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Research Article

Evaluating the Impact of Artificial Intelligence on Customer Satisfaction and Acceptance in Banking: A Structural Equation Modeling Approach

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Abstract: Purpose: The study examines the influence of AI-based banking service quality on acceptance and satisfaction of retail customers; AI-based service quality includes responsiveness, reliability, ease of use, security, efficiency, and transparency. The study also examines customer satisfaction's mediating role and technology experience's moderating effect on the service quality. **Research Methodology:** A quantitative, cross-sectional design was applied, with purposive sampling ending up giving 421 valid responses from the users of AI-powered banking tools (i.e., chatbots, robo-advisors, fraud detection). A structured questionnaire adopting five-point Likert scales was used to capture the perceptions of service quality, satisfaction, acceptance, and technology experience. The analyses involved descriptive statistics and SEM through SmartPLS, comprising bootstrapped mediation and moderation tests. **Findings:** Perceived AI service quality significantly predicts customer satisfaction ($\beta = 0.424$, $p < 0.001$) and acceptance ($\beta = 0.272$, $p < 0.001$). Customer Satisfaction partially mediates the quality–acceptance link ($\beta = 0.098$, $p < 0.001$). Technology experience amplifies the impact of service quality on acceptance ($\beta = 0.098$, $p = 0.033$). The measurement model demonstrated high reliability (Cronbach's $\alpha > 0.90$) and excellent fit (SRMR < 0.04; NFI > 0.95). **Originality/Value:** Derived from the technology acceptance model (TAM) and the SERVQUAL framework, the study attempts through a focused SEM model to enrich theoretical identification about AI adoption in banking. The model not only bridges theoretical gaps but also provides actionable insights for practitioners to design expectation-confirming, experience-tailored AI solutions that promote sustained digital engagement.

Keywords: *AI Adoption; Banks; Customer Acceptance; Customer Satisfaction; Service Quality; Technology Experience*

INTRODUCTION

Artificial intelligence (AI) has emerged as a revolutionary influence in the banking sector. Contemporary banks use AI in customer-facing positions, such as chatbots and virtual assistants that manage routine enquiries continuously, as well as in back-office operations such as fraud detection and risk evaluation (Noreen, et al., 2023). Customer-side front-line intelligent chatbots and virtual assistants handle mundane inquiries and troubleshooting 24/7, along with cutting down wait times, thus allowing human agents to deal with more complicated processes (Kondybayeva, et al., 2024). Behind the scenes, machine-learning algorithms work to catch and stop frauds by monitoring transactions in real time, while robo-advisors give investment recommendations tailored to the client's individual risk profiles (Stojanović, et al., 2021). Predictive analytics analyzes massive data sets in order to identify the ever-changing needs of customers-they might suggest the appropriate product or even signal in advance the creditworthiness of a customer (Alexander, 2024). Those AI applications promise to combine operational efficiency and cost savings with fast response times, ultimately leading to gratifying customer experiences (Ris, et al., 2020).

Table 1: Summary of AI Applications and Customer Impact in Banking

AI Application	Benefit	Customer Impact	Citations
Chatbots/Assistants	24/7 query resolution, reduced response time	Higher satisfaction and perceived reliability	Klarin-Petrina, (2021); Ruan, & Mezei, (2022)
Fraud Detection	Real-time transaction monitoring	Increased trust and reduced anxiety	Khurana, (2020); Awosika, et al., (2023)
Robo-advisors	Personalized investment suggestions	Enhanced financial planning experience	Kumar (2020); Capponi, et al., (2019)
Biometrics	Secure authentication and quick access	Improved usability and confidence	Tassabehji, & Kamala, (2012); Liang, et al., (2020).

Placing customer satisfaction at the soul of successful AI deployment in banking is paramount. When AI-based services deliver more-than-expected speed, accuracy, and personalization, trust and loyalty find nurture within customers; these satisfied customers go on to use such new digital channels more, recommend them to peers, and search for more AI-enabled offerings for themselves (Kondybayeva, et. al., 2024).

Despite banks investing significantly in AI initiatives, prior research lacks a definitive understanding of client responses (Hentzen, et. al., 2022; Rodrigues, et. al., 2022). Traditional metrics like system availability or transaction volumes do not adequately elucidate the fundamental issues affecting adoption. Important questions remain: which AI traits have the most impact on customer satisfaction? How much do worries about data privacy and algorithmic transparency make people less likely to accept? Without clear guidance on these issues, banks may prioritise technology talents above the human factors that ultimately determine success. This problem of research concerning the study of the relationship between AI characteristics, as well as customer satisfaction and acceptance, stresses the need for an integrated, theory-based investigation (Basri, et. al., 2023).

The current study adds considerable status to the ongoing narrative on AI adoption in banking by filling a stark lacuna: the absence of any unifying, empirical framework describing the client perception and reaction to AI-enabled financial services. By applying Structural Equation Modelling, this study provides a comprehensive theory-based analysis investigating the interplay between some basic service quality constructs, particularly performance expectancy, perceived ease of use, trust, and customer satisfaction directed toward customer acceptance, thereby moving away from fragmented analyses. Based on some established theories such as the Unified Theory of Acceptance and Use of Technology and Technology Acceptance Model, the study provides an advanced understanding of how AI service quality directly and indirectly affects customer behaviour. The study's objective is to present a provision for converting AI investments into maximum returns by maximising user satisfaction and maintaining ongoing engagement at a digital level.

REVIEW OF LITERATURE

Theoretical Framework

Before diving into each theoretical perspective, it's important to understand how these different models work together to explain the human side of AI adoption in banking. By bringing together views on why customers initially accept AI (such as TAM and UTAUT), how satisfied they are after using it (like ECT), and their perceptions of service quality (from SERVQUAL), this integrated framework gives us a well-rounded understanding. It helps explain both why customers decide to try AI-enabled financial services and how their experiences influence whether they stick with them. Collectively, these theories inform our choice of key concepts and hypotheses in the Structural Equation Modeling process, making sure the study captures the technical, psychological, and experiential factors that influence AI adoption all in one place.

Technology Acceptance Model (TAM): Davis (1989) came up with the Technology Acceptance Model to help explain why people start using new tech systems. TAM says that two things matter: Perceived Usefulness (PU) refers to the extent to which an individual believes that a technology will help him or her to perform his or her job better. Another construct is Perceived Ease of Use (PEOU), which has to do with the perceived ease of working with such a system. So, when people believe that a technology is useful and also easy to work with, TAM says it is more likely to be accepted (Holden, et. al., 2010). In today's AI-driven banking environment, customers tend to feel more comfortable and satisfied when they see chatbots, robo-advisors, or fraud detection systems as tools that genuinely improve performance and are easy to use.

Unified Theory of Acceptance and Use of Technology (UTAUT): Venkatesh, Morris, Davis, and Davis (2003) reviewed eight popular models of technology adoption and developed the Unified Theory of Acceptance and Use of Technology (UTAUT). This model extends the traditional Technology Acceptance Model (TAM) by incorporating four essential factors that shape users' behavioral intentions: Performance Expectancy, Effort Expectancy, Social Influence, and Assisting Conditions. Besides, UTAUT takes into account how personal variables like age, gender, experience, and whether the technology use is voluntary or mandatory can influence these effects (Venkatesh, et. al., 2003). When it comes to AI in banking, Performance Expectancy shows how clients think these AI technologies will improve their banking experience. Effort Expectancy looks at how simple it is for clients to utilise these technologies. Social Influence looks at how suggestions from peers and leaders in the field might change behaviour. (Mensah, et. al., 2024).

a) Expectation–Confirmation Theory (ECT): Oliver (1980) came up with the Expectation–Confirmation Theory, which helps us understand how consumers feel about their experience when they buy something and how likely they are to keep using it. The concept is rather simple: individuals possess certain expectations when making a purchase. They feel good about the product and are more inclined to keep using it if it works as anticipated or better. But when the actual performance doesn't meet expectations, which we term disconfirmation, people tend to be unhappy (Hossain et al., 2011). While assessing AI services in the banking sector, ECT demonstrates how consumer expectations--say, whether fraud detection warning is accurate, or robo-advisor is useful--intervene into their post-usage satisfaction. Customers are happier and more inclined to trust and employ AI solutions again in their banking activities if the AI does better than they expected (Bhatnagr, et. al., 2024).

This theoretical framework amalgamates TAM's emphasis on perceived usefulness and ease of use, UTAUT's comprehensive acceptance determinants, ECT's focus on expectation confirmation and satisfaction, thereby establishing a multidimensional foundation for examining the impact of AI characteristics on customer satisfaction and acceptance in the banking sector.

Review of Literature

AI-Based Banking Services Quality Factors and Customer Satisfaction: Seven motivational factors for risk participation were technological know-how, intellectual curiosity, willingness to take risks, past experience of working in risky environments, culture of innovativeness, charismatic leadership, and capability of taking up risks. Rehman et al. (2019) identified eight elements that motivated managers to partake in risky project management: technology know-how, intellectual curiosity, willingness to take risks, previous experience of working in risky situations, culture of innovativeness, charismatic leadership, and capability of taking up risks. Managing risk-taking activities in risky projects included using various forms of analysis, ranging from qualitative and quantitative to simulated methods.

While existing research demonstrates positive impacts of individual AI-driven service quality dimensions on customer satisfaction, it remains fragmented across technologies and contexts. To fill this gap:

- ***H1:*** *There is a significant relationship between AI-based banking services quality factors and customer satisfaction.*

AI-Based Banking Services Quality Factors and Customer Acceptance

Generative AI voice chatbots had significantly boosted customer satisfaction and productivity in banking by enhancing expectation confirmation, perceived performance, visual appeal, problem-solving abilities, and communication quality (Kondybayeva et al., 2024). Positive customer interactions with mechanical AI considerably influenced overall satisfaction with AI-enhanced service operations, but negative interactions did not markedly affect satisfaction (Mariani et al., 2023). The ongoing desire of Jordanian customers to use m-banking was influenced by effort expectation, performance expectations, perceived risk, trust, social influence, and service quality, although enabling conditions had less effect (Abu-Taieh, et al., 2022). Awareness, attitude, norms, perceived benefit, and comprehension of AI technology positively influenced consumers' inclination to utilise AI in the banking sector; conversely, perceived risk had a significant negative impact (Noreen, et al., 2023). Customers were more likely to be happy with e-banking and used it more when they thought the e-service quality was high.

No single study had yet examined how a wide range of AI-based banking service quality factors collectively influenced customer acceptance. Additionally, while trust, social influence, and perceived risk are known to affect acceptance, how these factors interact with core service-quality attributes in an AI setting hasn't been fully explored. To address this, the current study combines multiple AI service quality dimensions into one comprehensive framework, leading to the following hypothesis:

- ***H2:*** *There is a significant relationship between AI-based banking service quality factors and* customer acceptance.

Customer Satisfaction Affects AI-Based Banking Services and Customer Acceptance

User satisfaction with AI chatbots was determined by perceived performance, expectation confirmation, visual appeal, problem-solving ability, and communication quality (Kondybayeva et al., 2024). Customer satisfaction and retention were influenced by the efficiency, reliability, and service quality of e-banking, with customer satisfaction mediating customer retention (Khan et al., 2022). The ES-QUAL model effectively measured online banking customer satisfaction, with perceived value and trust serving as intervening variables between the ES-QUAL dimensions and satisfaction (Ahmed et al., 2020). Positive experiences of customers with mechanical AI greatly influenced overall satisfaction with AI-assisted service operations; however, negative experiences did not influence satisfaction (Mariani et al., 2023). In the Qatar banking industry, customer satisfaction linked the quality of e-banking services to clients' intentions to purchase (Khatoon, et. al., 2020).

No previous study has examined how a wide range of AI quality factors together influence acceptance through customer satisfaction. To fill this gap, this study proposes the following hypothesis:

- ***H3:*** *There is a significant mediating effect of customer satisfaction between AI-based banking service quality factors and customer acceptance.*

Tech Experience in AI-Based Banking Services Quality Factors and Customer Acceptance

Previous technological and AI experience underpins consumer acceptance of AI-integrated banking. Shukri et al. (2024) discovered that past use experience and structural assurances, such as security guarantees, affect the intention to utilize mobile banking; moreover, performance expectation, effort expectancy, and self-efficacy each favorably impact behavioral intention. According to Pandey and Dangi (2024), banks consistently use AI to improve the fundamental perception factors—reliability, responsiveness, and personalization—to sustain and amplify engagement. The specific quality parameters of AI services further influence acceptability. Sabir et al. (2023) demonstrate that clients generally exhibit a favorable disposition towards robo-advisors when they are seen as user-friendly, beneficial, and convenient.

- ***H4:*** *Technology experience significantly moderates the relationship between AI-based banking service quality factors and customer acceptance.*

Objective of the study

- To assess the relationship between AI-based banking services quality factors and customer satisfaction.
- To assess the relationship between AI-based banking services quality factors and customer acceptance.
- To test the mediating role of customer satisfaction between AI-based banking services quality factors and customer acceptance.
- To explore the moderating effect of tech experience on the relationship between AI-based banking services quality factors and customer acceptance.

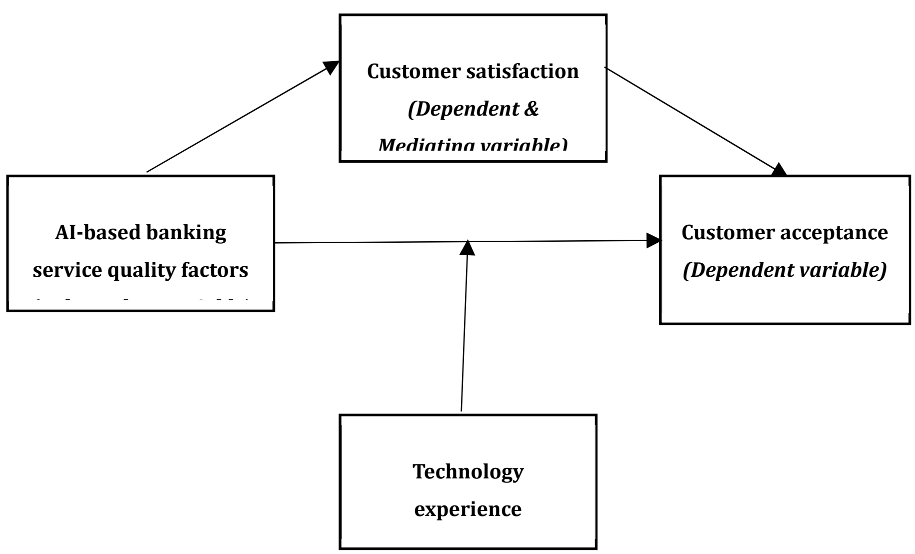

Figure 1: Conceptual Framework
Source: Self-prepared by author

RESEARCH METHODOLOGY

- **Research Design**: This study employs a quantitative, cross-sectional method to examine the influence of AI service quality on customer satisfaction and acceptance within the banking sector. Data is gathered from retail banking customers with experience using AI-powered services, capturing a clear snapshot of their current views and intentions.
- **Sampling and Sample Size**: The study employs purposive sampling to concentrate on customers who consistently utilise AI tools such as chatbots, robo-advisors, and fraud-detection systems. These customers are chosen because their direct experience allows them to provide valuable insights into satisfaction and acceptance. Based on Cochran's formula, a minimum of 365 responses is required, leading to the distribution of 450 questionnaires both online (through Google Forms) and in-branch. Following a thorough review for completeness, the final sample comprises 421 valid responses.
- **Pilot Study and Instrument Development**: A pilot survey is conducted with 85 respondents to enhance the questionnaire and ensure all items are clear. Following feedback from the participants, minor adjustments were made to the wording prior to commencing the main data collection.
- **Data Collection**: Data collection involves a structured questionnaire utilising five-point Likert scales, grounded in established measures of technology acceptance and service quality. The survey enquires about opinions on AI service features, levels of satisfaction, and the willingness to utilise AI-based banking services.
- **Analytical Approach**: The study uses descriptive statistics to summarise respondent profiles and item responses and then applies Structural Equation Modelling in Smart PLS to test the hypothesised relationships. This SEM framework examines mediation and moderation analysis to understand the direct and indirect pathways from AI service quality to customer acceptance. The study also utilises MS Excel, SPSS, and Smart PLS as analytical tools.

RESULTS

This section comprised the findings and interpretation of the data. The reliability and validity, demographic characteristics, and objectives, as well as hypotheses, have been used to categorize the outcomes. A table displaying the results, and an explanation of those results have been included in the aims and hypotheses.

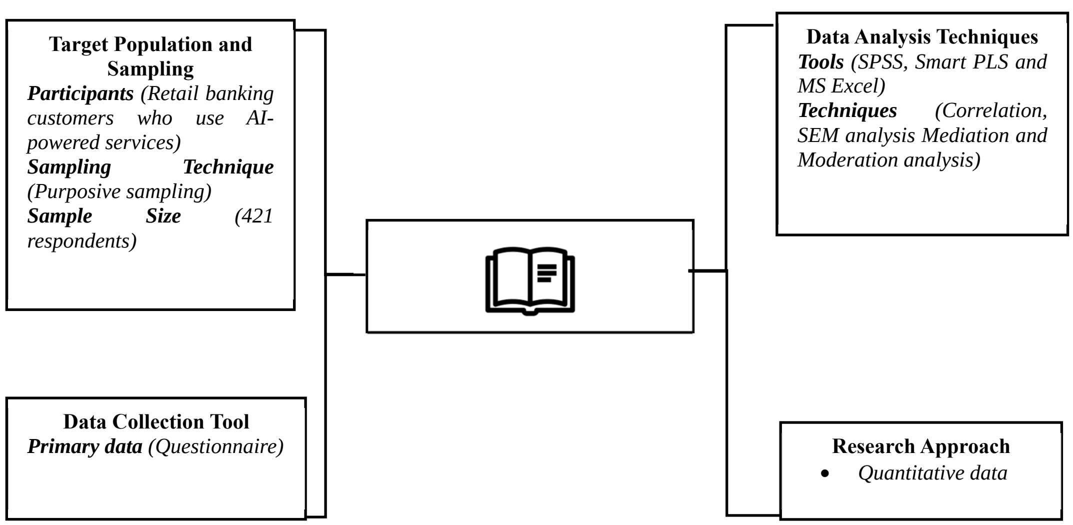

Figure 2: Research Methodology
Source: Self-prepared by author

Table 2: Reliability Statistics of the constructs

Reliability Statistics				
Label	Cronbach's Alpha	N of Items	KMO and Bartlett's value	Sig. value
AI-based banking service quality factors	0.927	6	0.916	0.000
Customer satisfaction	0.957	6	0.937	0.000
Customer acceptance	0.962	6	0.913	0.000

Table 3: Demographic Characteristics of the Respondents

Sr. no.	Demographics	Category	Frequency	Percentage
1.	Gender	Male	262	62.2%
		Female	159	37.8%
2.	Age	18-28 years old	150	35.6%
		29-39 years old	133	31.6%
		40-50 years old	73	17.3%
		Above 50 years old	65	15.4%
3.	Highest Educational Qualification	Higher Secondary Education	60	14.3%
		Diploma	126	29.9%
		Graduation	149	35.4%
		Post Graduation	86	20.4%
4.	Occupation	Self-employed	127	30.2%
		Private Sector Employee	206	48.9%
		Government Employee	66	15.7%
		Retired	22	5.2%
5.	Tech Experience	Less than 5 years	191	45.4%
		5-10 years	126	29.9%
		More than 5 years	104	24.7%
6.	Region	Urban	242	57.5%
		Rural	179	42.5%

Table 4: Communalities Table

Communalities	Initial	Extraction
AIQ 1 (Responsiveness)	1.000	.766
AIQ 2 (Reliability)	1.000	.695
AIQ 3 (Ease of Use / Accessibility)	1.000	.700
AIQ 4 (Security and Privacy)	1.000	.687
AIQ 5 (Efficiency)	1.000	.679
AIQ 6 (Transparency)	1.000	.740
CS 1 (User Experience)	1.000	.819
CS 2 (Security Satisfaction)	1.000	.767
CS 3 (Problem-Solving Effectiveness)	1.000	.775
CS 4 (Convenience)	1.000	.801
CS 5 (Consistency of Service)	1.000	.795
CS 6 (Reduction in Effort)	1.000	.780
CA 1 (Perceived Usefulness)	1.000	.836
CA 2 (Attitude Toward Using AI)	1.000	.829
CA 3 (Behavioral Intention to Use)	1.000	.811
CA 4 (Social Influence)	1.000	.785
CA 5 (Compatibility)	1.000	.799
CA 6 (Emotional Comfort)	1.000	.838

Extraction Method: Principal Component Analysis

Table 2 presents the results of reliability and validity checks using Cronbach's Alpha, KMO, and Bartlett's Test of Sphericity. The results demonstrate a very good internal consistency of all three constructs. All Cronbach Alpha values are above the 0.7 deemed acceptable, with AI-based banking service quality factors at 0.927, Customer Satisfaction at 0.957, and Customer Acceptance at 0.962, confirming the items within each scale as reliable measures of their associated constructs. The Kaiser-Meyer-Olkin measures for sampling adequacy are above 0.9, indicating that the sample is suitable for factor analysis, with values of 0.916 for AI-based service quality, 0.937 for customer satisfaction, and 0.913 for customer acceptance. Bartlett's Test of Sphericity shows significance (p = 0.000) in all variables, which implies correlation matrices are not identity matrices and that factor analysis is appropriate.

Table 3 displays "the demographic characteristics of the respondents" in terms of their gender, age, education, occupation, tech experience, and region. The data indicates a gender distribution inclined towards males (62.2%) compared to females (37.8%). In terms of age, the majority falls within the 18-28 years bracket (35.6%). Education-wise, a significant portion holds a bachelor's degree (35.4%). Regarding occupation, the majority are private sector employees (48.9%). Regarding tech experience, the majority have less than 5 years of experience (45.4%). Finally, the majority of the respondents are from urban areas (57.5%).

Results Based on the Hypothesis

Factor Analysis: Table 4, generated from the Principal Components Analysis, shows the extent to which the extracted components explain the variance of an item. All the items across the three prominent constructs of AI-based Banking

Service Quality (AIQ), Customer Satisfaction (CS), and Customer Acceptance (CA) have extracted communality values well above the minimum threshold of 0.5, thereby showing that the factor model accounts for a very good percentage of the variance in each item. From the other perspective, for AIQ, communalities go from 0.679 (Efficiency) to 0.766 (Responsiveness), implying that these dimensions are well defined in the extracted factors. On the Customer Satisfaction end of things, items like User Experience (0.819) and Convenience (0.801) yielded highly instructive communalities, thus confirming their strong contributions to the latent construct of satisfaction. On the other hand, great communality values have been maintained, showing a strong structure of factors, for all items of Customer Acceptance, with the value range stretching from 0.785 (Social Influence) to 0.838 (Emotional Comfort). These results overall establish that the chosen items are appropriate for factor analysis and have significant representation of their respective latent variables; thereby supporting the structural integrity of the model and justifying the use of these indicators in further multivariate analyses like Structural Equation Modeling (SEM).

Construct Validity

Table 6 exhibits strong reliability and convergent validity for the three critical constructs: AI-based service quality, customer satisfaction, and customer acceptance. All standardized loadings, exceeding the 0.70 mark-from 0.815 to

Table 5: Rotated Component Matrix Table

	Component		
Rotated Component Matrix	1	2	3
AIQ 1 (Responsiveness)			.826
AIQ 2 (Reliability)			.803
AIQ 3 (Ease of Use / Accessibility)			.811
AIQ 4 (Security and Privacy)			.785
AIQ 5 (Efficiency)			.801
AIQ 6 (Transparency)			.823
CS 1 (User Experience)		.866	
CS 2 (Security Satisfaction)		.848	
CS 3 (Problem-Solving Effectiveness)		.853	
CS 4 (Convenience)		.857	
CS 5 (Consistency of Service)		.860	
CS 6 (Reduction in Effort)		.843	
CA 1 (Perceived Usefulness)	.882		
CA 2 (Attitude Toward Using AI)	.880		
CA 3 (Behavioral Intention to Use)	.871		
CA 4 (Social Influence)	.857		
CA 5 (Compatibility)	.855		
CA 6 (Emotional Comfort)	.877		

Extraction Method: Principal Component Analysis, Rotation Method: Varimax with Kaiser Normalization, a. Rotation converged in 5 iterations

Table 6 Convergent Validity of the Constructs

S. no.	Construct	Items	Standardized Loadings	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
1.	AI-based banking service quality factors	AIQ 1	0.880	0.918	0.936	0.710
		AIQ 2	0.832			
		AIQ 3	0.830			
		AIQ 4	0.835			
		AIQ 5	0.815			
		AIQ 6	0.863			
2.	Customer Satisfaction	CS 1	0.905	0.946	0.957	0.788
		CS 2	0.873			
		CS 3	0.874			
		CS 4	0.896			
		CS 5	0.890			
		CS 6	0.886			
3.	Customer Acceptance	CA 1	0.915	0.955	0.964	0.816
		CA 2	0.908			
		CA 3	0.900			
		CA 4	0.883			
		CA 5	0.896			
		CA 6	0.917			

Table 7: Discriminant Validity

Parameters	AIQ	CA	CS
AIQ	0.843	-	-
CA	0.417	0.903	
CS	0.424	0.387	0.887

Table 8: Goodness of Model Fit Indices

Parameters	Saturated model	Estimated model
SRMR	0.032	0.033
d_ULS	0.197	0.212
d_G	0.126	0.122
Chi-square	311.358	298.458
NFI	0.954	0.956

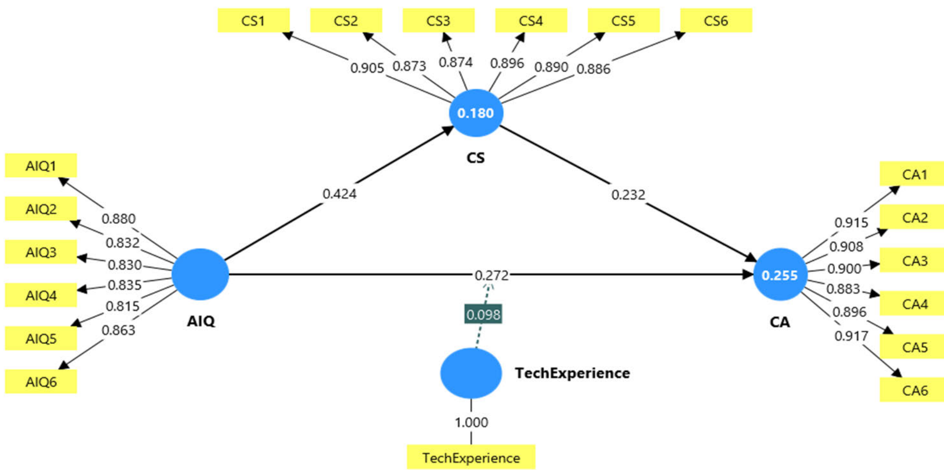

Figure 1: SEM Model

0.917, show that each observed variable substantially contributes to determining its latent construct. Cronbach's Alpha values of 0.918 for AI-based service quality, 0.946 for customer satisfaction, and 0.955 for customer acceptance indicate excellent internal consistency. Likewise, the Composite Reliability (CR) values remain highly consistent over each construct (0.936, 0.957, and 0.964, respectively), rendering the scales reliable. The Average Variance Extracted (AVE) values of 0.710 for AIQ, 0.788 for CS, and 0.816 for customer acceptance also provide evidence supporting convergent validity, with a strong portion of the variance explained by each construct for its respective indicators. Hence, all findings jointly support the notion that this measurement model

Table 7 shows that the discriminant validity was assessed using the Fornell-Larcker criterion, which compares the square root of AVE (on the diagonals) of a construct to the correlations between the constructs considered (on the off-diagonals). The square roots of the AVE were found to be 0.843 for AI-based Banking Service Quality (AIQ), 0.903 for Customer Acceptance (CA), and 0.887 for Customer Satisfaction (CS). Each of these values on the diagonal is higher than the correlations between constructs off-diagonal: AIQ–CA (0.417), AIQ–CS (0.424), and CA–CS (0.387). Hence, the results indicate that each construct shares more variance with its own indicators than with other constructs; hence, the Fornell-Larcker criteria for discriminant validity are met, indicating strong discriminant validity. That implies that these three constructs of AI-based service quality, customer acceptance, and customer satisfaction are conceptually different and well distinguished from a statistical standpoint. This discriminant validity ensures that the constructs truly measure different aspects of the customer experience with AI in banking and justifies them being modeled as separate variables in the structural model.

Table 8 shows the model fit indices for the saturated and estimated models show a strong and robust model fit, thereby confirming the structural soundness of the proposed modeling framework. SRMR values for the SRMR model were 0.032, and for the estimated model, it was 0.033, thus much below an acceptable value of 0.08, depicting practically nil discrepancy in the observed and predicted correlations. d_ULS (0.197 and 0.212) and d_G (0.126 and 0.122) values support the goodness-of-fit of the model by representing residual differences at a very low magnitude. Chi-square values are 311.358 and 298.458, respectively, for the saturated and estimated models and are well within acceptable limits, considering the complexity of the model. Most importantly, NFI values of around 0.954 and 0.956 are well above the acceptable threshold of 0.90, suggesting a truly acceptable level of model fit. All of these suggest that the proposed

Table 9: Hypothesis Testing Table

Hypothesis	Predicted Relationship	Original sample	Sample mean	Standard deviation	T statistics	P values
H1	AIQ -> CS	0.424	0.424	0.048	8.904	0.000
H2	AIQ -> CA	0.272	0.274	0.050	5.426	0.000
H3	AIQ -> CS -> CA	0.098	0.098	0.026	3.731	0.000
H4	Tech Experience x AIQ -> CA	0.098	0.098	0.046	2.128	0.033

H1: There is a significant impact of AI-based banking services quality factors on customer satisfaction

structural equation model is a perfect fit with the data among AI-based service quality, customer satisfaction, and customer acceptance in the banking environment.

Figure 1, The structural model illustrates the relationships among AI-based Banking Service Quality (AIQ), Customer Satisfaction (CS), Customer Acceptance (CA), and the moderating variable Tech Experience. The direct path from AIQ to Customer Satisfaction is strong and significant ($\beta = 0.424$), indicating that perceived quality of AI services positively influences customer satisfaction. Similarly, Customer Satisfaction significantly contributes to Customer Acceptance ($\beta = 0.232$), suggesting that satisfied customers are more inclined to accept AI-based services. The direct effect of AIQ on Customer Acceptance is also meaningful ($\beta = 0.255$), confirming that quality in AI services directly fosters user acceptance. Importantly, the interaction term (Tech Experience * AIQ -> CA) reveals a positive and statistically significant moderating effect ($\beta = 0.098$), indicating that customers with higher technological experience are more responsive to improvements in AI service quality, leading to higher acceptance levels. This supports the idea that tech-savvy users perceive and react more favorably to AI innovations in banking. All indicator loadings are high (ranging from 0.815 to 0.917), ensuring strong measurement reliability. The overall model confirms both the direct and moderated influences of AI quality and customer satisfaction on customer acceptance, emphasizing the strategic importance of enhancing AI quality and tailoring services to different tech experience levels.

The results of the above hypothesis, presented in Table 8, are strongly supported by the data, indicating a significant and positive relationship between AI-based factors of banking service quality and customer satisfaction ($\beta = 0.424$, $T = 8.904$, $p = 0.000$). This means that customers who view AI-enabled services like responsiveness, reliability, ease of use, security, and transparency are considered high quality would also consider themselves highly satisfied.

H2: There is a significant impact of AI-based banking service quality factors on customer acceptance

The results of the above hypothesis, presented in Table 8, were confirmed with the existence of significant direct effects of AI-based banking service quality on customer acceptance ($\beta = 0.272$, $T = 5.426$, $p = 0.000$). This means that customers who perceive AI services as dependable, accessible, and valuable will be more willing to accept and use the services. These findings indicated that AI quality directly plays a role in shaping user behavior, which is much more than satisfaction, within a willingness to accept and work with AI-enabled systems.

H3: There is a significant mediating effect of customer satisfaction between AI-based banking service quality factors and customer acceptance

The results of the above hypothesis, presented in Table 8, posit the mediating effect of customer satisfaction in the relationship between AI service quality and acceptance and are statistically supported ($\beta = 0.098$, $T = 3.731$, $p = 0.000$). The findings show AI service quality not just as an immediate influence on acceptance, but mediated in part by satisfaction. That is, partial mediation is observed. If the customers perceive AI service as high quality, their satisfaction is increased, which then leads to greater acceptance of those services on their part.

H4: Technology experience significantly moderates the impact of AI-based banking service quality factors on customer acceptance

The results of the above hypothesis, presented in Table 8, are supported, with a significant moderating effect of technology experience on interactions between AI-based service quality and customer acceptance ($\beta = 0.098$, $T = 2.128$, $p = 0.033$). This means customers with high technology experience tend to react positively to increases in AI service quality, and hence, support the acceptance of AI-enabled banking services. On the other hand, customers with low digital knowledge may not strongly perceive the benefits of the AI features or may simply find it difficult to use them.

DISCUSSION

Essentially, AI in banking is a mechanism for a paradigm shift in service delivery and radically impacts customer satisfaction and acceptance. According to the structural equation modeling (SEM) technique, the study indicated that factors of AI-based service quality, namely, responsiveness, reliability, ease of use, security, efficiency, and transparency, directly impact customer satisfaction ($\beta = 0.424$, *p* < 0.001) and acceptance ($\beta = 0.272$, *p* < 0.001). It is very

Table 10: Research Gaps and Contributions

Citation	Key Findings	Research Gap	How The Present Study Fills the Gap
Alnaser et al. (2023)	Expectation confirmation and visual attractiveness drive satisfaction.	Narrow focus on digital banking; ignored mediation pathways.	Tested holistic AI service quality (6 factors) and proved satisfaction's mediation between quality and acceptance.
Kondybayeva et al. (2024)	Chatbots improve productivity via problem-solving and communication quality.	Limited to voice chatbots; did not examine user heterogeneity.	Revealed tech experience as a moderator, enabling segmentation strategies.
Nguyen et al. (2021)	Trust is the strongest predictor of continuance intention.	Overlooked how trust is built through service quality dimensions.	Linked trust to security, transparency, and reliability within the SEM framework.
Mei et al. (2024)	Technological literacy is crucial for AI adoption.	Did not explore literacy's interaction with service attributes.	Showing tech experience amplifies acceptance when AI quality is high.

important to mention that customer satisfaction mediates the interaction between service quality and acceptance (β = 0.098, *p* < 0.001), and the experience of technology moderates this relationship (β = 0.098, *p* = 0.033). This finding corroborates world studies but goes beyond by integrating hitherto fragmented insights into one framework.

Trust forms the paramount predictor in the continuation of AI use (Nguyen et al., 2021), mediated by perceived usefulness and security. Personalization (such as personalized robo-advice) can boost satisfaction if it aligns with performance expectations (Lee et al., 2023), but customizations in isolation hardly make any difference (Kondybayeva et al., 2024). When perceived performance relates to efficiency, problem-solving capabilities, and reliability, satisfaction follows when expectations are fulfilled (Alnaser et al., 2023; Kondybayeva et al., 2024). A case could be made that an AI chatbot improves productivity only if the best-practice GUI and communications manage to intuitively resolve queries to the user's satisfaction (Kondybayeva et al., 2024). At the same time, security concerns uphold a blockade against acceptance (Roy et al., 2017; Noreen et al., 2023), demanding that AI be transparent. Based on mediation, satisfaction stands between service quality and acceptance, describing the case where AI of great functionality (such as fraud detection) fails without an excellent user experience. Moderation analysis shows that technology experience significantly strengthens the AI service quality-acceptance link for digitally proficient users ($\beta = 0.098$, $p < 0.05$), while also building adoption barriers for less technologically experienced customers finding consistent with Mei et al. (2024) in emphasizing disparities in digital literacy.

Banks should focus on service design, emphasizing expectation confirmation and solving problems effectively, such as the accurate alerting of fraud, rather than acquiring mere trendy implementations. Visually intuitive interfaces and anthropomorphic AI elements may further comfort users in communicating with and trusting the system.

While prior studies focus on isolated AI applications, such as chatbots in Kazakhstan (Kondybayeva et al., 2024), our integrated model, on the contrary, demonstrates that multidimensional service quality, from reliability to transparency, all together shapes satisfaction and acceptance. Whereas Koyluoglu and Acar (2023) found security to only affect attitudes and not intentions.

Banks must treat AI not as a cost-saving tool but rather as an experience enhancer from every perspective. Anchoring the deployment of AI in the confirmation of expectations, performance reliability, and trust-building through sheer transparency, whilst considering the technology literacy of the user, permits the satisfaction to evolve into long-term acceptance on the part of the client.

CONCLUSION

Banks should see AI not only as a cost-reduction instrument but as a means to improve the experience from all viewpoints. The use of AI to validate expectations, ensure performance dependability, and foster trust via transparency, while taking into account the user's technological literacy, enables satisfaction to develop into long-term customer acceptance. Subsequent inquiry is necessary about cultural disparities in the adoption strategy and the long-term impacts of AI use on customer retention. From a theoretical standpoint, the amalgamation of TAM, & SERVQUAL within a single SEM framework propels knowledge by bringing forth both the direct and indirect processes via which the quality of AI services shapes the customer action. Customer satisfaction acting as a mediator emphasizes the emotional and experiential pathways for technology adoption, whereas experience with technology as a moderator stresses the heterogeneity in the digital literacy levels of the users. From a practical perspective, banks should look at ensuring and confirming customer expectations with fraud alerts and chatbots accurately, invest in transparent authentication to foster trust, and further recognize varying degrees of technology proficiency among customers when designing interfaces and support resources so as to ensure maximum acceptance among all classes of users.

Future Research

Longitudinal studies could analyze whether satisfaction and acceptance are, indeed, correlated with continuous user engagement and cross-usage of products. Comparative approaches in settings of varying cultural and regulatory environments can establish how generalizable the findings would be. Qualitative studies could elucidate the subtle barriers experienced by users with little experience and provide input into the design of inclusive AI interfaces. Further research into the emerging AI applications, including predictive financial coaching and emotion-aware virtual assistants, will further advance understanding of evolving service dimensions of quality.

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