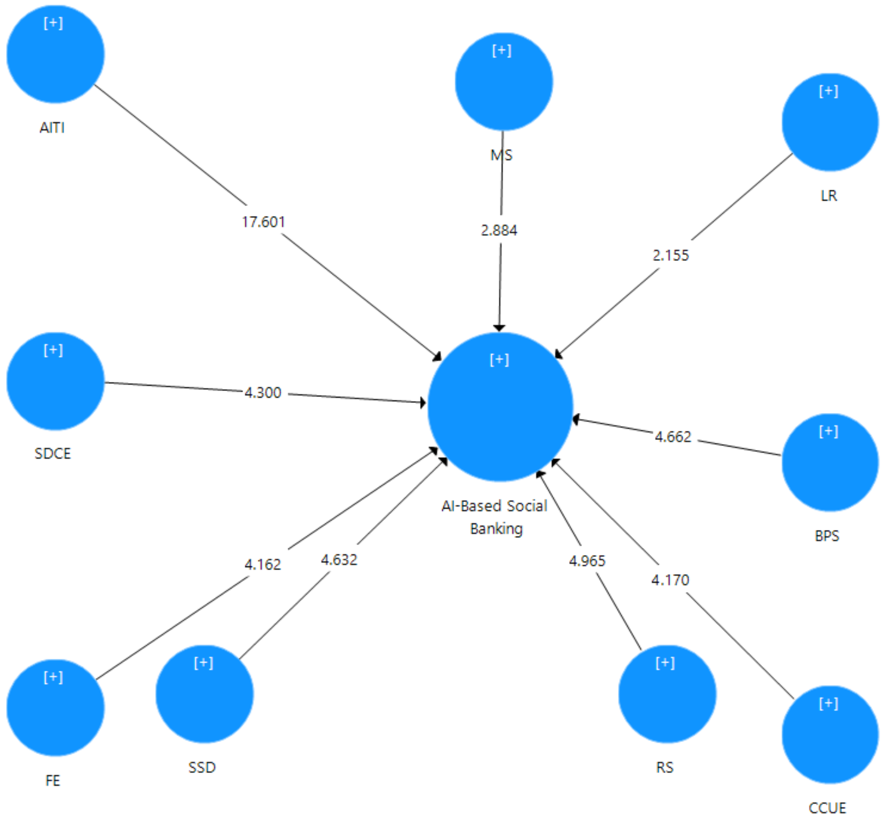

Figure 4. Structural Model with Coefficient Significance

Table 4. Significance of Relationships

No.	Relationship	t-value	p	Path Coefficient	Result
1	AI Technology and Infrastructure → AI-Based Social Banking in Cooperative Banks	17.601	0.000	0.830	Confirmed
2	Social Development and Community Empowerment → AI-Based Social Banking in Cooperative Banks	4.300	0.000	0.517	Confirmed
3	Financial and Economic → AI-Based Social Banking in Cooperative Banks	4.162	0.000	0.408	Confirmed
4	Management and Strategic → AI-Based Social Banking in Cooperative Banks	2.884	0.004	0.429	Confirmed
5	Legal and Regulatory → AI-Based Social Banking in Cooperative Banks	2.155	0.032	0.717	Confirmed
6	Banking Products and Services → AI-Based Social Banking in Cooperative Banks	4.662	0.000	0.532	Confirmed
7	Customer-Centricity and User Experience → AI-Based Social Banking in Cooperative Banks	4.170	0.000	0.455	Confirmed
8	Risk and Security → AI-Based Social Banking in Cooperative Banks	4.965	0.000	0.644	Confirmed
9	Sustainability and Sustainable Development → AI-Based Social Banking in Cooperative Banks	4.632	0.000	0.525	Confirmed

The findings confirm the significance of all relationships within the structural model. The dimensions of AI Technology and Infrastructure and Risk and Security exhibit the highest path coefficients, highlighting their critical role in the successful implementation of AI-based social banking in cooperative banks.

4. Discussion and Conclusion

The findings of this study provide strong empirical support for the multidimensional structure of AI-based social banking in cooperative banks and confirm the statistical significance of all proposed relationships within the structural model. The high Goodness of Fit (GOF = 0.815) and the significance of all path coefficients indicate that the extracted model offers a coherent and practically applicable framework for integrating artificial intelligence into socially oriented banking systems. Among the nine dimensions, “AI Technology and Infrastructure” demonstrated the strongest effect on AI-based social banking, confirming that technological readiness is the foundational driver of transformation in cooperative banks. This result aligns with prior evidence emphasizing that AI adoption enhances service quality, predictive accuracy, and operational efficiency in banking organizations [8, 9]. Furthermore, the importance of advanced analytics, machine learning, and intelligent systems corresponds with findings that super-intelligent financial services reshape competitive advantage in modern banking ecosystems [7]. Studies on credit scoring and risk assessment in cooperative and microfinance contexts further reinforce that AI-based analytical tools significantly improve credit allocation precision and financial stability [11, 12]. In addition, neural-network-supported efficiency evaluation in cooperative banks demonstrates the performance-enhancing potential of AI-enabled infrastructure [13]. These converging findings confirm that without robust AI infrastructure and data capabilities, social banking objectives cannot be effectively operationalized in a digital environment.

The “Legal and Regulatory” dimension emerged as one of the most influential determinants of model success, underscoring the necessity of regulatory alignment, data protection, and compliance frameworks. This finding corroborates earlier research highlighting that digital banking transformation requires strong governance mechanisms and clearly defined legal standards to mitigate systemic risks [28, 29]. The integration of AI within sustainable finance must be accompanied by transparent regulatory oversight and ethical safeguards [32]. In socially oriented banking systems, governance structures and corporate responsibility mechanisms are essential to maintaining stakeholder trust and legitimacy [33]. Furthermore, ESG-oriented cooperative banking literature emphasizes that sustainability reporting and regulatory compliance strengthen long-term institutional credibility [5, 6]. The significant effect of this dimension suggests that cooperative banks cannot rely solely on technological innovation; rather, regulatory clarity, financial transparency, and ethical compliance serve as enabling conditions for sustainable AI integration. This is consistent with the conceptualization of social finance as a regulated yet impact-driven financial paradigm [1].

The "Risk and Security" dimension also exhibited a strong and significant influence, highlighting that cyber risk management, fraud detection, and crisis management mechanisms are indispensable in AI-enabled cooperative banking systems. AI-based credit analysis and fraud monitoring systems have been shown to enhance predictive capabilities and minimize non-performing loans [10]. However, digitalization simultaneously introduces new vulnerabilities, including cybersecurity threats and data breaches [29]. Therefore, the strong path coefficient associated with risk and security reflects the dual nature of AI in banking: while it enhances analytical power, it also necessitates advanced protective architectures. This finding resonates with research demonstrating that digital banking challenges must be strategically managed through integrated risk frameworks and organizational adaptation [30]. Moreover, crisis-context studies indicate that socially responsible banking institutions must reinforce risk governance during systemic shocks to sustain community trust [20]. Thus, the model appropriately captures the structural interdependence between AI infrastructure and security governance in cooperative banking.

The dimension of "Banking Products and Services" showed a substantial impact on AI-based social banking, indicating that digital banking solutions, personalized financial products, and innovative payment systems are central to operationalizing social objectives. AI-driven personalization and intelligent advisory systems enhance customer engagement and decision-making processes [14, 26]. Moreover, digital transformation initiatives have been shown to strengthen innovative social banking models in emerging markets [27]. Cooperative banks that adopt digital inclusion strategies can expand outreach to underserved populations and SMEs, thereby reinforcing social development missions [18, 25]. The empirical significance of this dimension indicates that AI is not merely a back-office optimization tool but a front-end enabler of inclusive, customer-centric financial services. Furthermore, research on customer experience models grounded in social responsibility demonstrates that service quality, interface design, and involvement mechanisms significantly influence user adoption of digital banking services [36, 37]. These findings collectively validate the role of AI-enabled product innovation in achieving both financial performance and social value creation.

The "Social Development and Community Empowerment" and "Sustainability and Sustainable Development" dimensions also showed meaningful and statistically significant contributions to the model. Cooperative banking literature consistently emphasizes that social capital, local engagement, and community-oriented financial intermediation are critical to institutional success [22]. Empirical evidence indicates that social banking reduces financial conflicts between banks and productive enterprises and strengthens inclusive development [19, 24]. Moreover, post-pandemic social banking models underscore the importance of resilient and locally embedded financial ecosystems [21]. Responsible investment, environmental accountability, and stakeholder-oriented governance further reinforce sustainable banking trajectories [3, 34]. The integration of sustainability within AI-based social banking is also conceptually aligned with integrated frameworks combining AI, social business, and sustainable development goals [39]. In addition, Islamic finance perspectives highlight ethical alignment and value-based financial intermediation as complementary to social banking principles [2, 43]. These convergent insights explain why sustainability and community empowerment are not peripheral components but structural pillars within the validated model.

Finally, the "Management and Strategic" and "Financial and Economic" dimensions demonstrated moderate yet significant effects, confirming that strategic planning, knowledge management, organizational culture, and financial efficiency are necessary for long-term implementation success. Digital transformation literature emphasizes that intelligent organizational models require adaptive leadership and cultural change [31]. Moreover, scoring models and cost optimization strategies enhance financial prudence without compromising social objectives [11]. Sustainable financial modeling within social banking contexts has been shown to balance profitability and stakeholder value creation [17]. Research on alternative social banking systems further highlights the importance of structured decision-making frameworks in aligning economic and social priorities [35]. Additionally, knowledge diffusion and digital communication channels influence customer trust and transparency in financial ecosystems [38]. Taken together, the empirical findings confirm that AI-based social banking in cooperative institutions is inherently multidimensional and requires synchronized development across technological, regulatory, strategic, financial, and social domains.

Despite its comprehensive design, this study is subject to certain limitations. First, the quantitative phase relied exclusively on expert opinions within cooperative banks, which may limit the generalizability of findings to broader stakeholder groups, including customers and regulators. Second, the rapid pace of technological advancement in AI and fintech may render some technological assumptions time-sensitive. Third, the cross-sectional design of the study restricts causal inference regarding long-term performance impacts. Finally, contextual factors specific to the cooperative banking environment may influence the applicability of the model in different institutional or national settings.

Future studies should empirically test the longitudinal impact of implementing the proposed AI-based social banking model on financial performance, risk reduction, and community development indicators. Comparative cross-country analyses could explore how regulatory environments and cultural contexts influence AI integration in cooperative banks. Research incorporating customer perceptions and behavioral adoption models would enrich understanding of user acceptance dynamics. Additionally, future scholars should develop measurable performance indices to evaluate the social and environmental outcomes of AI-enabled banking systems. Finally, investigating organizational resistance, ethical implications, and data governance challenges associated with AI deployment remains a promising direction for further inquiry.

For practitioners, the findings highlight the necessity of investing simultaneously in AI infrastructure, cybersecurity systems, and regulatory compliance frameworks. Cooperative banks should design integrated digital transformation strategies that align technological innovation with social mission objectives. Training programs must be implemented to enhance employees' digital competencies and change management capabilities. Policymakers should establish clear AI governance standards to ensure transparency and ethical accountability. Ultimately, cooperative banks should adopt a balanced approach that leverages AI to improve efficiency and competitiveness while reinforcing their foundational commitment to community empowerment and sustainable development.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

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

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Conflict of Interest

The authors report no conflict of interest.

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