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DRIVERS OF AI-ENABLED FINANCIAL SERVICE ADOPTION IN RURAL INDIA: MEDIATING ROLE OF CUSTOMER ATTITUDE

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Abstract
This research analyzes the factors influencing the adoption of AI-enabled financial services among rural populations in India, focusing on the mediating effect of customer attitude in the relationship between key determinants trust, perceived value, and digital financial literacy and adoption intention. This study employed a quantitative research design and utilized a structured survey to collect data from 521 rural respondents in various Indian states. The research framework was based on the Theory of Planned Behavior, with customer attitude acting as the mediating construct. This study employed structural equation modeling to investigate both direct and indirect relationships among variables. The findings indicate that trust, perceived value, and digital financial literacy have a significant impact on the adoption of AI-enabled financial services in rural India. Customer attitude has been identified as a significant mediating factor. Trust exhibited the significant direct and indirect impact on customer attitude, similarly perceived value and digital financial literacy revealed both direct and attitude-mediated routes to adoption. This study enhances the existing literature on technology adoption in emerging markets and offers practical insights for developing culturally appropriate AI financial solutions for rural communities.

Keywords- Artificial intelligence; Customer Attitude; Digital Financial Literacy; Financial Services; Theory of Planned Behavior

Introduction

The expansion of artificial intelligence into financial sector enhanced financial assess (Khan et al., 2022). These AI-driven applications such as chatbots and voice assistants deliver financial services (Ahmadi, 2024). However, diverse socio-economic conditions of rural areas have been inadequately served by traditional banking infrastructure (Ohlan, 2013).

The rural context, have challenges such as the digital divide, disparate levels of financial literacy, and infrastructural deficiencies (Agwu, 2021). Therefore, the emergence of artificial intelligence technologies in financial services providing cost-effective, and personalized solutions that are specifically designed for rural customers (David et al., 2025). Moreover, transition from traditional digital financial services signifies unique challenges of trust, transparency, and user acceptance associated with AI integration in financial services (Vuković et al., 2025). Interestingly, facilitating situations can alter the technology adoption behavior of semi-rural women, underscoring the significance of contextual elements in rural environments (Anagreh et al., 2024). Additionally, India's resilient digital ecosystem comprising Aadhaar-based identity verification and UPI payment infrastructure has established a framework for the large-scale implementation of AI-driven financial innovations (Shandilya et al., 2024). Moreover, AI promotes financial inclusion by automating processes such as KYC and risk assessment (Kshetri, 2021). Furthermore, AI enabled services are providing real-time access to financial products such as microloans and micro-insurance (Mhlanga, 2020a). Despite, this technological context, a significant gap exists to comprehend the psychological and behavioral aspects. The existing literature recognizes the influence of trust, perceived value, and digital financial literacy on technology adoption. Moreover, literature examines attitude formation through information processing models (Ajzen, 1991a), social learning influences (Montgomery & Casterline, 1996), and cultural factors that influence perceptions (Pantano, 2011). However, considerable research has focused on the adoption of digital financial services in urban areas and developed economies; there is a lack of studies that specifically explore the distinct drivers and barriers to AI-enabled financial services in rural Indian markets (Kumar et al., 2021).

The current literature primarily emphasizes general technology acceptance models, failing to sufficiently explore the mediating role of customer attitude in the relationship between adoption drivers and actual usage behavior, especially related to AI enabled financial services (Venkatesh et al., 2020). Moreover, the A methodological gap exists in understanding the applicability of traditional technology acceptance frameworks to AI-specific financial services. These applications have distinct features including algorithmic decision-making, personalization, and autonomous functionality (Davenport et al., 2020). This study seeks to examine the mediating role of customer attitude in influencing the relationships among perceived value, trust, digital financial literacy, and the intention to use AI-enabled financial services within underserved population in rural India.

2. Literature Review

AI-driven platforms enable financial advisory services through the utilization of predictive analytics (Mhlanga, 2020b). In the rural context of India, the incorporation of AI in FinTech has facilitated the personalization of services, the reduction of transaction costs, and multilingual support (Javaid et al., 2022). These technological interventions are consistent with the objective of digital financial inclusion, for equitable access to affordable financial products (Tay et al., 2022). Digital financial literacy refers to the knowledge and skills required to effectively use digital financial products and services (Koskelainen et al., 2023). It has been observed, financial inclusion in rural India has been impeded by low levels of literacy. However, AI-enabled interfaces, voice-based applications (Tyagi et al., 2023; Tyagi & Jain, 2023a; Tyagi & Mishra, 2023), and language support have partially removed these barriers (Jerold, 2008). It has been claimed by the researchers that, the potential benefits of AI solutions may be limited by the lack of sufficient user training and awareness (Tyagi et al., 2025). Previous researches acknowledge trust as the determinant of technology-enabled financial transactions (Tyagi, 2025). In rural areas, trust is reducing perceptions of risk and uncertainty (Kamila & Jasrotia, 2025). Perceived value significantly influences behavioral intentions, AI-based personalization, rapid loan approvals, and reduced processing fees all contribute to increased user engagement (Pathak & Bansal, 2025). Furthermore, established frameworks, including the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT), are frequently employed in research on financial technology adoption (Rejali et al., 2023). These models highlight the importance of constructs such as perceived usefulness and subjective norms (Williams et al., 2015). The next section proceeds with hypothesis development and conceptual framework.

3. Development of Hypotheses and Conceptual Framework

3.1 Trust and Predicting the Adoption Intention

According to previous researches, trust is a crucial element in the adoption of technology-mediated financial services (Dimitriadis & Kyrezis, 2010). In the context of AI-enabled financial services, trust is defined as the confidence in the integrity of the service provider and the efficacy of the technology (Salih et al., 2025). Previous research on the adoption of FinTech and mobile banking has indicated that increased trust is associated with increased adoption intentions (Roh et al., 2024). Therefore, in rural India, where digital platforms continue to encounter uncertainty, it is anticipated that users' intentions to use AI-enabled financial services will be positively influenced by trust.

H1: The adoption intention of AI enabled financial services is positively influenced by trust.

3.2 Perceived Value and Predicting the Adoption Intention

Perceived value, is the trade-off between the perceived benefits and costs of adoption (Anwar et al., 2021), has been identified as a predictor of behavioral intention (Baird & Raghu, 2015). In the context of AI-enabled financial services, the perceived value of rural consumers is improved by benefits such as speed, accuracy, personalization, and reduced transaction costs (Sheth et al., 2022). It is anticipated that these perceived value will increase customer intention to interact with AI-driven platforms.

H2: The adoption intention of AI enabled financial services is positively influenced by perceived value.

3.3 Digital Financial Literacy and Adoption Intention

Digital financial literacy is the ability of individuals to effectively navigate and utilize financial technologies (Bhat et al., 2025; Tyagi & Jain, 2023b). Prior empirical research has shown that digital literacy not only enhances users' confidence in using financial services but also improves their ability to access financial products (Hidayat-ur-Rehman, 2025). AI-enabled tool can amplify the positive impact of digital literacy on adoption decisions in rural India (Grover et al., 2025). Therefore,

H3: The adoption intention of AI-enabled financial services is positively influenced by digital financial literacy.

3.4 The Mediating Role of Customer Attitude

The literature from the Technology Acceptance Model and its extensions posits that cognitive factors, such as trust, perceived value, and literacy, indirectly influence adoption by influencing attitudes (Pavlou, 2003). In rural areas, where there is potentially a high level of skepticism toward new technologies, a favorable attitude can serve as a critical psychological mechanism that converts beliefs into behavioral intentions (Bhattacherjee & Sanford, 2009). Previous research indicates that attitudes frequently function as a mediating variable between cognitive beliefs (e.g., utility, trust) and behavioral outcomes (Chang et al., 2016). Nevertheless, there is a substantial gap in the empirical research that specifically examines this mediation in rural Indian contexts. Thus,

H4a: The relationship between trust and usage intention of AI-enabled financial services is mediated through customer attitude.

H4b: The relationship between perceived value and usage intention of AI-enabled financial services is mediated through customer attitude.

H4c: The relationship between digital financial literacy and usage intention of AI-enabled financial services is mediated through customer attitude.

3.5 Conceptual Framework

The conceptual framework (Figure 1) proposes that trust, perceived value, and digital financial literacy influence usage intention both directly and indirectly through customer attitude as a mediator, as per the preceding discussion. The empirical testing of this framework employs Partial Least Squares Structural Equation Modeling (PLS-SEM) and incorporates cognitive, affective, and behavioral dimensions of technology adoption.

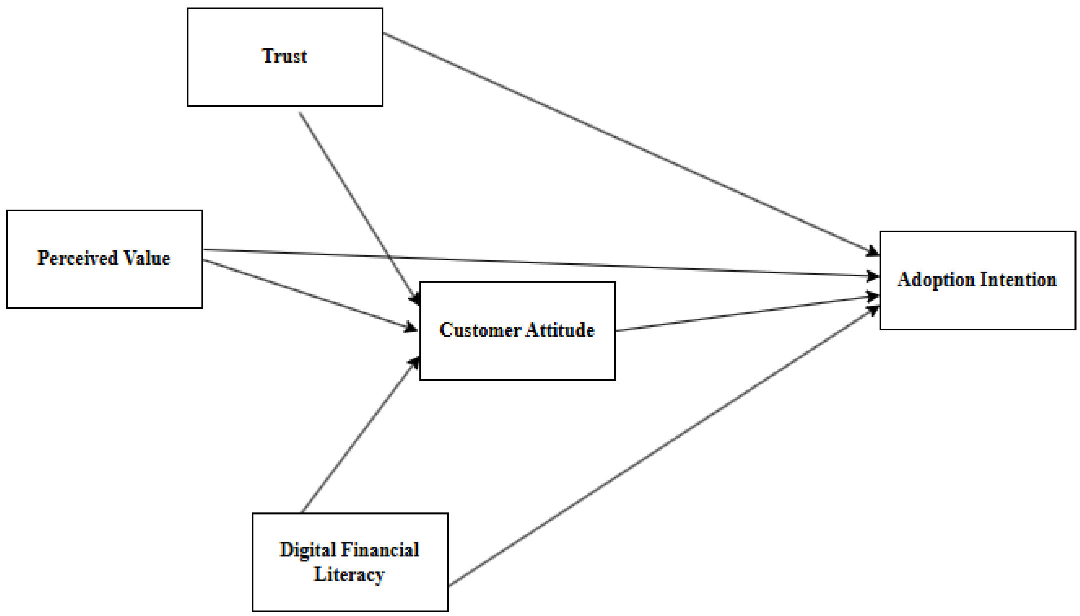

Figure number 1. Conceptual framework

4 Research Methodology

This research employs a quantitative, cross-sectional survey methodology to investigate the relationships between trust, perceived value, digital financial literacy, customer attitude, and the intention to use AI-enabled financial services in rural India. In this study Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilized for complex model involving latent constructs (Ali et al., 2018).

4.2 Sampling framework

The target population consists of adult individuals living in rural areas of India who have shown interest in AI-enabled financial services, including AI-powered mobile banking applications, voice-assisted payment platforms, or AI-based credit scoring services. Purposive sampling was utilized to ensure that respondents possessed pertinent exposure to these services. The minimum sample size was established according to the 10-times rule (Wagner & Grimm, 2023), which ensures sufficient statistical power for mediation analysis. Data collection was performed using a structured questionnaire, which was administered both online and offline with the support of local facilitators.

4.3 Measurement of Constructs

All constructs were assessed on multi-item Likert scales, tailored to the study context, and assessed on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree).The trust (TR) is assessed through items modified from (Johnson-George & Swap, 1982), perceived Value items are derived from the PERVAL scale by (Sweeney & Soutar, 2001), adapted for financial service contexts. Further, digital Financial Literacy components are derived from the (Lyons & Kass-Hanna, 2021), customer Attitude items are derived from (Stock & Hoyer, 2005). Furthermore, usage Intention items are derived from (Kim & Malhotra, 2005).

4.4 Data Collection

The questionnaire was pilot tested with 30 rural respondents to verify clarity, contextual relevance, and cultural appropriateness of the items. Minor linguistic adjustments were implemented to support respondents with lower literacy levels, including translations into regional languages. The data collection process occurred over six weeks, with trained field researchers supporting participants who were not familiar with digital survey tools. The study included 521 respondents from rural areas, 270 were male (51.8%) and 251 were female (48.2%), providing a diverse and representative sample to capture different perspectives on the adoption of AI-enabled financial services. The sample included diverse age groups, predominantly consisting of younger individuals (18 to 25 years), 198 respondents (38.0%) and, 176 (33.8%), middle-aged participants (26 to 40 years), with 97 (18.6%) of respondents over 40 years. Additionally, 50 (9.6%) respondents were above 50 years of age. The participants' educational backgrounds ranged from secondary schooling to postgraduate qualifications, enabling the study to address differences in digital financial literacy linked to diverse educational levels. The respondents represented various occupational categories, including students 154 (29.6%), self-employed individuals 112 (21.5%), farmers 98 (18.8%), salaried employees 87 (16.7%), and homemakers 70 (13.4%). Thus study reflecting diverse economic segments within rural communities. The varied composition of rural respondents yielded an evenly distributed dataset, thereby improving the reliability and generalizability of the study's findings.

5 Analysis of Data

The PLS-SEM analysis utilized Smart PLS 4.0, employing a two-stage methodology: evaluation of the measurement model for reliability and validity, and assessment of the structural model for hypothesis testing. Reliability was evaluated using Cronbach’s alpha and composite reliability (CR), whereas convergent validity was analyzed through average variance extracted (AVE). The significance of path coefficients was assessed through a bootstrapping procedure involving 5,000 samples.

5.1 Assessment of Common Method Bias

Common technique bias is a notable issue in cross-sectional survey research when all variables are assessed through the same methodology and data source (Wang & Cheng, 2020). The SEM framework offers many methods for identifying and mitigating common method bias. Harman's single-factor test serves as a preliminary evaluation, determining whether a single component explains the predominant variance in the data. If one component accounts for over 50% of the variance, common technique bias could be an issue. The common latent factor (CLF) methodology provides a more nuanced evaluation by incorporating an unobserved latent technique factor into the model, which influences all observable indicators (Afthanorhan et al., 2021). The next section includes measurement model analysis.

5.2 Measurement Model Assessment

The measurement model was assessed for reliability, convergent validity, and discriminant validity. All constructs exhibited Cronbach’s alpha (α) and composite reliability (CR) values above the recommended threshold of 0.70, indicating strong internal consistency (Cheung et al., 2024). Average variance extracted (AVE) values for all constructs approximately exceeded the 0.50, confirming adequate convergent validity. Factor loadings for all items were above 0.70.

Constructs	*Item Code*	*Factor Loadings*	*Cronbach's Alpha*	*AVE*	*CR*
Trust					
I believe AI-based financial services act in my best interest.	TR1	0.892			
I feel secure sharing my personal details with AI financial platforms.	TR2	0.776	0.850	0.659	0.858
I can rely on AI financial services to work accurately and consistently.	TR3	0.760			
Perceived Value					
Using AI financial services gives me better results than traditional methods.	PV1	0.930			
The benefits of AI financial tools are greater than the effort required to use them.	PV2	0.902	0.913	0.780	0.858
I find AI financial services to be worth the time and money I invest.	PV3	0.814			
Digital Financial Literacy					
I can complete financial transactions online without assistance.	DL1	0.849			
I understand how to use digital tools to track my finances.	DL2	0.464	0.740	0.568	0.841
I know how to keep my financial information safe on digital platforms.	DL2	0.876			
Customer Attitude					
Investing in financial products is a wise decision.	CA1	0.839			
I feel positive about financial investment in sustainable firms.	CA2	0.900	0.833	0.644	0.860
I am interested in financial products that align with my values.	CA3	0.646			
AI enabled services adoption Intention					
I am willing to use AI-based financial services in the future.	AI1	0.900	0.747	0.471	0.776
I intend to invest in financial products in the near future.	AI2	0.530			

I am likely to recommend AI financial services to others.	AI3	0.567

Table no 1. Reliability and Validity values for all the Constructs

5.3 Structural Model Assessment

This study utilizes a comprehensive two-step structural equation modeling (SEM) analysis (Anderson & Gerbing, 1988). The SEM framework facilitates the concurrent analysis of many connections while considering measurement error (Sarstedt et al., 2020). Variance inflation factor (VIF) values for all predictor constructs were below 3.0, suggesting no multicollinearity concerns. The PLS-SEM primarily emphasizes prediction and parameter estimation, however various fit indices can be employed to assess model adequacy. The standardized root mean square residual (SRMR) is the principal fit index for PLS-SEM, with values under 0.08, Normed fit index (NFI) = 0.806, signifying an acceptable model fit (Cepeda-Carrion et al., 2019). The large standardized residuals may signify model misspecification (Kaplan, 1988). In this study (shown in figure number 2), trust ($\beta = 0.05$, $p < 0.05$), perceived value ($\beta = 0.12$, $p < 0.05$), and digital financial literacy ($\beta = 0.18$, $p < 0.05$), significantly positively affected customer attitude, which subsequently had a significant influence on AI-enabled financial services ($\beta = 0.61$, $p < 0.05$).

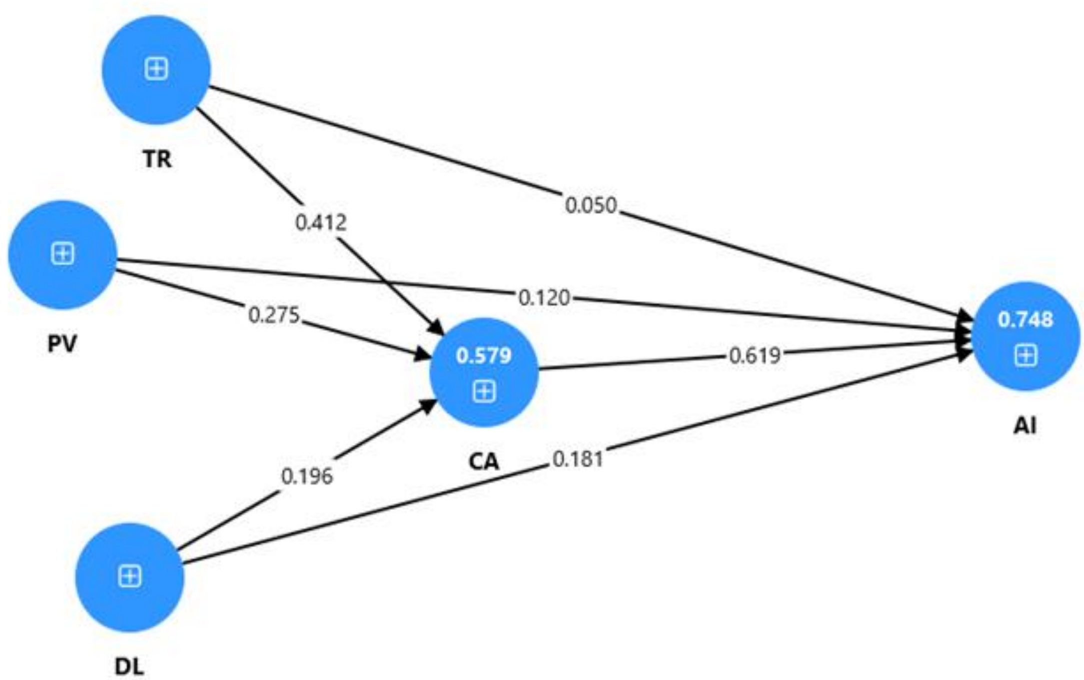

Figure number 2. Structural model outcome

5.4 Mediation Analysis

The PLS-SEM algorithm utilizes an iterative process that alternates between estimating the inner and outer models, enhancing the prediction of endogenous latent variables by estimating path coefficients that aim to maximize the R^2 values of dependent constructs (Hair & Alamer, 2022). The testing of indirect effects in PLS-SEM is significant due to the use of bootstrapping procedures (Streukens & Leroi-Werelds, 2016). The mediation effects of Customer Attitude were examined using bootstrapped indirect effects. Path analysis demonstrated significant relationships among the study constructs. The mediation analysis revealed that customer attitude partially mediated the relationships between trust and AI-enabled financial services ($\beta = 0.255$, $p < 0.05$) and between perceived value and AI-enabled financial services ($\beta = 0.170$, $p < 0.05$). Additionally, customer attitude partially mediated the relationships between Digital financial literacy and AI-enabled financial services ($\beta = 0.122$, $p < 0.05$). The model showed $R^2 = 0.748$ of AI-enabled services adoption intention and $R^2 = 0.579$ of the customer attitude, indicating substantial explanatory power. The standardized root mean square residual (SRMR) value of 0.070 was below the 0.08 threshold, suggesting a good model fit in accordance with the mediation framework established by (Pavlov et al., 2021).

Discussion

This study's findings offer important insights into the factors influencing the intention to adopt AI-enabled financial services among underserved rural population in India. In alignment with previous studies, trust was identified as a significant and positive factor influencing usage intention, underscoring its critical function in mitigating perceived risk and increasing the propensity to adopt new technologies (Appiah & Agblewornu, 2025). In rural areas, where there may be skepticism towards advanced financial technologies, trust serves as both a transactional safeguard and a relational mechanism that enhances user commitment. The findings corroborate the impact of perceived value on usage intention, consistent with value-based adoption models (Chawla et al., 2023). This finding supports the notion that perceived value in financial services is multi-faceted, incorporating both utilitarian and emotional benefits, which together increase the intention of adoption (Sánchez-Fernández & Iniesta-Bonillo, 2007). Digital financial literacy significantly positively influences adoption intentions. This is consistent with the previous study, posits that knowledge and skills are essential for effective technology utilization (Al-Emran et al., 2025). In rural India, digital literacy facilitates the navigation of AI-driven interfaces, interpretation of transaction data, and management of online security risks, thereby enhancing confidence in technology utilization. A significant finding is the mediating role of customer attitude in the relationships among trust, perceived value, digital financial literacy, and usage intention. The customer attitude showed partial mediation in this study, indicates that literacy by itself may not lead to adoption unless it cultivates a positive attitude toward the technology. The findings align with the recent study (Emon & Khan, 2025), claimed attitude as a crucial psychological construct that converts cognitive beliefs into behavioral intentions.

This study advances technology adoption literature by incorporating trust, perceived value, and digital financial literacy within a framework, with attitude serving as a mediator. This approach corroborates established theories (Ajzen, 1991b), while contextualizing them within an underserved rural environment, a setting that remains underexplored in AI-enabled financial service research. The findings suggests financial service providers to prioritize trust-building initiatives, improve perceived value through localized service innovations, and invest in targeted digital literacy programs. This study suggests that in rural India, culturally relevant marketing, and community-based awareness initiatives can cultivate positive user attitudes.

6. Conclusion and Implications

This study investigated the influence of trust, perceived value, and digital financial literacy on the usage intention of AI-enabled financial services among rural people in India, with consumer attitude serving as a mediating variable. The findings indicated that trust and perceived value positively influence adoption intentions. This research theoretically enhances the literature on technology adoption by incorporating the elements of trust, perceived value, and financial literacy into an AI adoption model in an emerging market environment. The results offer recommendations for fin-tech innovators, policymakers, and microfinance institutions. Organizations must establish confidence by transparent policies, reliable service performance, and explicit data privacy guarantees. Moreover, policy makers and organizations must advancing digital financial literacy through specialized training sessions, community-oriented workshops, and interactive AI-enhanced educational tools. By systematically addressing both functional and attitudinal elements, stakeholders can expedite the uptake of AI-enabled financial services, thus enhancing financial inclusion in rural India.

Limitations

Despite providing valuable insights, it is important to recognize the specific limitations of this study. The research is geographically restricted to rural areas of India, constraining the applicability of the findings to metropolitan or semi-urban settings. Secondly, the study depends on self-reported data, which may be influenced by social desirability bias or respondent’s lower understanding of Artificial Intelligence enabled financial services, thereby compromising data accuracy. Third, the cross-sectional design captures perceptions at a singular moment, limiting the capacity to infer causality or detect changes in attitudes and adoption behavior over time. Fourth, although the study includes essential dimensions such as trust, perceived value, and digital financial literacy, it neglects to consider other potentially significant factors, such as cultural norms or technological infrastructure, which may also influence adoption behavior. Finally, the model emphasizes the mediating role of customer attitude while neglecting potential moderating influences such as age, gender, and income level.

Directions for Future Researches

Future research can address the limitations of this study by enhancing the understanding of the adoption of Artificial Intelligence enabled financial services in various ways. Future studies should incorporate diverse geographic contexts by comparing rural, semi-urban, and urban regions to improve the generalizability of findings and account for contextual variations in financial behavior. Longitudinal research designs may be utilized to monitor shifts in customer attitudes and adoption behavior over time. Further by incorporating additional variables, including cultural values, social influence, institutional trust, and technological infrastructure, can yield a more comprehensive understanding of the factors influencing adoption. Future research should investigate the potential moderating effects of demographic factors such as age, education, gender and income to reveal segment-specific insights not addressed in this study. Qualitative or mixed-method approaches may enhance quantitative findings by providing deeper, contextual insights into the motivations, limitations, and lived experiences of rural users interacting with AI-enabled financial services.

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