

Artificial Intelligence and Personalized Financial Marketing: Implications for Financial Inclusion and Customer Engagement

***Raveendranpp**, Research Scholar, Srivenkiteswara University, Almora, Up

Dr Pankaj Kumar, Srivenkiteswara University, Management Department, Almora, Gajraula, Up

Abstract

Artificial Intelligence (AI) is reshaping the financial services industry through data-driven decision-making, advanced automation, and customised customer experiences. This paper examines how AI adoption and personalised financial marketing (PFM) jointly shape financial inclusion and customer engagement. Using a quantitative research design, primary data were collected from 130 users of digital financial services through a structured questionnaire built on a five-point Likert scale. Descriptive statistics and simple linear regression, run in IBM SPSS Statistics, were used to analyse the data. Findings show that AI adoption and personalised financial marketing each have a positive and significant effect on financial inclusion and customer engagement, with personalised marketing carrying the larger effect. This points to tailored communication and customised product recommendations as key drivers of stronger engagement and longer-lasting customer relationships. Bringing AI capabilities together with customer-focused marketing can widen accessibility, raise service quality, and deepen engagement, supporting broader financial inclusion. The findings give banks, fintech firms, marketers, and policymakers practical direction for building inclusive, ethical, and innovative digital financial systems that support sustainable growth and greater customer value in an increasingly digital economy.

Keywords: Adoption of Artificial Intelligence, Personalised Financial Marketing, Financial Inclusion, Customer Engagement, Digital Financial Services, FinTech, Customer-Centric Marketing.

Introduction

Within financial services, AI has become one of the technologies most responsible for reshaping how organisations operate, make decisions, and serve customers. The term covers technologies such as machine learning (ML), natural language processing (NLP), deep learning, and generative AI (GenAI), all used to process large volumes of data, spot patterns, generate forecasts, and automate complex workflows. Unlike conventional software that runs on fixed rules, AI systems learn from data and adjust as conditions change. This lets financial institutions extract useful insight, run leaner operations, and match products more closely to customer needs.

Banking, insurance, capital markets, and payment systems were among the first areas of the economy to adopt AI, largely because they generate enormous volumes of data every day and face constant pressure to operate efficiently while staying compliant. Institutions now rely on AI to handle routine tasks, sharpen fraud detection, manage risk more effectively, and deepen customer engagement. AI-powered tools give firms better information for decision-making, help them run more efficiently, and open new revenue opportunities, all while trimming costs and lifting overall performance. As digital transformation reshapes the sector, AI has become a core part of how modern financial ecosystems function.

AI has also reshaped the customer experience by supporting personalised recommendations, conversational chatbots, and tailored products. By reading transaction history, behaviour, and stated preferences, AI lets firms customise their offerings at scale. Alongside these gains sit real concerns, including data privacy, algorithmic bias, explainability, cybersecurity, and regulatory compliance, so financial institutions must weigh innovation against these ethical and regulatory pressures if AI adoption is to remain sustainable (V., 2026).

Evolution of AI in the Financial Sector

AI's use in finance has evolved gradually, moving from basic automation toward systems capable of autonomous decisions. Through the 1980s and into the early 2000s, institutions relied on rule-based expert systems built on fixed "if-then" logic, applied mainly to transaction processing, reconciliation, tax planning, and financial analysis. These systems handled repetitive work reliably but could not learn from new data or adjust to changing conditions.

A significant shift came in the 2010s with the rise of machine learning. Greater computing power, cloud infrastructure, and big-data capability let institutions process large volumes of structured and unstructured information. Machine learning strengthened credit scoring, fraud detection, and predictive risk analytics during this period, and it was also when algorithmic trading and robo-advisory platforms gained ground, giving investors access to automated, data-driven portfolio management (Malay Sarkar & Sanjida Rahman, 2025).

Deep learning, which matured in the late 2010s and early 2020s, allowed financial firms to work with more complex inputs such as text, images, and customer interaction data. Natural language processing powered chatbots, virtual assistants, and sentiment-analysis tools capable of interpreting customer emotion and everyday language, improving service, sharpening risk management, and supporting more accurate forecasting.

More recently, generative and agentic AI systems have advanced quickly. Generative AI can draft content, produce reports, assist with code, and carry on natural conversation, while agentic AI adds the ability to run multi-step processes autonomously, coordinate tasks, and make context-aware decisions. Financial institutions increasingly use these tools for compliance monitoring, fraud prevention, personalised advisory services, and real-time operations. AI is no longer just a set of discrete tools; it is becoming an enterprise-wide capability that drives innovation and competitive advantage (Paramesha et al., 2024).

AI-Driven Transformation of Financial Operations and Marketing

AI is reshaping both the operational and marketing sides of financial institutions. On the operations side, it automates repetitive work such as data entry, transaction reconciliation, reporting, forecasting, and document handling. Paired with Robotic Process Automation (RPA), it streamlines workflows, cuts manual effort, and reduces errors, letting firms lower costs while improving productivity and service quality (Aldasoro et al., 2025).

Risk management and fraud detection stand out as one of AI's most valuable operational applications. Machine learning models outperform traditional rule-based systems here because they can scan transactions in real time and flag anomalies as fraud patterns evolve, giving institutions a way to stay ahead of new threats and limit losses. AI-driven credit scoring extends this advantage by drawing on alternative data, such as transaction history and digital footprints, to assess creditworthiness more accurately and extend credit to a wider population, supporting financial inclusion (Pattanayak, 2021).

AI also supports regulatory compliance and portfolio management. Automated systems monitor transactions continuously, flag possible compliance breaches, and report them to regulators as required. In investment management, AI-powered trading systems and robo-advisors read market trends, project price movements, and adjust portfolio allocations, giving institutions stronger tools for managing risk and improving returns.

In marketing and customer engagement, AI enables far more precise targeting by drawing on customer demographics, preferences, financial behaviour, and transaction history. This lets institutions segment customers more effectively and deliver personalised advice, product recommendations, and offers. AI chatbots and virtual assistants add round-the-clock support, improving responsiveness and satisfaction while lowering service costs.

Generative AI adds another layer by producing marketing content, refining campaigns, and shaping how firms communicate with customers. It lets marketers adjust strategy in real time based on anticipated customer response, boosting engagement. Hyper-personalised experiences delivered across digital channels build loyalty, improve retention, and open new revenue streams, positioning AI as central to both operational efficiency and customer-centred service in finance (Dr. S. Jeyakumar, 2025).

Research Objectives

- Examine how the adoption of Artificial Intelligence influences Financial Inclusion and Customer Engagement.
- Assess how Personalised Financial Marketing (PFM) influences Financial Inclusion and Customer Engagement.

Need of the Study

Financial services have moved rapidly toward digital delivery, changing how institutions reach and communicate with customers. AI carries real potential to improve operational efficiency, automate financial processes, and personalise service delivery, while tailored marketing has helped firms understand customer needs, craft relevant product recommendations, and improve the overall customer experience. Even with this progress, a large number of people remain outside the formal financial system, and institutions continue to struggle with holding customers' attention over time. This makes it worth examining how AI adoption and personalised marketing work together to affect financial inclusion and engagement.

Much of the existing literature treats AI adoption, fintech services, and financial inclusion as separate topics, and few studies test AI adoption and tailored marketing together as joint drivers of inclusion and engagement. This study addresses that gap by examining how these variables interact within financial services. The findings are intended to give banks, fintech firms, policymakers, and marketers practical guidance for building customer-focused, technology-driven strategies that improve accessibility, satisfaction, and inclusive outcomes while supporting sustainable digital transformation.

Literature review

Ma (2024) looked at how big data supports personalised marketing as the financial services industry has digitised rapidly, examining how firms use consumer purchasing habits, behavioural signals, social-network activity, and feedback to build customer profiles and design tailored products. Drawing on case studies, interviews, and quantitative analysis, the paper found that big data helps financial institutions segment markets more precisely, expand cross-selling and value-added services, and run more targeted, predictive marketing. Realising these benefits, however, depends on institutions having strong data-management systems, analytical capability, sound privacy practices, and effective personalisation strategies.

Apriadi et al. (2025) reviewed how fintech has changed the way individuals manage personal finances, noting that digital financial services bring convenience and efficiency but also shift consumer behaviour, particularly among younger and urban users. Through a systematic literature review covering 2018 to 2025, the study found that fintech supports greater financial literacy, saving, and investment activity while also encouraging impulsive spending through easy digital credit and widening the gap between urban and rural adoption. The authors call for stronger financial literacy programmes and consumer protections to support safe, inclusive digital finance.

Mishra et al. (2025) examined how AI shapes customer relationships in finance, focusing on intelligence-driven engagement and the tailored solutions AI can offer clients. The chapter discusses how natural language processing and machine learning sharpen the focus on customer interactions and relevant data, and how AI supports personalised promotional offers and stronger service delivery. It closes by outlining future trends likely to shape customer engagement in finance, concluding that AI is helping make the industry more client-centred, efficient, and accountable.

Mhlanga (2023) used conceptual and documentary analysis to examine the risks tied to using AI for financial inclusion of underserved populations. While AI-enabled digital tools open real opportunities for the excluded, the study found accompanying risks including consumer-protection gaps, data-protection weaknesses, and exposure to cyberattacks, along with broader concerns such as reduced competition, careless AI deployment, and a widening digital divide. The paper concludes that building stronger digital infrastructure, in partnership with the private sector, should be a policy priority so that excluded populations can fully participate, and that doing so would also help address wider infrastructure gaps.

Sharma and Priya (2025) studied how AI features and IT mindfulness affect financial wellbeing, inclusion, and perceived service quality among 469 fintech users in North India, spanning Generation X, Millennials, and Generation Z, using Partial Least Squares Structural Equation Modelling (PLS-SEM). AI adoption was positively linked to IT mindfulness, technological self-efficacy, and financial self-efficacy, each of which in turn raised performance expectancy, effort expectancy, and hedonic motivation, with IT mindfulness showing a smaller effect on hedonic motivation specifically. Technophobia weakened the link between behavioural intention and actual fintech use, and higher fintech usage was tied to greater financial wellbeing and inclusion overall. The authors argue for user-centred AI design, stronger security, ethical oversight, and clearer communication to ease technophobia and build trust in AI-powered fintech.

Research Methodology

Research Design

This research applied a quantitative, descriptive, and explanatory design to test how AI adoption and personalised financial marketing affect financial inclusion and customer engagement. A cross-sectional survey captured data at a single point in time, which suited the goal of mapping relationships among the study variables and is well suited to studying customer perceptions of technology and marketing practices in financial services.

Population and Sampling

The target population consisted of bank and fintech customers with direct experience of AI-enabled and personalised digital financial services. Given time and resource constraints, participants were recruited through convenience sampling, and 130 usable responses were collected and analysed.

Data Collection

Primary data were collected through a structured questionnaire built on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree), covering demographic items alongside measures of AI adoption, personalised financial marketing, and financial inclusion and customer engagement. The survey ran in both online and offline formats to broaden participation and improve response quality.

Data Analysis Techniques

Data were coded and processed in IBM SPSS Statistics. Frequencies and percentages summarised the sample's demographic profile, while simple linear regression tested the relationship between AI adoption and personalised financial marketing on one side and financial inclusion and customer engagement on the other. Each model was tested for significance at the 5% level ($p < 0.05$) using the Model Summary, ANOVA, and coefficient outputs, which together established the strength, direction, and statistical significance of the relationships between variables.

Result

Table 1: Age

Age		
	Frequency	Percent
18–25 years	24	18.5
26–35 years	27	20.8
36–45 years	30	23.1
46–55 years	20	15.4
Above 55 years	29	22.3
Total	130	100.0

Table 1 shows a reasonably even spread across the 130 respondents' age groups. The 36-45 bracket was the largest at 30 respondents (23.1%), followed by those above 55 at 29 respondents (22.3%) and the 26-35 bracket at 27 respondents (20.8%). The 18-25 bracket held 24 respondents (18.5%), while the 46-55 bracket was smallest at 20 respondents (15.4%). This spread across age groups suggests the sample carries limited age-related bias.

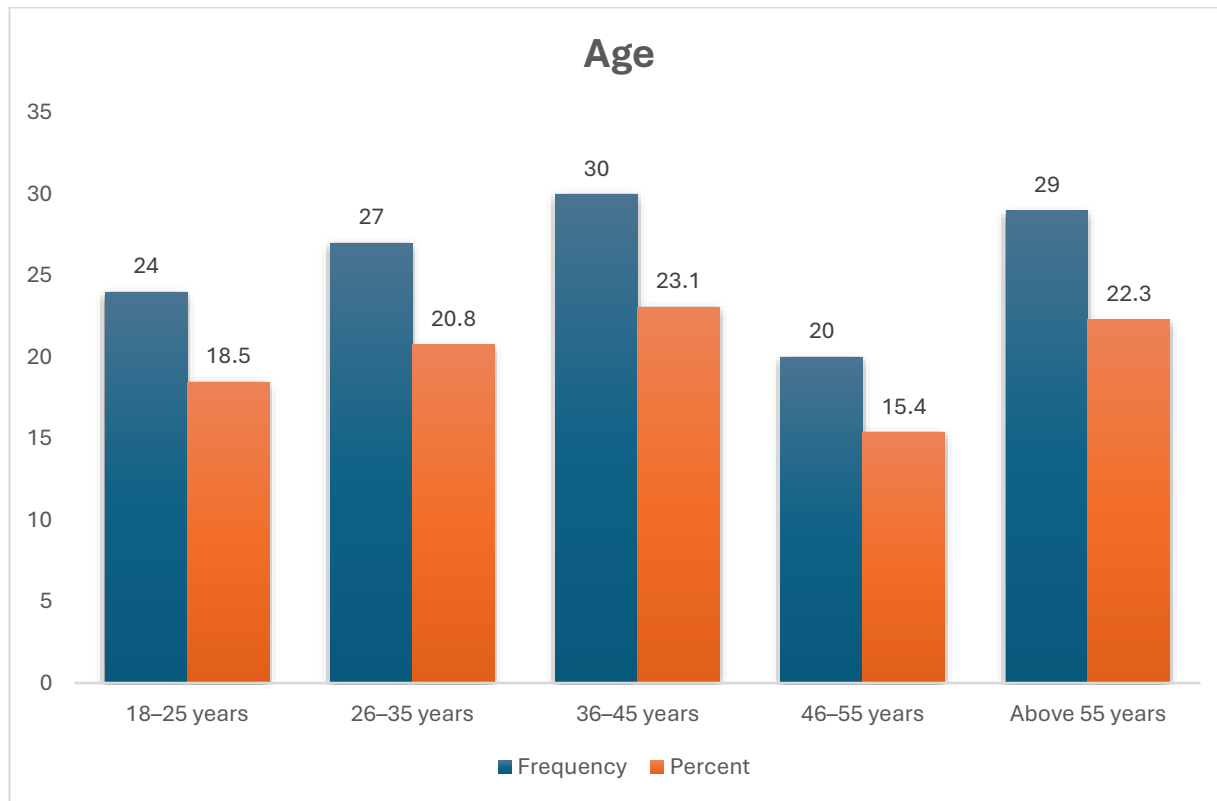


Figure 1: Graphical presentation of age responses distribution

Table 2: Gender responses distribution

Gender		
	Frequency	Percent
Male	69	53.1
Female	61	46.9
Total	130	100.0

Table 2 shows a broadly balanced gender split: 69 of the 130 respondents were male (53.1%) and 61 were female (46.9%). The small gap between the two groups is not meaningful in practical terms, so both genders are fairly represented in the sample. This balance strengthens the study's credibility by limiting gender-related sampling bias and supports a reliable reading of how men and women perceive AI, personalised financial marketing, financial inclusion, and customer engagement.

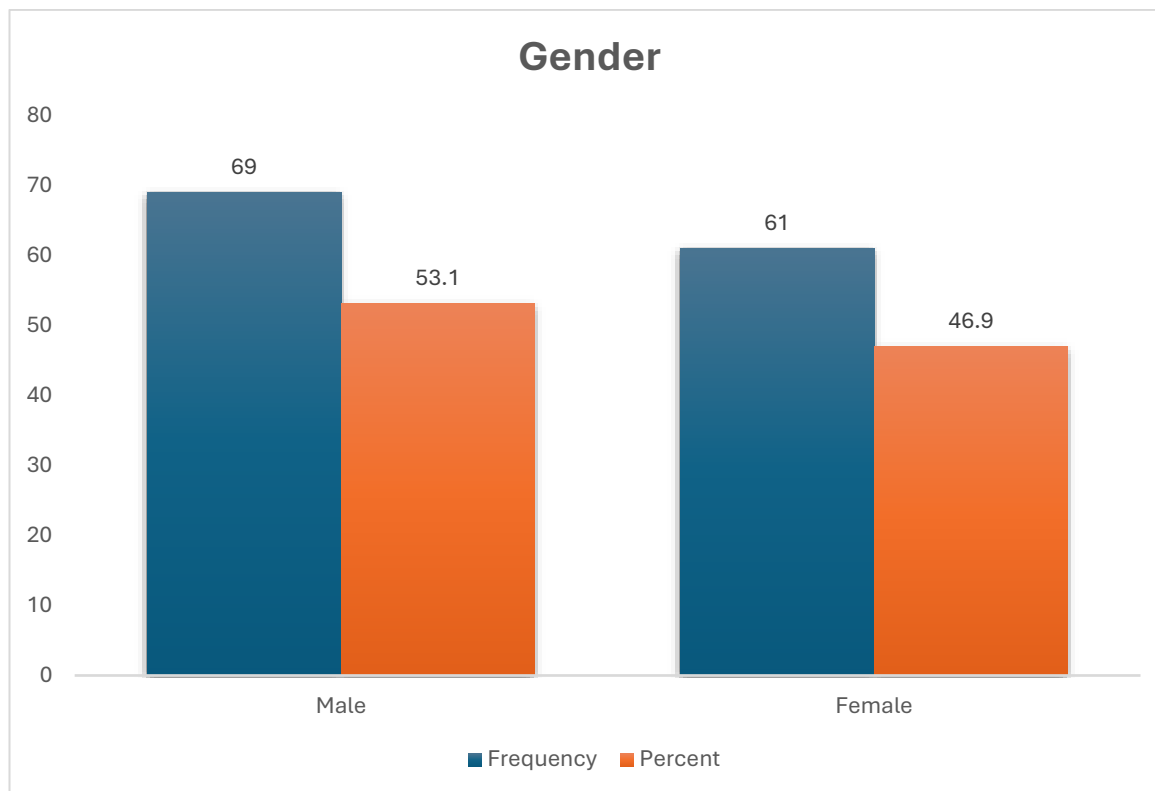


Figure 2: Graphical presentation of Gender responses distribution

Table 3: Educational qualification responses distribution

Educational Qualification		
	Frequency	Percent
Higher Secondary or Below	22	16.9
Diploma	20	15.4
Graduate	34	26.2
Postgraduate	30	23.1
Doctorate	24	18.5
Total	130	100.0

Table 3 shows a broad academic mix among respondents. Graduates made up the largest group at 34 respondents (26.2%), followed by postgraduates at 30 (23.1%) and doctorate holders at 24 (18.5%). Respondents with Higher Secondary education or below accounted for 16.9%, and diploma holders were the smallest group at 20 respondents (15.4%). With most respondents holding education beyond secondary level, the sample likely has a reasonable baseline understanding of AI-driven financial services and personalised marketing, which may support more informed responses on these topics.

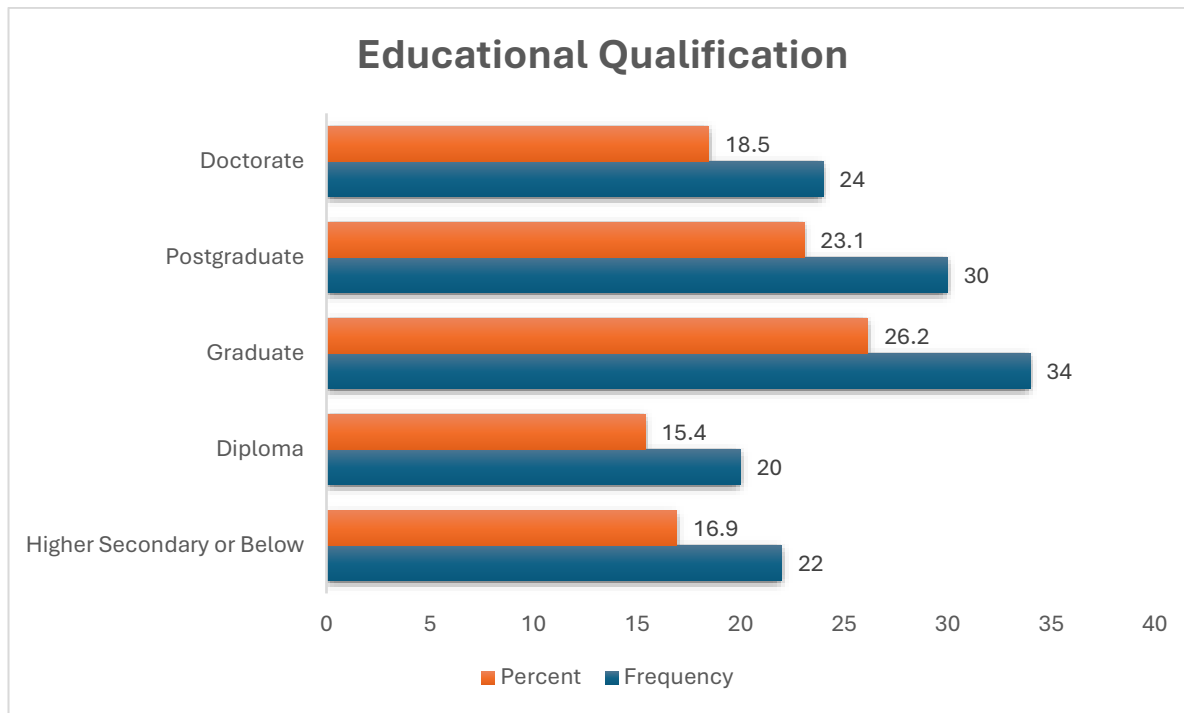


Figure 3: Graphical presentation of educational qualification responses distribution

Table 4: Preferred Digital Financial Platform qualification responses distribution

Preferred Digital Financial Platform		
	Frequency	Percent
Mobile Banking App	26	20.0
Internet Banking	29	22.3
UPI Applications	40	30.8
Digital Wallets	35	26.9
Total	130	100.0

Table 4 shows varied platform preferences among respondents. UPI applications were the most used, chosen by 40 respondents (30.8%), reflecting the growing popularity of instant digital payments. Digital wallets followed, and internet banking was used by 29 respondents (22.3%), while mobile banking apps were the least preferred at 26 respondents (20.0%). Respondents clearly lean toward payment options that are quicker and more convenient than traditional banking channels, a pattern consistent with rising adoption of AI-supported financial services that improve convenience and engagement.

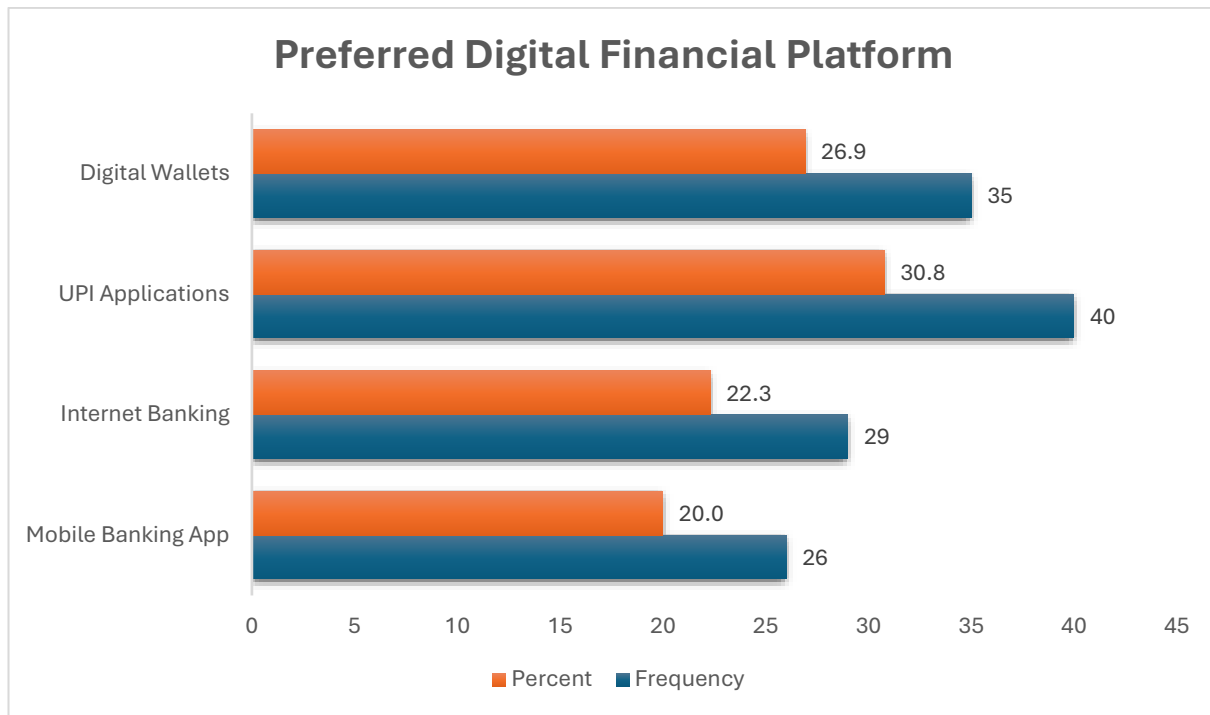


Figure 4: Graphical presentation of Preferred Digital Financial Platform qualification responses distribution

Table 5: Type of Financial Institution Mostly Used qualification responses distribution

Type of Financial Institution Mostly Used		
	Frequency	Percent
Public Sector Bank	33	25.4
Private Sector Bank	35	26.9
Cooperative Bank	35	26.9
FinTech Platform	27	20.8
Total	130	100.0

Table 5 shows a fairly even spread of primary financial institution used. Private sector banks and cooperative banks were each used by 35 respondents (26.9%), public sector banks by 33 (25.4%), and fintech platforms by 27 (20.8%), the smallest group. Traditional banks remain the dominant source of financial services for this sample, though digital-first platforms have a meaningful presence too. This spread suggests that established banks and newer fintech providers each play a distinct, complementary part in advancing financial inclusion and customer engagement.

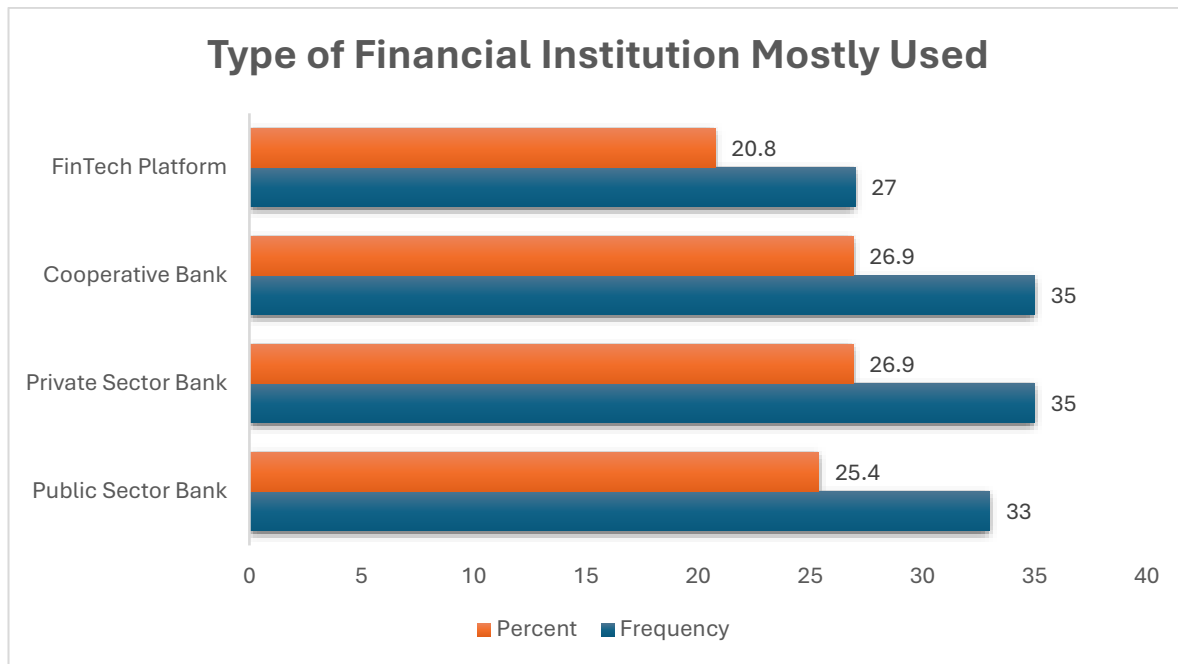


Figure 5: Graphical presentation of Preferred Digital Financial Platform qualification responses distribution

Hypothesis 1

Table 6: Linear regression Impact of Personalized Financial Marketing on Financial Inclusion and Customer Engagement

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.363 ^a	.132	.125	.992
a. Predictors: (Constant), Personalized Financial Marketing				

The Model Summary points to a moderate positive relationship between Personalised Financial Marketing and Financial Inclusion and Customer Engagement, with $R = 0.363$. The R Square value of 0.132 means the model explains 13.2% of the variance in the dependent variable, leaving 86.8% attributable to factors outside the model.

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19.073	1	19.073	19.388	.000 ^b
	Residual	125.919	128	.984		
	Total	144.992	129			
a. Dependent Variable: Financial Inclusion and Customer Engagement						
b. Predictors: (Constant), Personalized Financial Marketing						

The ANOVA output confirms the model is statistically significant, with $F = 19.388$ and $p = 0.000$ ($p < 0.001$). This confirms that Personalised Financial Marketing has a meaningful effect on Financial Inclusion and Customer Engagement, and that the regression model fits the data well enough to explain the relationship between the two variables.

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.951	.386		5.052	.000
	Personalized Financial Marketing	.425	.096	.363	4.403	.000
a. Dependent Variable: Financial Inclusion and Customer Engagement						

The coefficient results confirm a positive, statistically significant relationship between Personalised Financial Marketing and Financial Inclusion and Customer Engagement ($\beta = 0.363$, $B = 0.425$, $p = 0.000$). In practical terms, stronger personalised marketing tracks with higher financial inclusion and engagement, confirming this predictor's positive contribution to the model.

Hypothesis 2

Table 7: Linear regression Impact of Artificial Intelligence Adoption on Financial Inclusion and Customer Engagement

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.286 ^a	.082	.075	1.020
a. Predictors: (Constant), Artificial Intelligence Adoption				

The Model Summary shows a positive relationship between AI Adoption and Financial Inclusion and Customer Engagement, with $R = 0.286$. The R Square value of 0.082 indicates that AI Adoption accounts for 8.2% of the variance in financial inclusion and customer engagement, with the remaining 91.8% explained by variables outside this model.

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.852	1	11.852	11.394	.001 ^b
	Residual	133.140	128	1.040		
	Total	144.992	129			
a. Dependent Variable: Financial Inclusion and Customer Engagement						
b. Predictors: (Constant), Artificial Intelligence Adoption						

The ANOVA results confirm this model is statistically significant, with $F = 11.394$ and a significance value of 0.001, below the 0.05 threshold. This confirms that AI Adoption has a meaningful effect on Financial Inclusion and Customer Engagement, and that the regression model captures this relationship well.

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.249	.412		5.455	.000
	Artificial Intelligence Adoption	.359	.106	.286	3.376	.001
a. Dependent Variable: Financial Inclusion and Customer Engagement						

The coefficients table confirms that AI Adoption is positively and significantly linked to Financial Inclusion and Customer Engagement ($B = 0.359$, $\beta = 0.286$, $p = 0.001$), meaning the two variables move together: as one rises, so does the other. This confirms AI Adoption as a statistically significant, positively contributing predictor in the model.

Discussion

Overall, both Personalised Financial Marketing and AI adoption show a significant positive effect on Financial Inclusion and Customer Engagement, with AI carrying a slightly weaker effect than marketing ($\beta = 0.363$, $p < 0.001$ for PFM versus $\beta = 0.286$, $p = 0.001$ for AI Adoption). This suggests that tailored communication, customised product recommendations, and targeted marketing do more to drive customer participation and engagement than AI adoption alone. This is consistent with the industry's growing emphasis on customer-centric marketing and with evidence that AI-driven personalisation strengthens engagement, campaign results, and customer relationships more broadly.

Personalised Financial Marketing explains 13.2% of the variance in Financial Inclusion and Customer Engagement, compared with 8.2% for AI Adoption. Though modest, both figures confirm these as significant predictors, with other technological, behavioural, and institutional factors also shaping engagement outcomes. AI's positive contribution here fits earlier research showing that AI-powered chatbots, predictive analytics, and recommendation engines improve accessibility, service quality, and customer experience in financial institutions. At the same time, AI's comparatively modest explanatory power suggests that technology alone is not enough without being paired with genuine personalisation and customer-focused service.

This points to AI functioning best as a supporting tool for banks rather than a standalone fix. Combined with personalised marketing, AI can deepen engagement, widen access to financial services, and advance financial inclusion, but delivering this in practice requires attention to data privacy, transparency, ethical AI use, and sustained customer trust to ensure long-term, sustainable value.

Conclusion

Overall, both AI Adoption and Personalised Financial Marketing have a positive and statistically significant influence on Financial Inclusion and Customer Engagement within financial services. Both independent variables proved statistically significant in explaining the dependent variable, with Personalised Financial Marketing carrying the larger effect. Beyond streamlining operations, predictive analytics, and intelligent customer interaction, AI has a more direct role in shaping customer experience and encouraging uptake of formal financial services through personalised marketing. The findings further show that AI can support more tailored financial offerings, wider customer reach, and deeper relationships, central goals of customer-centric marketing. The relatively modest explanatory power of both regression models indicates that other technological, behavioural, and institutional factors also influence financial inclusion and customer engagement. Taken together, the results highlight the value of financial institutions adopting AI responsibly, alongside ethical data practices, transparency, and customer-focused service design, to deliver maximum value and support inclusive digital finance. These findings offer practical direction for banks, fintech firms, marketers, and regulators pursuing sustainable digital transformation and inclusion.

Suggestions

- Invest in current AI capabilities to deliver accurate, customer-focused financial services promptly.
- Strengthen customer-centric marketing strategies using data analytics and behavioural insight.
- Raise digital financial literacy through awareness campaigns around AI-enabled financial services.
- Strengthen data privacy, cybersecurity, and ethical AI governance to build customer trust and confidence.
- Design financial products that are accessible to underserved and rural populations still outside the formal system.
- Deploy AI-powered chatbots and virtual advisors to offer continuous, personalised customer support.
- Offer incentives that encourage innovation among banks, fintech firms, and regulators while preserving regulatory integrity.
- Periodically review and refine AI use and engagement practices to sustain long-term financial inclusion.

References

- Aldasoro, I., Gambacorta, L., Korinek, A., Shreeti, V., & Stein, M. (2025). Intelligent financial system: How AI is transforming finance. *Journal of Financial Stability*. <https://doi.org/10.1016/j.jfs.2025.101472>
- Apriadi, D., Adelin, D., Mutumanikam, P. R., & Lanjarsih, L. (2025). Personal Finance Transformation in the Digital Era: The Impact of Financial Technology on People's Economic Behavior. *Oikonomia: Journal of Management Economics and Accounting*. <https://doi.org/10.61942/oikonomia.v2i3.356>
- DR. S.JEYAKUMAR. (2025). THE IMPACT OF AI: ADVANCING ACCURACY AND EFFICIENCY IN THE BANKING INDUSTRY. *International Research Journal of Education and Technology*.
- Ma, Y. (2024). Research on Personalized Marketing Strategy of Financial Products Based on Big Data. *SHS Web of Conferences*, 200, 01014. <https://doi.org/10.1051/shsconf/202420001014>
- Malay Sarkar, & Sanjida Rahman. (2025). Artificial Intelligence in Modern Banking: Revolutionizing Financial Services, Risk Management and Customer Experience. *World Journal of Advanced Engineering Technology and Sciences*, 16(2), 260–270. <https://doi.org/10.30574/wjaets.2025.16.2.1289>
- Mhlanga, D. (2023). Artificial Intelligence (AI) Solutions for Financial Inclusion of the Excluded: What Are the Challenges? In *Advances in African Economic, Social and Political Development*. https://doi.org/10.1007/978-3-031-31431-5_14
- Mishra, S., Joshi, A., & Lakshmi, D. (2025). Transforming the financial market using AI generated personalized content. In *Intersecting Natural Language Processing and FinTech Innovations in Service Marketing*. <https://doi.org/10.4018/979-8-3693-9944-6.ch024>
- Paramesha, M., Rane, N., & Rane, J. (2024). Artificial intelligence, machine learning, deep learning, and blockchain in financial and banking services: a comprehensive review. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.4855893>
- Pattanayak, S. K. (2021). The Impact of Artificial Intelligence on Operational Efficiency in Banking: A Comprehensive Analysis of Automation and Process Optimization. *International Research Journal of Engineering and Technology*.
- Sharma, V., & Priya, B. (2025). Bridging the gap: AI-powered FinTech and its impact on financial inclusion and financial well-being. *Discover Artificial Intelligence*. <https://doi.org/10.1007/s44163-025-00465-9>
- V., S. S. (2026). "Impact of Artificial Intelligence and Machine Learning on Personalized Financial Services in Banking and Insurance." *Research Gate*. https://www.researchgate.net/publication/400907486_Impact_of_Artificial_Intelligence_and_Machine_Learning_on_Personalized_Financial_Services_in_Banking_and_Insurance