



International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Impact of Artificial Intelligence on Customer Satisfaction in the Banking Sector

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DOI : <https://doi.org/10.55248/gengpi.07.1026.3304>

ABSTRACT :

Artificial Intelligence (AI) is transforming the way banks provide services, but there is not much evidence on the impact AI-enabled services have on customer satisfaction. This study investigates the effect of AI based banking service on customer satisfaction and evaluates the mediating role of AI service quality, perceived ease of use, perceived usefulness, AI reliability and accuracy, customer trust and perceived security and privacy as well as difference in terms of age, bank type, income and digital literacy. The study was conducted using non-probability sampling of the bank customers in Andhra Pradesh and a structured 5-point Likert type scale was administered online. Duplicate records and one incomplete response were excluded leaving 44 valid responses which were analysed using chi-square tests, one-way ANOVA and simple, multiple and hierarchical linear regression with ancillary bootstrapping mediation and interaction analysis. The overall satisfaction of the customers was at a moderate level ($M = 3.53$, $SD = 0.68$). The satisfaction was greatly predicted by AI-enabled banking services ($\beta = .66$, $R^2 = .435$, $p < .001$) and each perception construct had a positive association with satisfaction. This effect was partially mediated by customer trust and perceived security and privacy (indirect effects = 0.27 and 0.19; both bootstrap 95% confidence intervals (BCIs) were non-zero). Satisfaction level was associated with digital literacy, $\chi^2(4) = 14.21$, $p = .007$, and mean satisfaction differed by age group, $F(3, 40) = 4.29$, $p = .010$, and by digital-literacy level, $F(2, 41) = 4.76$, $p = .014$, but not by gender, income or bank type. There was no moderation effect by digital literacy on the relationship between AI and satisfaction. Results are only indicative due to the small non-probability sample. Trust building, clear communication of security and privacy protection, reliable AI results, and digital-literacy support for customers should be the main areas of focus for banks.

Keywords: Artificial Intelligence (AI), Customer Satisfaction, AI-Enabled Banking Services, Customer Trust, Service Quality, Perceived Security and Privacy, Digital Banking, Digital Literacy.

1 Introduction

The banking sector is vital for economic development of countries by offering various financial services like deposits, loans, payments, investment, fund transfer and other financial facilities. A lot has changed in banking the last few years with the technology advancement continuously. The traditional banking system, which mainly depended on physical branches and face-to-face interactions, has gradually shifted towards digital and technology-driven banking. Artificial Intelligence (AI) is one of the recent technologies that are proving valuable to the banking sector in terms of operational changes and enhanced customer service. Banking institutions can leverage AI to process vast amounts of data, detect patterns, automate tasks, assist decision-making, and deliver enhanced and tailored customer support. (P. Jain, 2024)

The term Artificial Intelligence (AI) is used to describe technologies which allow computers to accomplish tasks that are typically done by humans, such as learning, decision-making, predicting, problem solving, and understanding customer needs. AI is being used across the banking sector to improve customer service, prevent fraud, evaluate credit, manage risk, manage investments and provide personalized financial services. According to P. Jain, AI's role in the bank sector has grown more significant owing to its capacity to handle vast amounts of data and aid in financial decision-making. This means that the use of AI can bring greater efficiency to the operation as well as impact the quality, reliability and responsiveness of services that customers experience.

The most significant use of AI in the financial sector is in customer service. Customers can use AI-powered chatbots and virtual assistants to get information, ask questions, troubleshoot common issues, and even get help without making the trip to a bank branch or waiting for a human customer-service representative. R. Jain (2023) suggests that AI Virtual Assistants can offer tailored and efficient customer assistance by addressing queries, solving problems, and giving suggestions. These services can help in cutting down the waiting time and make it convenient for customers to access banking services. In today's fast-paced world, where customers are getting more demanding than ever, AI-powered customer support has emerged as a crucial aspect of the banking sector.

AI also plays a part in the effectiveness and precision of financial transactions. In the banking and financial sector, AI has the power to analyze vast amounts of data, detect trends, and assist in decision-making (Narang, Vashisht, and Bajaj, 2024). Credit scoring, fraud detection, investment management, and customer service are examples of the applications of AI. AI can also be used in fraud detection, where it can analyze transaction

patterns and flag any unusual activity that could indicate fraud. AI can also be used for fraud detection, which involves analyzing transaction patterns and identifying any unusual activity that might suggest fraud. Likewise, AI-powered credit evaluation can analyse various kinds of data to help with lending choices. All of these enhancements have the potential to indirectly impact customer satisfaction as customers typically have expectations that banking services are accurate, reliable, secure and efficient.

In Banking, Customer satisfaction becomes of great importance due to the different expectations of the customers for the services they receive. This includes convenience, speed, reliability, responsiveness, security, personalization and ease of use. One of the reasons driving the banks to embrace advanced technologies like Artificial Intelligence is its ability to meet changing customer expectations (Hinge, 2022). Today, customers are increasingly demanding seamless banking experience via digital channels. To meet the expectations of customers, AI can offer banks a range of benefits, including improved speed of service, customisation, automated support, and data-driven solutions. Thus, the use of AI can have an impact on the customer experience and satisfaction in banking services.

But the role of AI in customer satisfaction doesn't stop at convenience and service efficiency. Other factors to consider are trust, privacy, security and ethical use of customer information. Banks manage financial and personal sensitive data, and AI systems need a lot of customer information. Narang et al. (2024) cite data security, privacy issues, algorithmic bias, and ethical concerns as significant challenges to consider with AI applications. P. Jain (2024) also discusses concerns related to privacy, bias, and human oversight. Even if the technology is offering a more convenient and faster experience, the use of AI could raise concerns if customers are not assured that their personal and financial data is sufficiently protected.

By enhancing the security of banking transactions, AI-based fraud detection can help build trust in the banking system. According to R. Jain (2023), AI is employed for analysing transaction patterns and detecting any suspicious activities. By leveraging effective fraud detection, banks can better safeguard their customers and enhance the security of their digital banking offerings. Likewise, AI-powered risk-management platforms can aid banks in recognizing and dealing with possible risks. The examples show how AI can impact customer satisfaction, not just by interacting with customers, but also by enhancing the security, reliability, and accuracy of banking processes.

Credit scoring and financial decision making are also important uses of AI. According to Narang et al. (2024), AI credit-scoring models can use various data points and historical information to aid in credit evaluation. AI can also be used in the field of investment management, where it can help to process market information and uncover trends that can inform financial decisions. These applications can enhance the efficiency of financial services, and can offer financial services customers more data-driven and personalized solutions. Similarly, credit scoring and other financial applications are also highlighted as significant use cases of AI in banking by R. Jain (2023).

But, the same time customers can react differently to AI adapted banking services. Age, digital literacy, income, technological familiarity, and prior to digital banking experience can impact customer perception of AI. Some customers might prefer certain automated services and around-the-clock availability, others prefer human interaction, especially when it comes to the complex financial aspects. When studying customer satisfaction, one needs to consider and explore the customer perception regarding AI service quality, ease of use, usefulness, reliability, security, privacy and trust.

In summary, Artificial Intelligence is reshaping the banking industry by providing applications like Customer Service, Fraud detection, Credit scoring, Risk Management, Investment management and Data analysis (P. Jain, 2024; R. Jain, 2023; Narang et al., 2024; Hinge, 2022). Although AI offers benefits in efficiency, convenience, personalization, responsiveness, and security, privacy, data protection, ethical use, and customer trust are also crucial considerations. Hence, the current research, "The Impact of AI on Customer Satisfaction in the Banking Sector", aims to examine the effect of AI-powered banking services on customer satisfaction. This study investigates customers' experience and satisfaction with AI-powered banking services, covering various aspects, including service quality, usability, usefulness, reliability, security, privacy, and trust.

Review of Literature

Prisha Jain(2024)-AI in Banking Sector Descriptive study using secondary data/graphs on AI adoption, customer preferences, and market growth on Indian banking. AI improves customer experience and fraud detection, but faces data quality, cybersecurity, and regulatory challenges.

Ritu Jain (2023)-Role of AI in Banking and Finance Literature review of AI applications (fraud detection, credit scoring, customer service) using real bank case studies (JPMorgan, Citibank, Wells Fargo). AI boosts decision-making and profitability but raises data privacy, bias, and ethical concerns.

Narang, Vashisht & Bajaj (2024)-AI in Banking and Finance Comprehensive literature review of AI integration benefits/difficulties plus a forward-looking "Future Scope" section. AI improves efficiency and profit but needs stronger legal/ethical frameworks for future adoption.

Deepa Hinge (2022)-Impact of AI in Banking Sector Descriptive study on AI's effect on Indian banking operations and human resources, referencing five prior studies. AI cuts costs and improves service/fraud detection but causes job displacement and requires high investment.

Noreen et al. (2023)-Banking 4.0: AI & Consumer's Perspective Empirical TPB-based survey (799 respondents, 5 Asian countries) on consumer intention, while perceived risk negatively affects it.

Gyau et al. (2024)-AI innovation & Bank Financial Performance Cross-country panel study (20 countries) using FGLS/GMM testing AI innovation's effect on bank ROA. AI innovation boosts ROA, especially short-term, mediated by ICT development and moderated by economic growth.

Hafez et al. (2025)-AI Techniques in Credit Card Fraud Detection Systematic review comparing ML, DL, and meta-heuristic optimization techniques for fraud detection. Deep learning outperforms traditional ML in pattern recognition, but continuous model updates are needed.

Polireddi (2024)-AI/ML in Banking Sector Survey-based study on adoption intention factors (attitude, usefulness, risk) using a TAM-style framework. Attitude and perceived usefulness are the strongest positive predictors of AI adoption intention.

Mytnyk et al. (2023)-AI for Fraudulent Banking Operations Empirical ML comparison study using the Kaggle fraud dataset with feature engineering and ensemble stacking. A stacked ensemble model outperformed individual classifiers, achieving the highest fraud detection accuracy (AUC=0.954).

Ampumuza et al. (2026)-AI-Driven Fraud Detection in SACCOs Systematic PRISMA review (28 studies) of fraud patterns and detection methods in SACCOs. Rule-based detection is ineffective; ML models show promise but SACCOs lack tailored fraud models and ICT infrastructure.

Olowu et al. (2024)-AI-Driven Fraud Detection & Cybersecurity Systematic review synthesizing 47 studies on AI/data science techniques for banking fraud detection. AI systems achieve 87-94% detection rates and cut false positives by 40-60% detection. AI systems achieve 87-94% detection rates and cut false positives by 40-60% versus traditional methods.

Yaseen & Al-Amarnah (2025)-Trust, Transparency & Fairness in Fraud Detection AI PLS-SEM study (UAE and Qatar) testing trust, transparency, and fairness as drivers of AI adoption. Trust is the strongest adoption driver; fairness perception significantly moderates the trust-adoption like.

Goyal, Garg & Malik-AI Credit Risk & Fraud Detection (SEM-ANN) Hybrid SEM-ANN study on continued AI using intention among Indian bank employees. Ease of use and IT competence are the strongest predictors of attitude and continues usage.

Dr. Aakash Ramchand Dil (2025)-AI/ML in Credit Risk Assessment Review of AI/ML applications in predicting borrower default risk, weighing benefits against ethical/regulatory risks. AI adoption cuts default risk, weighing benefits against ethical/regulatory risks. AI adoption cuts default rates by 40% but still lags human evaluators by about 81% in performance.

Engan, Hjelkrem & Ristad (2026)-Credit Risk: Deterministic to Probabilistic AI PRISMA systematic review (77 studies) on AI/ML models in bank credit risk assessment. Tree-based and neural models dominate; probabilistic AI remains underused despite better uncertainty quantification.

Gates & Flynn (2025)-AI-Driven Credit Risk Modeling Multi-chapter review tracing credit modelling evolution from statistical scoring to explainable ML. ML/XAI models improve accuracy and transparency; alternative data expands financial inclusion but raises privacy concerns.

Michael Brown (2024)-AI's Influence on Credit Risk Assessment conceptual review grounded in Decision Theory, TAM, and FAT framework examining AI's role in credit risk. AI improves risk identification and transparency, but literature has regional and methodological gaps.

Ciumara Tudor (2024)-AI's Impact on Credit Risk & Business Model Transformation conceptual discussion of AI-driven credit scoring and its effect on financial institutions' business models. AI improves inclusion and efficiency but raises "black-box" transparency and regulatory compliance concerns.

Shreya & Pathak (2025)-Explainable AI Credit Risk Assessment Empirical study building an XAI-based ensemble ML system (XGBoost, LightGBM, Random Forest) for loan default prediction. LightGBM performed best overall; SHAP/LIME added interpretability, though precision-recall remained limited.

Ahmed, Mehdi & Mohamed (2023)-AI- Based Banking Risk Index (ANFIS) Empirical study using Mahalanobis Distance and ANFIS to rank GCC bank using financial ratios. Net Interest Margin and Cost/Income ratio were the most significant risk drivers among GCC banks.

Graham et al. (2025)-Chatbots in Banking Customer Service Mixes-method study (interviews + case studies) on chatbot adoption drivers using TAM/UTAUT framework. Chatbots aid simple-task automation but remain limited in handling complex customer queries.

Teja Reddy Gatla (2018)-AI Chatbots for Customer Service Early review comparing chatbot vs. human service quality and identifying adoption challenges. Chatbots scored well on satisfaction/speed, but customers still prefer humans for complex issues.

Karri et al. (2024)-AI Chatbots in Banking: Efficiency Systematic review (13 studies) with Power BI analysis of chatbot feature using and satisfaction. 87% adoption rate with 86.9% query resolution; trust and complex-query handling remain limitations.

Winner Olabiya (2025)-AI Chatbots & Customer Experience Mixes-method study (300 responding + interviews) on chatbot usability and personalization in digital banking. Usability strongly correlates with satisfaction, but empathy gaps still affect customer trust.

Kikani & Ramchandani (2025)-AI Chatbots: Efficiency vs. Human Touch Study combining secondary industry data and interviews comparing chatbot efficiency to human service. Chatbot cut costs and response time, but 58% of customers still prefer human for complex issues.

Kaakandikar et al. (2025)-Customer Perception Of AI Chatbots Exploratory review with bank case study examining trust and satisfaction with banking chatbots. Chatbots are valued for speed/availability, but privacy and trust concerns persist among customer.

Mv, Gupta, Vinoth & Gopalakrishnan (2024)-Effects of AI Chatbots on Users Survey study (n=124) analyzing usage frequency and demographic factors in financial chatbot use. Accuracy and availability are most valued; poor personalization and lack of human support are top complaints.

Kovacevic, Radenkovic & Nikolic (2024)-AI and Cybersecurity in Banking Conceptual review framing AI as dual-use technology, covering efficiency gains and adversarial ML risks. Nearly 50% of banks have adopted AI, with sharp planned increases in cybersecurity investment for 2025.

Dr. Kishor P. Bholane (2023)-AI Adoption in Indian Banking Descriptive overview of AI market growth and sector-wide adoption using secondary data and case studies. BFSI leads AI adoption in Indian (65%), with chatbots like SBI's SIA and HDFC's Eva widely used.

Tshewang, Joshi, DR & Govindaraj (2024)-AI's Impact on Banking Job Market Decade-long (2012-2023) trend analysis of employee counts by role and bank type amid AI adoption. Clerical roles declined sharply while officer-level employment rose, signaling a shift toward upskilling.

1.1 Research Gap

The previous researches on the Artificial Intelligence in banking have concentrated on the adoption of AI, fraud detection, financial performance, credit risk assessment, operational efficiency and chatbot applications. According to several studies, AI can enhance banking services, speed, and accuracy as well as customer experiences. Yet, there has been limited research on the total effect of AI on customer satisfaction, as indicated in the literature. The studies conducted on chatbots have focused on usability, trust, personalization, and customer experience, but these are just a few aspects of AI in banking services. Moreover, issues of trust, privacy, security, transparency, and reliability persist as challenges to customers' willingness to use AI-driven services and their satisfaction with them. As a result, there is a research gap in studying the effect of the interaction of AI service quality, ease of use, usefulness, reliability, customer trust, and perceived security and privacy on customer satisfaction in the banking sector. This study is an empirical study which examines this gap.

1.2 Problem Statement

While the banking industry is increasingly leveraging AI to enhance the efficiency of banking services and customer experience, there are lingering

concerns regarding service quality, reliability, usability, trust, security, and privacy. Research on the influence of these factors on customer satisfaction has been inadequate. Hence, the purpose of this study is to explore the effect of AI banking services on customer satisfaction.

1.3 Research Questions

1. How is AI affecting customer satisfaction in the banking industry?
2. What is the impact of AI service quality, ease of use, usefulness and reliability on customer satisfaction?
3. What is the relationship between Customer trust and perceived security and privacy with customer satisfaction of AI-based Banking services?

1.4 Conceptual Framework

The conceptual framework (Figure 1) suggests that customer satisfaction with AI-supported banking services (dependent variable) is directly influenced by AI-supported banking services, AI service quality, ease of use, usefulness and reliability/accuracy of AI banking services (independent variables). The mediators placed between the independent variables are “customer trust” and “customer sense of security and privacy.” Bank type, digital literacy, income level and age are considered as moderating/differentiating features of customers.

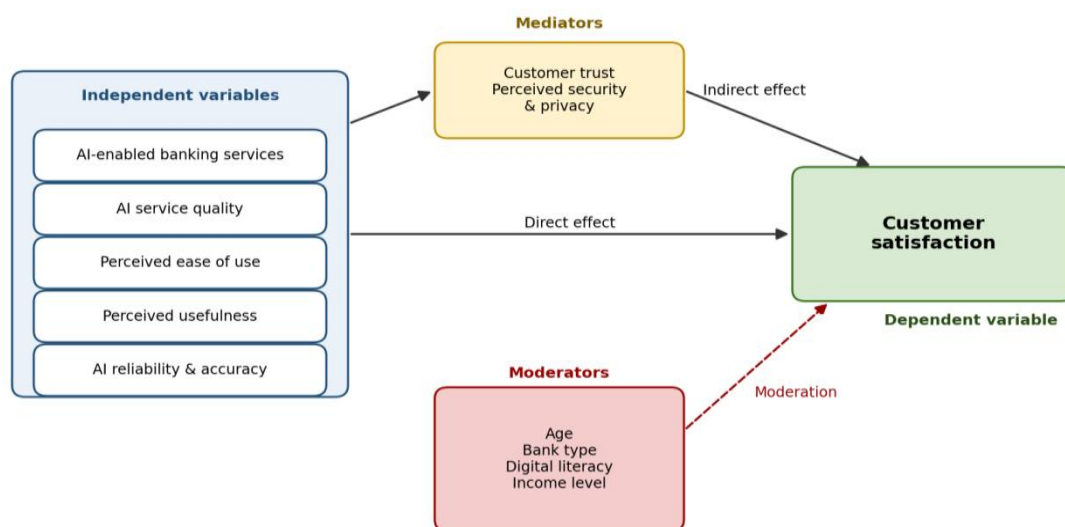


Figure 1. Conceptual framework of the study

1.5 Research Objectives

1. To analyze the effect of Artificial Intelligence on the customer satisfaction in banking industry.
2. To investigate the relationship between customer satisfaction and the quality of AI services, their user-friendliness and their usefulness and reliability.
3. To explore the role of customer trust and perceived security and privacy in AI-powered banking solutions.
4. To find out if these four variables (Age, Bank Type, Digital Literacy, Income Level) have moderating effects on Customer Satisfaction.
5. To suggest improvements in customer satisfaction based on efficient use of AI in the banking industry.

1.6 Research Hypotheses

1.Null Hypothesis (H₀): The adoption of AI in banking does not appear to have a major influence on customer satisfaction.

Alternative Hypothesis (H₁): The AI-powered banking services make a high impact on customer satisfaction.

2.Null Hypothesis (H₀): The quality of AI services does not significantly affect customer satisfaction.

Alternative Hypothesis (H₂): AI service quality has a significant impact on customer satisfaction.

3.Null Hypothesis (H₀): There was no significant relationship between perceived ease of use and customer satisfaction.

Alternative Hypothesis (H₃): The ease of use is one of the factors that significantly influence customer satisfaction.

4.Null Hypothesis (H₀): Perceived usefulness has no significant impact on customer satisfaction.

Alternative Hypothesis (H₄): Perceived usefulness has a significant impact on customer satisfaction.

5.Null Hypothesis (H₀): Customer satisfaction is not affected by the reliability and accuracy of AI.

Alternative Hypothesis (H₅): AI reliability and accuracy have a significant impact on customer satisfaction.

6.Null Hypothesis (H₀): AI-powered banking services do not directly influence customer satisfaction, but rather through customer trust.

Alternative Hypothesis (H₆): The relationship between AI-powered banking services and customer satisfaction is indirect and goes through the process of customer trust.

7.Null Hypothesis (H₀): AI powered banking services and customer satisfaction are not mediated by perceived security and privacy.

Alternative Hypothesis (H₇): How secure and private the AI services are in banking influences the link between AI services in banking and customer satisfaction.

8.Null Hypothesis (H₀): AI in banking services has no impact on customer satisfaction, as there is no need for digital literacy as a moderator.

Alternative Hypothesis (H_a): Digital literacy moderates the relationship between AI-enabled banking services and customer satisfaction.

Further, the differences in customer satisfaction between each group based on age, gender, occupation, income, bank type, frequency of use of AI, and the most used AI service, and level of digital-literacy are explored using chi-square tests and one-way ANOVA.

Research Methodology

2.1 Research Design

The research design is quantitative, cross sectional and survey in nature. It is descriptive in its description of customers' perceptions of such AI-powered banking services and explanatory in its test of the hypothesised relationships between such perceptions of AI enabled banking services, customers' trust and security and privacy, and their customers' satisfaction. The conceptual framework and the questionnaire were developed using secondary literature.

2.2 Population, sampling and data collection

The target audience was the banking services users of Andhra Pradesh who are using AI features like chatbots, virtual assistants, alert messages on app for fraud alerts etc. Structured self-administered online questionnaire was used to gather data. The sample was obtained using non-probability (convenience) sampling, which means that the sample is not representative of the larger population. Responses were taken on 1 – 3 September 2026.

The exported response file had 90 rows. Every respondent was seen by the inspector on two occasions (45 respondents being seen once – one of these was a duplicate with a corrupted time stamp – was not characteristic of genuine repeat submissions). Duplicate records were eliminated based on matching the e-mail address and complete answer pattern. The number of respondents answering only one demographic item was 1 for a total of 45 unique respondents, and was excluded. The analytic sample is thus $n = 44$ (Table 1).

Table 1. Sample screening flow

Step	Number of records
Rows in exported response file	90
Exact duplicate records removed	–45
Unique respondents	45
Respondent with no attitude-item responses (excluded)	–1
Usable responses analysed	44

Note. Sample size limits statistical power: with $n = 44$ the study has 80% power (two-tailed $\alpha = .05$) to detect only correlations of about $r \geq .41$, so smaller effects may go undetected.

2.3 Instrument Development and Measurement

The questionnaire consists of 30 items in nine sections (Appendix A) and was designed based on the constructs in the conceptual framework. The other sections (A to I) include demographic information (age, gender, occupation, monthly income, primary bank type), AI-enabled banking services (frequency of use, most used service, convenience), AI service quality, perceived ease of use, perceived usefulness, customer trust, security and privacy, and digital literacy and customer satisfaction. Attitude items are rated on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The items were aggregated to form constructs as outlined in Table 2.

There are two measurement decisions to be noted. First, Section C (AI service quality) has four items; to match the framework, which views service quality and AI reliability and accuracy as different constructs, the items were split by content, with reliability and accuracy (Q9, accurate information; Q11, reliable support); and service quality (Q10, quick response; Q12, availability). Secondly, convenience is the only item associated with AI-enabled banking services. Cronbach's alpha was used to determine reliability.

Table 2. Constructs, items and reliability

Construct	Role in model	Items	No. of items	Cronbach's α
AI-enabled banking services	Independent	Q8	1	–
AI service quality	Independent	Q10, Q12	2	.76
AI reliability & accuracy	Independent	Q9, Q11	2	.76
Perceived ease of use	Independent	Q13–Q15	3	.87

Construct	Role in model	Items	No. of items	Cronbach's α
Perceived usefulness	Independent	Q16–Q18	3	.85
Customer trust	Mediator	Q19–Q21	3	.83
Security & privacy	Mediator	Q22–Q24	3	.63
Digital literacy	Moderator	Q25, Q26	2	.38
Customer satisfaction	Dependent	Q27–Q30	4	.84

Note. Sample size limits statistical power: with $n = 44$ the study has 80% power (two-tailed $\alpha = .05$) to detect only correlations of about $r \geq .41$, so smaller effects may go undetected.

2.4 Data Screening and Preparation

Responses were screened before analysis. (i) Two respondents ticked two options (“4, 5”) on the single-choice items Q19, Q21 and Q22; these six cells were treated as missing and construct scores for those respondents were calculated from the remaining items in the scale. (ii) Monthly income was missing for three respondents and bank type for one; these respondents drop out only of the analyses that use those variables. (iii) Construct scores were computed as the mean of their items. (iv) For chi-square analysis, customer satisfaction was classified as Low (mean < 3.0), Moderate (3.0–3.99) or High (≥ 4.0), and digital literacy as Low (≤ 3.0), Medium (3.5) or High (≥ 4.0). (v) The response-option labels for the categorical questions (age, gender, occupation, income, bank type, frequency and service used) were not present in the exported data, so those categories are reported by their numeric codes. (vi) Eight respondents (18.2%) gave the same answer to all 23 attitude items; they were retained because uniform answers cannot be distinguished from genuine agreement or neutrality, but this is acknowledged as a limitation.

2.5 Statistical Tools and Procedures

Analyses correspond to the SPSS procedures Descriptives, Reliability Analysis, Crosstabs (chi-square), One-Way ANOVA and Linear Regression. They were carried out with spreadsheet formulas in Microsoft Excel (companion workbook) and reproduced and extended in Python (SciPy and statsmodels) for the tests that Excel does not provide. The significance level was 5%.

- Descriptive statistics and correlation: means, standard deviations, skewness, kurtosis and Pearson correlations for all constructs.
- Chi-square test of independence: association between satisfaction level and each demographic or usage variable, with Cramér's V as effect size. Because many cells had expected counts below 5, Monte Carlo (permutation) p -values based on 10,000 permutations are reported alongside the asymptotic p -values.
- One-way ANOVA: differences in mean customer satisfaction across groups, with η^2 as effect size, Levene's test for homogeneity of variance, Welch and Kruskal–Wallis tests as robustness checks, and Tukey HSD post-hoc comparisons.
- Linear regression: simple regressions for H1–H5, a multiple regression with the four perception constructs, and a hierarchical regression adding trust and security & privacy. Assumptions were checked with variance inflation factors (VIF), the Durbin–Watson statistic, Shapiro–Wilk tests of residuals, the Breusch–Pagan test and Cook's distance; heteroscedasticity-robust (HC3) p -values are reported as a sensitivity check.
- Mediation and moderation: mediation followed the regression-based causal-steps approach with the indirect effect ($a \times b$) tested by a percentile bootstrap (5,000 resamples) and the Sobel test; moderation by digital literacy was tested with a mean-centred interaction term.

Data Analysis and Results

3.1 Profile of Respondents

Table 3 describes the 44 respondents. Because the response-option labels were not exported, categories are shown by code. The largest groups were age group 1 ($n = 17$, 38.6%) and age group 2 ($n = 16$, 36.4%); gender code 2 accounted for 63.6% of the sample; and occupation code 1 was the most common ($n = 28$, 63.6%). Income code 1 accounted for 61.0% of the 41 respondents who reported income, and bank type 1 was mainly used by 46.5% of respondents reporting a bank type. Usage frequency code 3 was the modal category (36.4%).

Table 3. Demographic and usage profile of respondents ($n = 44$)

Variable	Category	n	% of valid
Age group	Group 1	17	38.6%
	Group 2	16	36.4%
	Group 3	6	13.6%
	Group 4	5	11.4%
Gender	Code 1	16	36.4%
	Code 2	28	63.6%
Occupation	Code 1	28	63.6%

Variable	Category	n	% of valid
	Code 2	7	15.9%
	Code 3	3	6.8%
	Code 4	5	11.4%
	Code 5	1	2.3%
Monthly income	Code 1	25	61.0%
	Code 2	3	7.3%
	Code 3	3	7.3%
	Code 4	5	12.2%
	Code 5	5	12.2%
	Missing (excluded)	3	–
Type of bank mainly used	Code 1	20	46.5%
	Code 2	8	18.6%
	Code 3	13	30.2%
	Code 4	2	4.7%
	Missing (excluded)	1	–
Frequency of AI banking use	Code 1	11	25.0%
	Code 2	11	25.0%
	Code 3	16	36.4%
	Code 4	4	9.1%
	Code 5	2	4.5%
AI service used most	Code 1	8	18.2%
	Code 2	13	29.5%
	Code 3	7	15.9%
	Code 4	7	15.9%
	Code 5	9	20.5%

Note. Alpha values of .70 or above are conventionally regarded as acceptable. Security & privacy ($\alpha = .63$) is marginal and the two-item digital-literacy scale ($\alpha = .38$) is poor, so results involving these two scales should be interpreted with caution.

3.2 Descriptive Statistics

Table 4 and Figure 2 present the construct scores on the five-point scale. Perceived usefulness ($M = 3.58$), perceived ease of use ($M = 3.53$) and customer satisfaction ($M = 3.53$, $SD = 0.68$) recorded the highest means, whereas security & privacy ($M = 3.20$) and customer trust ($M = 3.25$) recorded the lowest, although still slightly above the scale midpoint. Overall satisfaction is therefore moderately favourable: 7 respondents (15.9%) fell in the Low satisfaction band, 20 (45.5%) in the Moderate band and 17 (38.6%) in the High band. The Shapiro–Wilk test for customer satisfaction gave $W = .960$, $p = .134$; skewness and kurtosis values for all constructs (Table 4) are within the commonly used ± 2 range for approximate normality except where noted.

Table 4. Descriptive statistics of study constructs (n = 44)

Construct	N	Mean	SD	Min	Max	Skewness	Kurtosis
AI-enabled banking services	44	3.43	0.95	1.00	5.00	-0.99	1.19
AI service quality	44	3.33	0.83	1.00	5.00	-0.20	0.50
AI reliability & accuracy	44	3.35	0.83	1.00	5.00	-0.70	1.76
Perceived ease of use	44	3.53	0.86	1.00	5.00	-0.84	1.42
Perceived usefulness	44	3.58	0.76	1.00	5.00	-0.77	2.02
Customer trust	44	3.25	0.80	1.00	5.00	-0.29	0.76
Security & privacy	44	3.20	0.76	1.67	5.00	0.36	0.17
Digital literacy	44	3.49	0.57	2.50	5.00	0.45	0.07
Customer satisfaction	44	3.53	0.68	2.25	5.00	0.25	-0.50

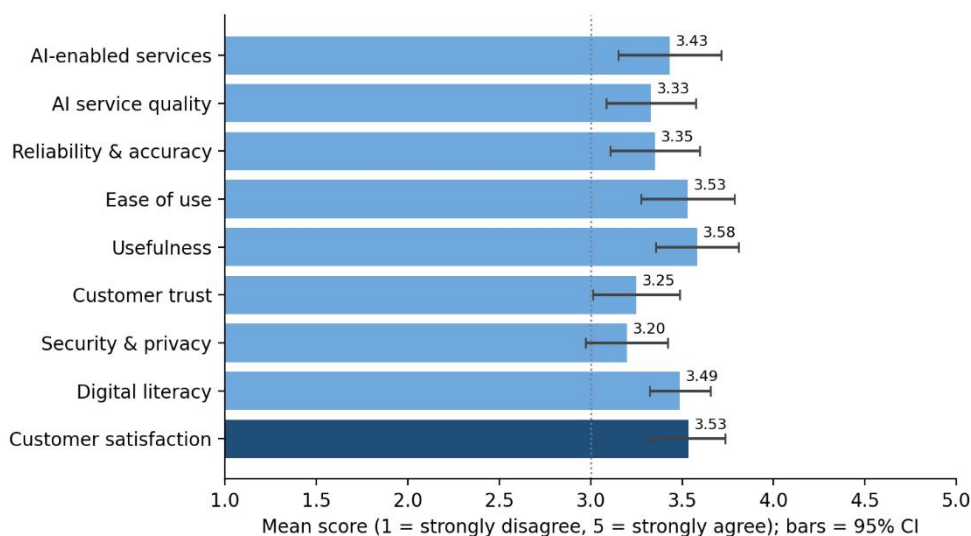


Figure 2. Mean construct scores with 95% confidence intervals

3.3 Correlation Analysis

Pearson correlations (Table 5) show that every construct is positively and significantly related to customer satisfaction. The strongest relationships were with customer trust ($r = .76$) and security & privacy ($r = .73$), followed by AI-enabled banking services ($r = .66$), AI reliability & accuracy ($r = .66$), perceived usefulness ($r = .60$), AI service quality ($r = .58$), perceived ease of use ($r = .51$) and digital literacy ($r = .42$). Several predictors were also strongly inter-correlated (for example, trust with security & privacy, $r = .82$; perceived usefulness with service quality, $r = .77$, and with ease of use, $r = .76$), which anticipates the overlap observed later in the multiple regression.

Table 5. Pearson correlation matrix

Variable	1	2	3	4	5	6	7	8	9
1. AIES	–								
2. SQ	.66***	–							
3. REL	.77***	.65***	–						
4. EOU	.59***	.66***	.64***	–					
5. PU	.67***	.77***	.66***	.76***	–				
6. Trust	.65***	.34*	.69***	.29	.36*	–			
7. Sec/Priv	.51***	.28	.57***	.34*	.35*	.82***	–		
8. Dig. lit.	.25	.33*	.11	.31*	.46**	.36*	.32*	–	
9. Satisf.	.66***	.58***	.66***	.51***	.60***	.76***	.73***	.42**	–

Note. $n = 44$. AIES = AI-enabled banking services; SQ = AI service quality; REL = AI reliability & accuracy; EOU = perceived ease of use; PU = perceived usefulness. $p < .05$, $p < .01$, $p < .001$ (two-tailed)

3.4 Chi-Square Tests of Independence

Chi-square tests examined whether the level of customer satisfaction (Low, Moderate, High) is associated with each demographic or usage variable. The null hypothesis in each test is that satisfaction level and the variable are independent. Results are summarised in Table 8. Small sample size meant that many cells had expected counts below 5 (between 33% and 87% of cells, against the customary limit of 20%), so the asymptotic p-values are unreliable; Monte Carlo p-values are therefore the primary basis for decisions.

Table 6. Chi-square tests: customer satisfaction level by demographic and usage variables

Variable	N	χ^2	df	Asymp. p	Monte Carlo p	Cramér's V	% cells E < 5
Age group	44	6.40	6	.380	.393	.27	67%

Variable	N	χ^2	df	Asymp. p	Monte Carlo p	Cramér's V	% cells E < 5
Gender	44	0.15	2	.927	1.000	.06	33%
Occupation	44	5.76	8	.674	.729	.26	87%
Monthly income	41	3.06	8	.930	.971	.19	87%
Type of bank used	43	5.81	6	.445	.469	.26	75%
Frequency of AI banking use	44	6.73	8	.566	.599	.28	73%
Most-used AI banking service	44	10.16	8	.254	.254	.34	87%
Digital literacy level	44	14.21	4	.007	.007	.40	33%

Note. E = expected cell count. Monte Carlo p-values are based on 10,000 permutations. Shaded row = significant at the 5% level.

Only digital-literacy level was significantly associated with satisfaction level, $\chi^2(4, N = 44) = 14.21, p = .007$ (Monte Carlo $p = .007$), with a moderate-to-large effect size (Cramér's $V = .40$). Table 9 and Figure 3 show the pattern: 76.9% of high-digital-literacy respondents were in the High satisfaction band compared with 12.5% of low-digital-literacy respondents, whereas 18.8% of the low-literacy group were in the Low satisfaction band. This test had the lowest share of sparse cells (33%), and the asymptotic and Monte Carlo p-values agree. For age group, gender, occupation, income, bank type, frequency of AI use and most-used AI service, the null hypothesis of independence was not rejected (all Monte Carlo $p > .05$). Failing to reject the null does not prove independence: with $n = 44$ and sparse cells, these tests have low power.

Table 7. Customer satisfaction level by digital-literacy level, n (column %)

Satisfaction level	DL: Low	DL: Medium	DL: High	Total
Low (<3.0)	3 (18.8%)	2 (13.3%)	2 (15.4%)	7 (15.9%)
Moderate (3.0-3.99)	11 (68.8%)	8 (53.3%)	1 (7.7%)	20 (45.5%)
High (>=4.0)	2 (12.5%)	5 (33.3%)	10 (76.9%)	17 (38.6%)
Total	16 (100%)	15 (100%)	13 (100%)	44 (100%)

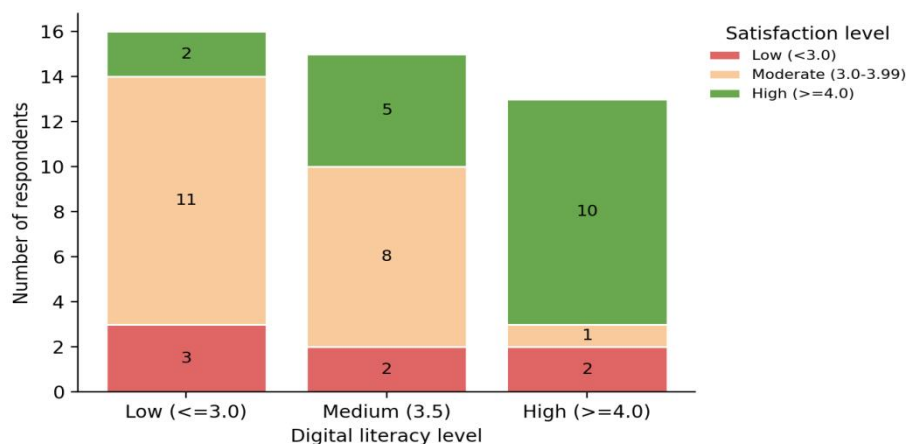


Figure 3. Satisfaction level by digital-literacy level

3.5 One-Way ANOVA

One-way ANOVA compared mean customer satisfaction across the groups of each variable (Table 8). Mean satisfaction differed significantly by age group, $F(3, 40) = 4.29, p = .010, \eta^2 = .24$, and by digital-literacy level, $F(2, 41) = 4.76, p = .014, \eta^2 = .19$; both are large effects by conventional benchmarks. Levene's test supported equal variances for these two factors ($p = .92$ and $.54$), and the Welch and Kruskal–Wallis tests reached the same conclusion. No significant differences were found by gender, occupation, income, type of bank, frequency of AI use or most-used AI service.

Table 8. One-way ANOVA: customer satisfaction by group

Factor	Groups	N	F (df)	p	η^2	Levene p	Welch p	K–W p
Age group	4	44	4.29 (3, 40)	.010	.243	.920	.037	.019
Gender	2	44	0.00 (1, 42)	.984	.000	.174	.985	.748
Occupation	5	44	1.54 (4, 39)	.209	.137	.311	.022	.156

Factor	Groups	N	F (df)	p	η^2	Levene p	Welch p	K-W p
Monthly income	5	41	0.71 (4, 36)	.591	.073	.382	.361	.399
Type of bank used	4	43	1.63 (3, 39)	.197	.112	.883	.264	.243
Frequency of AI banking use	5	44	0.25 (4, 39)	.906	.025	.034	.901	.903
Most-used AI banking service	5	44	0.97 (4, 39)	.435	.090	.421	.592	.422
Digital literacy level	3	44	4.76 (2, 41)	.014	.189	.538	.032	.010

Note. K-W = Kruskal-Wallis. Shaded rows = significant at the 5% level. Levene's test was significant only for frequency of AI use ($p = .034$), where the Welch test ($p = .901$) confirmed the non-significant result. The Welch test for occupation ($p = .022$) is unreliable because one occupation group has $n = 1$ and another has $n = 3$ with very low variance; the standard ANOVA and Kruskal-Wallis tests are non-significant. Excluding groups with fewer than three respondents (occupation code 5; bank type code 4) did not change any conclusion (occupation $p = .122$; bank type $p = .574$).

Tukey HSD post-hoc comparisons showed that, for age, respondents in age group 2 reported significantly higher satisfaction than those in age group 1 (mean difference = 0.69, $p = .013$); the difference between age groups 2 and 3 was borderline (0.79, $p = .051$). For digital literacy, the High group scored 0.72 points higher than the Low group ($p = .010$); the Medium group did not differ significantly from either. Table 9 and Figure 4 give the group means for age, digital literacy, income and bank type, the four characteristics named as moderating or differentiating factors in the framework.

Table 9. Mean customer satisfaction by age, digital literacy, income and bank type

Factor	Group	n	Mean	SD
Age group	Group 1	17	3.26	0.58
	Group 2	16	3.95	0.66
	Group 3	6	3.17	0.54
	Group 4	5	3.55	0.67
Digital literacy	Low	16	3.22	0.51
	Medium	15	3.52	0.55
	High	13	3.94	0.82
Monthly income	Code 1	25	3.46	0.76
	Code 2	3	3.83	0.58
	Code 3	3	3.92	0.38
	Code 4	5	3.20	0.48
	Code 5	5	3.45	0.62
Type of bank	Code 1	20	3.49	0.67
	Code 2	8	3.50	0.64
	Code 3	13	3.73	0.70
	Code 4	2	2.63	0.53

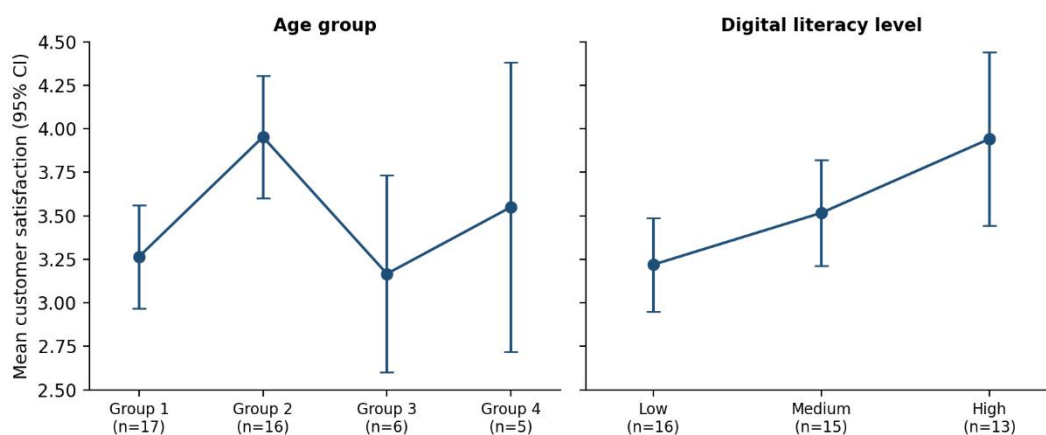


Figure 4. Mean customer satisfaction by age group and digital-literacy level (95% CI)

3.6 Linear Regression Analysis

3.6.1 Simple regression (H1–H5)

Each construct was first regressed separately on customer satisfaction (Table 10). AI-enabled banking services was a significant positive predictor of satisfaction, $B = 0.47$, $\beta = .66$, $t(42) = 5.69$, $p < .001$, explaining 43.5% of the variance (adjusted $R^2 = .422$, $F(1, 42) = 32.36$, $p < .001$). H1 is therefore supported: a one-point increase in perceived AI-enabled banking convenience is associated with a 0.47-point increase in satisfaction. Individually, AI reliability & accuracy ($\beta = .66$), perceived usefulness ($\beta = .60$), AI service quality ($\beta = .58$) and perceived ease of use ($\beta = .51$) were all significant predictors, supporting H2–H5 at the bivariate level. Customer trust ($\beta = .76$, $R^2 = .581$) and security & privacy ($\beta = .73$, $R^2 = .527$) were the strongest single predictors. The AI-enabled banking services result remained significant with heteroscedasticity-robust standard errors (HC3 $p < .001$), and residuals were approximately normal (Shapiro–Wilk $p = .055$; Durbin–Watson = 1.63).

Table 10. Simple linear regressions of customer satisfaction on each predictor

Predictor (hypothesis)	B	SE	β	t	p	R ²	F(1, 42)	p (HC3)
AI-enabled banking services (H1)	0.473	0.083	.660	5.69	< .001	.435	32.36	< .001
AI service quality (H2)	0.475	0.104	.578	4.59	< .001	.334	21.03	.009
Perceived ease of use (H3)	0.399	0.105	.506	3.80	< .001	.256	14.42	.021
Perceived usefulness (H4)	0.532	0.110	.597	4.83	< .001	.357	23.29	.058
AI reliability & accuracy (H5)	0.545	0.096	.661	5.70	< .001	.437	32.54	.005
Customer trust	0.646	0.085	.763	7.64	< .001	.581	58.34	< .001
Security & privacy	0.649	0.095	.726	6.85	< .001	.527	46.87	< .001

Note. Dependent variable: customer satisfaction; $n = 44$. All slopes $p < .001$ except ease of use (see p column). HC3 = heteroscedasticity-robust p-value.

3.6.2 Multiple regression

When AI service quality, ease of use, usefulness and reliability & accuracy were entered together (Table 11), the model was significant, $R^2 = .490$, adjusted $R^2 = .438$, $F(4, 39) = 9.37$, $p < .001$. Only AI reliability & accuracy made a significant unique contribution ($\beta = .45$, $p = .010$); service quality, ease of use and usefulness did not once the overlap among the predictors was controlled. Multicollinearity was acceptable (VIF = 2.08–3.50) and the Durbin–Watson statistic (1.72) indicated no autocorrelation. However, the residuals departed from normality (Shapiro–Wilk $p < .001$) and the reliability & accuracy effect was only borderline with robust standard errors (HC3 $p = .052$).

Table 11. Multiple regression: AI perception constructs predicting customer satisfaction

Predictor	B	SE	β	t	p	p (HC3)	VIF
(Constant)	1.310	0.388	–	3.37	.002	.302	–
AI service quality	0.117	0.154	.142	0.76	.453	.317	2.69
Perceived ease of use	-0.038	0.146	-.048	-0.26	.797	.811	2.60
Perceived usefulness	0.204	0.190	.228	1.07	.292	.463	3.50
AI reliability & accuracy	0.369	0.136	.448	2.72	.010	.052	2.08

Note. $R^2 = .490$; adjusted $R^2 = .438$; $F(4, 39) = 9.37$, $p < .001$; Durbin–Watson = 1.72.

3.6.3 Hierarchical regression with trust and security & privacy

To assess whether trust and security & privacy add explanatory power, they were entered in a second step after AI-enabled banking services and the four perception constructs (Table 12). Step 1 explained 51.8% of the variance in satisfaction (adjusted $R^2 = .454$, $F(5, 38) = 8.15$, $p < .001$). Adding trust and security & privacy raised this to 74.4% (adjusted $R^2 = .695$, $F(7, 36) = 14.98$, $p < .001$), a significant increase of $\Delta R^2 = .227$, $F(2, 36) = 15.98$, $p < .001$. In the final model only customer trust remained a significant unique predictor ($\beta = .48$, $p = .019$); once trust and security & privacy were included, the coefficient for AI-enabled banking services fell to approximately zero ($B = -0.000$), consistent with the mediating role of these variables examined in Section 4.7. VIF values ranged from 2.86 to 5.27, with trust slightly above 5 because of its strong association with security & privacy.

Table 12. Hierarchical regression predicting customer satisfaction

Predictor	Step 1 β	Step 1 p	B	SE	β	t	p	p (HC3)	VIF
AI-enabled banking services	.278	.150	-0.000	0.110	-.000	-0.00	.998	.998	3.32
AI service quality	.097	.609	0.195	0.117	.237	1.66	.105	.160	2.86
Perceived ease of use	-.047	.796	0.049	0.113	.062	0.43	.668	.822	2.89
Perceived usefulness	.175	.419	0.178	0.143	.200	1.25	.221	.449	3.63
AI reliability & accuracy	.300	.124	-0.112	0.138	-.136	-0.81	.422	.803	3.92
Customer trust	—	—	0.404	0.164	.476	2.46	.019	.313	5.27
Security & privacy	—	—	0.226	0.140	.253	1.62	.114	.298	3.43

Note. Step 1: AI-enabled banking services, service quality, ease of use, usefulness, reliability & accuracy ($R^2 = .518$). Step 2 adds customer trust and security & privacy ($R^2 = .744$; $\Delta R^2 = .227$). Columns B to VIF refer to Step 2.

Robustness of the multiple-regression results. The multivariate coefficients were sensitive to modelling choices. With HC3 robust standard errors no individual predictor was significant in the final model (trust $p = .313$), and when 6 influential respondents (Cook's $D > 4/n$; IDs 10, 15, 31, 33, 36, 38) were removed the significant predictors changed (perceived usefulness $p = .019$, AI-enabled banking services $p = .036$; trust $p = .063$). What is stable across these checks is that the perception constructs jointly explain a large share of the variance in satisfaction (R^2 between .52 and .74 for the full sample) and that trust and security & privacy add substantially to it. The ranking of individual predictors, by contrast, cannot be established reliably with $n = 44$ and strongly inter-correlated predictors, and should not be over-interpreted.

3.7 Mediation Analysis (H6 and H7)

Mediation was tested with AI-enabled banking services as the predictor, customer satisfaction as the outcome, and customer trust (H6) and security & privacy (H7) as mediators in separate models (Table 13, Figure 5). The total effect of AI-enabled banking services on satisfaction was significant ($c = 0.473$, $p < .001$). AI-enabled banking services significantly predicted trust ($a = 0.548$, $p < .001$) and security & privacy ($a = 0.410$, $p < .001$), and both mediators significantly predicted satisfaction with the predictor controlled ($b = 0.489$ and 0.471 , both $p < .001$). The indirect effect through trust was 0.268 (95% bootstrap CI [0.075, 0.401]; Sobel $z = 3.54$, $p < .001$) and through security & privacy was 0.193 (95% CI [0.044, 0.361]; Sobel $z = 3.01$, $p = .003$). Both bootstrap intervals exclude zero. Because the direct effect remained significant ($c' = 0.205$, $p = .027$ with trust; $c' = 0.280$, $p = .001$ with security & privacy), the mediation is partial: trust accounts for about 57% and security & privacy for about 41% of the total effect. H6 and H7 are supported. As the data are cross-sectional, this is statistical mediation consistent with, but not proof of, a causal sequence.

Table 13. Mediation analysis: AI-enabled banking services → mediator → customer satisfaction

Effect	Mediator: customer trust	Mediator: security & privacy
a: AI-enabled services → mediator	0.548 (SE 0.100)***	0.410 (SE 0.106)***
b: mediator → satisfaction (controlling X)	0.489 (SE 0.106)***	0.471 (SE 0.098)***
c: total effect	0.473***	0.473***
c': direct effect	0.205*	0.280***
Indirect effect ($a \times b$)	0.268	0.193
95% bootstrap CI (5,000 resamples)	[0.075, 0.401]	[0.044, 0.361]
Sobel z (p)	3.54 (< .001)	3.01 (.003)
Proportion of total effect mediated	57%	41%
R^2 of outcome model with mediator	.629	.640

Note. Unstandardised coefficients. $p < .05$, $p < .01$, $p < .00$

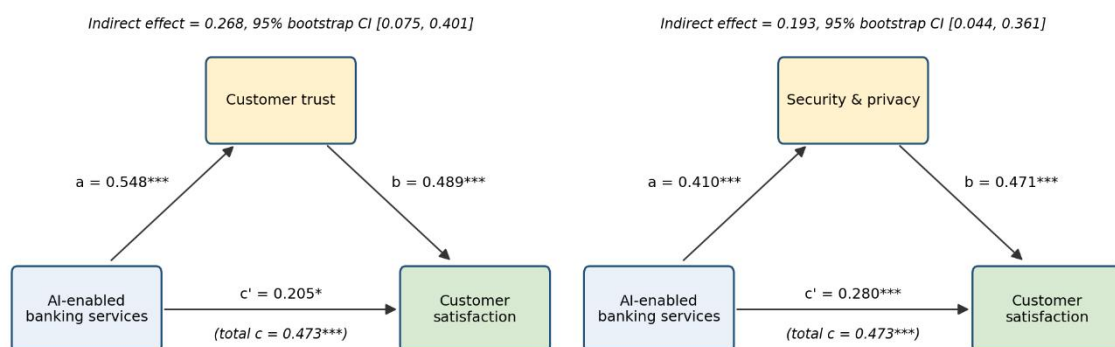


Figure 5. Mediation models for customer trust and security & privacy**3.8 Moderating Role of Digital Literacy (H8)**

A moderated regression tested whether digital literacy changes the strength of the relationship between AI-enabled banking services and satisfaction (Table 14; variables mean-centred). The interaction term was not significant ($B = 0.038$, $p = .781$; $\Delta R^2 = .0010$), so H8 is not supported: the AI–satisfaction relationship was similar for customers with lower and higher digital literacy. Digital literacy itself had a significant positive main effect on satisfaction ($B = 0.325$, $p = .028$), in line with the ANOVA and chi-square results. For age, bank type and income, the sample was too small to test interactions reliably; only the group differences in Section 4.5 are available, which show a significant difference by age but not by bank type or income.

Table 14. Moderated regression: AI-enabled banking services $\times$ digital literacy

Term	B	SE	t	p	95% CI
(Constant)	3.529	0.077	46.03	< .001	[3.37, 3.68]
AI-enabled banking services (centred)	0.414	0.089	4.68	< .001	[0.24, 0.59]
Digital literacy (centred)	0.325	0.142	2.28	.028	[0.04, 0.61]
Interaction (AIES $\times$ DL)	0.038	0.135	0.28	.781	[-0.23, 0.31]

Note. $R^2 = .508$; $n = 44$.

3.9 Summary of Hypothesis Testing**Table 15. Summary of hypothesis tests**

No.	Relationship tested	Test	Key result	Decision
H1	AI-enabled banking services $\rightarrow$ satisfaction	Simple regression	$\beta = .66$, $R^2 = .435$, $p < .001$	Supported
H2	AI service quality $\rightarrow$ satisfaction	Simple regression	$\beta = .58$, $p < .001$ (unique effect n.s., $p = .45$)	Supported (bivariate)
H3	Ease of use $\rightarrow$ satisfaction	Simple regression	$\beta = .51$, $p < .001$ (unique effect n.s., $p = .80$)	Supported (bivariate)
H4	Usefulness $\rightarrow$ satisfaction	Simple regression	$\beta = .60$, $p < .001$ (unique effect n.s., $p = .29$)	Supported (bivariate)
H5	Reliability & accuracy $\rightarrow$ satisfaction	Simple and multiple regression	$\beta = .66$, $p < .001$; unique $\beta = .45$, $p = .010$ (HC3 $p = .052$)	Supported (unique effect fragile)
H6	Trust mediates AI $\rightarrow$ satisfaction	Bootstrap mediation	Indirect = 0.268, CI [0.075, 0.401]	Supported (partial)
H7	Security & privacy mediates AI $\rightarrow$ satisfaction	Bootstrap mediation	Indirect = 0.193, CI [0.044, 0.361]	Supported (partial)
H8	Digital literacy moderates AI $\rightarrow$ satisfaction	Moderated regression	Interaction $B = 0.038$, $p = .781$	Not supported

4. Discussion**4.1 AI-enabled banking services and customer satisfaction**

The central finding is that perceived AI-enabled banking services are strongly and positively related to customer satisfaction ($\beta = .66$; $R^2 = .435$). This agrees with the general view in the literature that AI improves convenience, speed and the overall customer experience in banking (P. Jain, 2024; R. Jain, 2023) and with evidence that customers value the speed and availability of AI-based service channels (Karri et al., 2025). At the same time, satisfaction is only moderately high ($M = 3.53$; 38.6% of respondents in the High band), which suggests that a substantial share of customers are neutral rather than enthusiastic and that room for improvement remains.

4.2 AI service quality, ease of use, usefulness, and reliability

All four perception constructs were positively related to satisfaction when examined one at a time, supporting H2–H5. When entered together, however, only AI reliability & accuracy retained a unique effect, and that effect was fragile under robust standard errors. The most likely explanation is overlap

among the constructs rather than irrelevance: usefulness, ease of use and service quality were correlated at $r = .76$ to $.77$, so each carries largely the same information about satisfaction. This is in line with technology-acceptance thinking in which ease of use and usefulness are closely linked, and with studies that identify usefulness and ease of use as key predictors of AI adoption attitudes (Polireddi, 2024; Goyal et al., 2025). The prominence of reliability & accuracy is consistent with the emphasis that studies of AI fraud detection and credit assessment place on accurate, dependable outputs (Hafez et al., 2025; Olowu et al., 2024). Because the multivariate estimates were unstable with $n = 44$, we do not claim a definitive ranking of these drivers.

4.3 The role of trust and security & privacy

Customer trust and security & privacy were the strongest correlates of satisfaction and partially mediated the effect of AI-enabled banking services (indirect effects 0.27 and 0.19; roughly 57% and 41% of the total effect). Adding the two constructs to the regression raised explained variance from 52% to 74%. This supports the argument that the benefit of AI is realised through customers' confidence in it: it is consistent with findings that trust is the strongest driver of AI adoption in banking (Yaseen & Al-Amarneh, 2025), that perceived risk lowers consumers' intention to use AI-based banking (Noreen et al., 2023), and with the repeated warnings about privacy, data security and ethical use (Narang et al., 2024; Kovačević et al., 2024). It is notable that security & privacy ($M = 3.20$) and trust ($M = 3.25$) received the lowest scores among all constructs: in this sample, the weakest link in the AI banking experience appears to be confidence rather than usability. Because the direct effect of AI-enabled banking services remained significant, trust and security & privacy explain part, but not all, of the pathway.

4.4 Differences by customer characteristics

Digital literacy was the customer characteristic most consistently linked to satisfaction: it was associated with satisfaction level (chi-square), differentiated mean satisfaction (ANOVA) and had a significant main effect in the moderated regression. It did not, however, change the strength of the AI-satisfaction relationship (H8 not supported). Digital literacy therefore seems to raise the baseline level of satisfaction rather than to alter how AI perceptions translate into satisfaction. Mean satisfaction also differed by age group, with age group 2 highest, but the age categories cannot be interpreted substantively until their labels are attached to the codes. Age was significant in the ANOVA but not in the chi-square test; this is expected because collapsing satisfaction into three bands discards information and the sparse cells reduce power. No differences were found by gender, occupation, income, bank type, frequency of use or the AI service used most; given the small and uneven groups, these should be read as an absence of evidence, not evidence of absence. The digital-literacy scale was also weak in reliability ($\alpha = .38$), so these findings require confirmation with a stronger measure.

5. Conclusion and Recommendations

This study examined how AI-enabled banking services relate to customer satisfaction among bank customers in Andhra Pradesh. In response to the research questions: (1) AI-enabled banking services have a significant, positive and substantial association with customer satisfaction; (2) AI service quality, ease of use, usefulness and reliability & accuracy are each positively related to satisfaction, although their separate contributions cannot be reliably distinguished in this sample and reliability & accuracy shows the clearest unique effect; and (3) customer trust and perceived security & privacy are the strongest correlates of satisfaction and partially mediate the effect of AI-enabled services. Satisfaction varied with digital literacy and age group but not with the other characteristics examined, and digital literacy did not moderate the AI-satisfaction link.

Based on these findings, the following recommendations are made to address Objective 5:

1. 1. Build trust deliberately. Because trust carries a large part of the effect of AI on satisfaction, banks should explain in plain language how AI is used, make automated decisions and recommendations explainable, and label clearly when a customer is interacting with an AI system.
2. 2. Make security and privacy visible. Perceived security and privacy scored lowest of all constructs. Banks should communicate data-protection safeguards, give customers control over how their data are used, and highlight the fraud-detection benefits of AI (for example, real-time alerts) so that customers see AI as a protection.
3. 3. Prioritise reliability and accuracy. Consistent, accurate answers and dependable availability matter for satisfaction. Chatbot and virtual-assistant responses should be regularly audited and updated, with error rates monitored.
4. 4. Invest in digital-literacy support. Customers with lower digital literacy reported lower satisfaction. In-app tutorials, branch-based demonstrations, vernacular-language support and simplified interfaces can narrow this gap.
5. 5. Keep a human option. Earlier studies report that customers still prefer human help for complex issues (Graham et al., 2025; Karri et al., 2025). Seamless escalation from AI to a human agent should be built into digital channels.
6. 6. Monitor satisfaction by customer segment. Because satisfaction differed by age group, banks should track satisfaction across age segments and tailor AI features and communication accordingly.

5.1 Theoretical and practical implications

Theoretically, the results support a framework in which technology-related perceptions influence satisfaction partly through trust and security & privacy, extending acceptance-based models of AI in banking from adoption intention to satisfaction as the outcome. Practically, the results suggest that banks should treat trust and perceived security as core service-quality dimensions of AI channels, on a par with speed and ease of use.

6. Limitations and Future Research

The findings should be interpreted in light of the following limitations.

- Small, non-probability sample. The analysis rests on 44 usable responses obtained by convenience sampling, so the results cannot be generalised to all bank customers in Andhra Pradesh and statistical power is limited. Multivariate estimates were sensitive to robust standard errors and to a small number of influential cases.

- Data-quality issues. The exported file contained duplicated records, one incomplete response, ambiguous multiple-option entries on single-choice items, and a notable share of uniform (straight-line) responses (18.2%). These were handled as described in Section 3.4 but may still affect the results.

- Measurement. AI-enabled banking services was measured by a single item; digital literacy (two items, $\alpha = .38$) and security & privacy ($\alpha = .63$) had weak reliability; and the split of the service-quality section into two constructs was based on item content rather than a prior validated scale.

- Design. The cross-sectional, self-reported design limits causal interpretation, and the mediation results describe statistical rather than proven causal pathways.

- Categorical labels and multiple testing. Response-option labels for the categorical questions were unavailable, limiting substantive interpretation of the group differences. Sixteen chi-square and ANOVA tests were run without correction for multiple comparisons; the age and digital-literacy findings in particular should be replicated.

- Moderators. Only digital literacy could be tested as a moderator; the sample was too small to test interactions with age, bank type and income.

Future studies should use larger, probability-based samples across several states; adopt validated multi-item scales for each construct; test the full model with structural equation modelling (for example PLS-SEM) including all hypothesised moderators; use longitudinal or experimental designs; and compare AI-enabled and human-assisted service interactions.

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