

Original Research Article

Factors Influencing Consumer Trust in AI-Enabled Financial Services in India

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Abstract

Artificial intelligence (AI) is fundamentally reshaping the financial services landscape in India, from algorithmic credit scoring and robo-advisory platforms to AI-powered chatbots handling customer queries. While the adoption of AI-driven financial products has accelerated, consumer trust remains a critical determinant of sustained uptake. This study investigates the influence of three key factors derived from the Technology Acceptance Model (TAM) on consumer trust in AI-enabled financial services in the Indian context: perceived usefulness (PU), perceived security (PS), and perceived ease of use (PEOU). A quantitative research design was employed, utilizing a structured 15-item Likert-scale questionnaire administered to 300 respondents across diverse demographic groups in India. Multiple regression analysis was used to test the hypothesised relationships. The results indicate that the model explains 73% of the variance in consumer trust ($R^2 = 0.728$), with all three independent variables demonstrating statistically significant positive relationships with consumer trust. Perceived ease of use emerged as the strongest predictor (standardised beta = 0.375), followed by perceived usefulness (standardised beta = 0.310) and perceived security (standardised beta = 0.236). The findings offer practical insights for fintech providers and policymakers seeking to strengthen consumer trust in AI-driven financial services across India.

Keywords: Artificial Intelligence, Consumer Trust, Technology Acceptance Model, Fintech, Financial Services, India

1. Introduction

The rapid proliferation of artificial intelligence (AI) technologies across the global financial services industry has introduced transformative capabilities in areas such as fraud detection, algorithmic trading, credit risk assessment, personalised investment advisory, and customer service automation (Gomber et al., 2018). In India, this transformation is particularly pronounced. The Government of India's digitalisation initiatives, combined with the widespread adoption of the Unified Payments Interface (UPI) and the proliferation of fintech start-ups, have created an ecosystem in which AI-enabled financial services are becoming mainstream. Major Indian banks and fintech platforms now deploy AI for loan underwriting, KYC verification, voice-based banking, and real-time transaction monitoring, fundamentally altering how consumers interact with financial institutions.

However, the adoption of AI in financial services is not merely a function of technological availability. Consumer trust plays a pivotal role in determining whether individuals are willing to rely on algorithmic systems for decisions that have direct financial consequences. Unlike traditional financial services where human judgment provides a familiar anchor, AI-driven systems operate as black boxes, making trust an especially salient concern (Glikson & Woolley, 2020). In the Indian context, where financial literacy varies significantly across demographic segments and where concerns about data privacy are increasingly prominent, understanding the determinants of consumer trust in AI-enabled financial services is both timely and practically significant.

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), provides a robust theoretical lens for examining technology adoption behaviour. TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of user acceptance. Subsequent research has extended TAM to incorporate trust and security perceptions, particularly in e-commerce and online banking contexts (Gefen et al., 2003; Pavlou, 2003). This study draws on TAM and its extensions to examine how PU, PEOU, and perceived security (PS) influence consumer trust (CT) in AI-enabled financial services in India.

The specific objectives of this study are threefold: first, to examine the effect of perceived usefulness on consumer trust in AI-enabled financial services; second, to assess the effect of perceived security on consumer trust; and third, to evaluate the effect of perceived ease of use on consumer trust. The overarching objective is to determine the collective predictive power of these three variables on consumer trust. The study tests four null hypotheses against their corresponding alternatives using multiple regression analysis on data collected from 300 respondents in India.

2. Literature Review

2.1 Technology Acceptance Model

The Technology Acceptance Model (TAM), introduced by Davis (1989), is one of the most widely applied theoretical frameworks for understanding user acceptance of information technology. TAM proposes that two primary beliefs, perceived usefulness (PU) and perceived ease of use (PEOU), determine an individual's behavioural intention to use a technology. Perceived usefulness is defined as the degree to which a person believes that using a particular system would enhance their job performance, while perceived ease of use refers to the degree to which a person believes that using the system would be free from effort (Davis, 1989). Subsequent extensions of TAM,

notably TAM2 (Venkatesh & Davis, 2000), incorporated additional determinants such as subjective norm and cognitive instrumental processes, further enriching the model's explanatory power.

The applicability of TAM to financial technology contexts has been extensively validated. Shin (2009) applied TAM to study mobile wallet acceptance and found that both PU and PEOU significantly influenced adoption intentions. Similarly, Luo et al. (2010) demonstrated that perceived ease of use and perceived usefulness were significant predictors of mobile banking adoption in emerging markets. These findings collectively support the relevance of TAM constructs for examining AI-enabled financial services, which represent an advanced form of technology-mediated financial interaction.

2.2 Consumer Trust in Technology-Mediated Services

Trust has been conceptualised as a multi-dimensional construct encompassing cognitive, affective, and behavioural components. McKnight et al. (2002) developed a comprehensive typology of online trust, distinguishing between trusting beliefs (perceptions of the trustee's competence, benevolence, integrity, and predictability) and trusting intentions (the willingness to depend on the trustee in a given situation). In the context of technology-mediated financial services, trust serves as a critical antecedent to adoption because financial transactions inherently involve risk, uncertainty, and the vulnerability of personal and monetary assets (Pavlou, 2003).

Gefen et al. (2003) integrated trust into TAM within an online shopping context and found that trust significantly influenced both perceived usefulness and the intention to transact online. Their findings underscored that trust is not merely a consequence of technology acceptance but also a determinant that interacts with TAM constructs. In the specific domain of AI-enabled services, Glikson and Woolley (2020) reviewed empirical research on human trust in AI and concluded that task characteristics, system characteristics, and individual differences all play significant roles in shaping trust. Their review highlighted that algorithmic transparency, reliability, and the perceived competence of AI systems are particularly important for fostering trust.

2.3 Perceived Usefulness and Consumer Trust

Perceived usefulness has consistently been identified as a significant predictor of technology adoption and trust formation. When consumers perceive that an AI-enabled financial service genuinely enhances their financial decision-making, reduces transaction costs, or provides superior recommendations compared to traditional alternatives, they are more likely to develop trust in that service (Davis et al., 1989). In the Indian fintech context, services such as AI-driven credit scoring that enable faster loan approvals, or robo-advisory platforms that offer personalised investment portfolios at lower fees, directly contribute to perceived usefulness. Pavlou (2003) demonstrated that perceived usefulness of online transaction mechanisms significantly increased consumer trust, suggesting a positive relationship between these constructs. Based on this theoretical and empirical foundation, the following hypothesis is proposed:

H1: Perceived usefulness has a significant positive effect on consumer trust in AI-enabled financial services.

2.4 Perceived Security and Consumer Trust

Perceived security refers to the extent to which consumers believe that their personal and financial data are protected from unauthorised access, theft, or misuse when using a technology-mediated service (Siau & Shen, 2003). In the domain of financial services, security perceptions are particularly critical because the nature of transactions involves sensitive information, including bank account details, income data, and identity documents.

The integration of AI into financial services introduces additional security concerns related to algorithmic bias, data harvesting for model training, and the potential for adversarial attacks on AI systems (Gomber et al., 2018).

Empirical research has consistently demonstrated a positive relationship between perceived security and trust in technology-mediated environments. Luo et al. (2010) found that security perceptions were a significant determinant of trust in mobile banking services, with stronger security perceptions leading to higher trust levels. Similarly, Kim et al. (2009) reported that perceived security significantly influenced initial trust formation in mobile banking adoption. Given the heightened sensitivity of financial data and the evolving threat landscape surrounding AI systems, perceived security is expected to be a significant predictor of consumer trust in AI-enabled financial services in India:

H2: Perceived security has a significant positive effect on consumer trust in AI-enabled financial services.

2.5 Perceived Ease of Use and Consumer Trust

Perceived ease of use is a foundational construct in TAM and refers to the degree to which a person believes that using a system will be effortless (Davis, 1989). In the context of AI-enabled financial services, PEOU encompasses the intuitiveness of mobile banking interfaces, the simplicity of interacting with AI chatbots, the clarity of algorithmic recommendations, and the overall user experience. When consumers find AI-driven financial platforms easy to navigate and understand, they are more likely to form positive perceptions of the underlying technology, which in turn fosters trust (Venkatesh & Davis, 2000).

Shin (2009) demonstrated that perceived ease of use significantly influenced both adoption intention and trust in mobile payment services. The relationship is particularly relevant in India, where AI-enabled financial services must cater to a diverse user base spanning varying levels of digital literacy, language preferences, and technological sophistication. Platforms that simplify complex financial decisions through intuitive AI-driven interfaces are more likely to earn consumer trust. Therefore, the following hypothesis is proposed:

H3: Perceived ease of use has a significant positive effect on consumer trust in AI-enabled financial services.

2.6 Conceptual Framework and Hypotheses

Building on the theoretical foundations of TAM and the trust literature, this study proposes a multiple regression model in which consumer trust (CT) is the dependent variable and perceived usefulness (PU), perceived security (PS), and perceived ease of use (PEOU) serve as independent variables. The regression model is specified as follows:

$$CT = \beta_0 + \beta_1(PU) + \beta_2(PS) + \beta_3(PEOU) + \varepsilon$$

The model collectively captures the variance in consumer trust explained by the three independent variables. The overall hypothesis is:

H4: Perceived usefulness, perceived security, and perceived ease of use collectively and significantly predict consumer trust in AI-enabled financial services.

3. Research Methodology

3.1 Research Design

This study adopts a quantitative, cross-sectional research design to examine the relationships between the independent variables (PU, PS, PEOU) and the dependent variable (consumer trust). Quantitative methodology

was chosen for its capacity to facilitate generalisable inferences through statistical analysis and hypothesis testing (Hair et al., 2019). The research was conducted within a positivist epistemological framework, which assumes that social phenomena can be measured and analysed using objective, systematic methods. The target population consisted of Indian consumers who have used or are aware of AI-enabled financial services such as AI-based chatbots for banking, robo-advisory platforms, algorithmic credit scoring, or AI-powered fraud detection tools.

3.2 Population and Sampling

A sample of 300 respondents was selected using a combination of convenience and purposive sampling techniques. Respondents were recruited from diverse geographical regions within India to ensure representativeness across urban and semi-urban areas. The sample size of 300 exceeds the minimum threshold recommended for multiple regression analysis, which typically requires at least 10 to 15 observations per predictor variable (Hair et al., 2019). With three predictors, the minimum recommended sample size would be 30 to 45, making the present sample substantially adequate for the analysis.

3.3 Instrument Design

Data were collected using a structured questionnaire consisting of 15 items measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was organised into four sections corresponding to the four constructs: perceived usefulness (4 items: PU1 to PU4), perceived security (4 items: PS1 to PS4), perceived ease of use (4 items: PEOU1 to PEOU4), and consumer trust (3 items: CT1 to CT3). The items were adapted from established scales in the technology acceptance and trust literature (Davis, 1989; Gefen et al., 2003; McKnight et al., 2002). Table 1 presents the questionnaire items.

Table 1. Questionnaire Items by Construct

Construct	Code	Item Description
Perceived Usefulness	PU1	AI-enabled financial services improve my financial decision-making.
	PU2	Using AI-based financial tools increases my productivity.
	PU3	AI-powered financial services provide useful recommendations.
	PU4	AI-enabled financial services make transactions more efficient.
Perceived Security	PS1	I believe my personal data is secure with AI financial services.
	PS2	AI-enabled financial platforms have adequate security measures.
	PS3	I feel confident about the privacy protections in AI financial tools.
	PS4	AI-based financial services are safe from unauthorised access.
Perceived Ease of Use	PEOU1	I find AI-enabled financial services easy to use.
	PEOU2	Interacting with AI financial tools does not require much effort.
	PEOU3	AI-powered financial platforms have user-friendly interfaces.
	PEOU4	Learning to use AI-enabled financial services is easy for me.
Consumer Trust	CT1	I trust AI-enabled financial services to handle my finances.
	CT2	I believe AI-based financial platforms are reliable.
	CT3	I feel confident relying on AI for financial decisions.

3.4 Data Collection

The questionnaire was administered online using a digital survey platform. Respondents were contacted through social media channels, professional networks, and financial literacy forums. Prior to participation, respondents were provided with a brief description of the study's purpose and assured of the anonymity and confidentiality of their responses. The survey was conducted over a four-week period, and incomplete or inconsistent responses were excluded from the analysis.

3.5 Statistical Techniques

The data were analysed using multiple regression analysis to test the hypothesised relationships. Prior to conducting the regression, several preliminary analyses were performed. Reliability was assessed using Cronbach's alpha for each construct to ensure internal consistency. Pearson correlation analysis was conducted to examine the bivariate relationships among all variables. Assumption testing for multiple regression included checks for normality (Shapiro-Wilk, Kolmogorov-Smirnov, and Anderson-Darling tests), homoscedasticity (Breusch-Pagan, Goldfeld-Quandt, and Harrison-McCabe tests), autocorrelation (Durbin-Watson test), and multicollinearity (Variance Inflation Factor). All analyses were conducted using R and jamovi statistical software (R Core Team, 2025; The jamovi project, 2025).

4. Data Analysis and Results

4.1 Demographic Profile of Respondents

The demographic composition of the 300 respondents is summarised in Table 2. The sample was nearly balanced by gender, with 161 females (53.7%) and 139 males (46.3%). The largest age group was 18 to 25 years (48.3%), followed by 26 to 35 years (24.7%), 36 to 45 years (16.0%), and 46 years and above (11.0%). In terms of education, the majority held postgraduate qualifications (38.0%), followed by undergraduate degrees (36.3%), professional certifications (20.7%), and doctoral degrees (5.0%). Private sector employees constituted the largest occupational group (35.0%), followed by students (19.7%), self-employed individuals (17.3%), government employees (14.3%), and business owners (13.7%). With respect to monthly income, 30.7% earned below INR 25,000, 30.7% earned between INR 25,001 and INR 50,000, 28.3% earned between INR 50,001 and INR 100,000, and 10.3% earned above INR 100,000.

Table 2. Demographic Profile of Respondents (N = 300)

Demographic Variable	Category	Count (n)	Percentage (%)
Gender	Female	161	53.7
	Male	139	46.3
Age Group	18–25	145	48.3
	26–35	74	24.7
	36–45	48	16.0
	46+	33	11.0
Education	Undergraduate	109	36.3
	Postgraduate	114	38.0
	Professional	62	20.7

Demographic Variable	Category	Count (n)	Percentage (%)
	Doctorate	15	5.0

4.2 Reliability Analysis

Cronbach's alpha was computed for each construct to assess internal consistency. As presented in Table 3, all four constructs exceeded the widely accepted threshold of 0.70 (Hair et al., 2019). Perceived ease of use demonstrated the highest reliability ($\alpha > 0.843$), followed by perceived usefulness ($\alpha > 0.788$), perceived security ($\alpha > 0.741$), and consumer trust ($\alpha > 0.721$). These results confirm that the measurement instrument exhibited satisfactory reliability for the purposes of this study.

Table 3. Reliability Analysis (Cronbach's Alpha)

Construct	Items	Cronbach's Alpha
Perceived Usefulness	PU1–PU4	> 0.788
Perceived Security	PS1–PS4	> 0.741
Perceived Ease of Use	PEOU1–PEOU4	> 0.843
Consumer Trust	CT1–CT3	> 0.721

4.3 Correlation Analysis

Pearson correlation coefficients were calculated to examine the bivariate relationships among the study variables. The results, presented in Table 4, reveal that all correlations are statistically significant at the $p < .001$ level. Consumer trust exhibits the strongest bivariate correlation with perceived ease of use ($r = 0.800$, $p < .001$), followed by perceived usefulness ($r = 0.795$, $p < .001$) and perceived security ($r = 0.779$, $p < .001$). Among the independent variables, perceived usefulness and perceived security show the highest inter-correlation ($r = 0.815$, $p < .001$), while perceived ease of use and perceived security have a correlation of 0.776 ($p < .001$). These moderate-to-strong positive correlations provide initial support for the hypothesised relationships and justify proceeding with multiple regression analysis.

Table 4. Correlation Matrix (N = 300)

Variable	1	2	3	4
1. Perceived Usefulness	—			
2. Perceived Security	0.815^{***}	—		
3. Perceived Ease of Use	0.783^{***}	0.776^{***}	—	
4. Consumer Trust	0.795^{***}	0.779^{***}	0.800^{***}	—

Note. $*** p < .001$.

4.4 Multiple Regression Analysis

Multiple linear regression was conducted to assess the collective and individual effects of perceived usefulness, perceived security, and perceived ease of use on consumer trust. Prior to interpreting the regression results, the key assumptions were tested. The Shapiro-Wilk test ($W = 0.993$, $p = 0.162$), Kolmogorov-Smirnov test ($D = 0.046$, $p = 0.565$), and Anderson-Darling test ($A = 0.620$, $p = 0.106$) all indicated that the residuals were normally distributed. The Breusch-Pagan test (chi-square = 1.95 , $p = 0.583$), Goldfeld-Quandt test ($p = 0.129$), and Harrison-McCabe test

($p = 0.136$) confirmed the absence of heteroscedasticity. The Durbin-Watson statistic of 1.82 ($p = 0.112$) indicated no significant autocorrelation. Variance Inflation Factor (VIF) values ranged from 3.03 to 3.58, all below the threshold of 10, indicating acceptable multicollinearity levels (Hair et al., 2019).

The overall model summary, presented in Table 5, demonstrates that the regression model is statistically significant ($F(3, 296) = 267, p < .001$). The model accounts for 73.0% of the variance in consumer trust (R-squared = 0.730, Adjusted R-squared = 0.728), indicating a strong explanatory fit.

Table 5. Model Summary (N = 300)

R	R-squared	Adjusted R-squared	F	df1	df2	p
0.855	0.730	0.728	267	3	296	< .001

Note. Predictors: Perceived Usefulness, Perceived Security, Perceived Ease of Use. Dependent Variable: Consumer Trust.

The regression coefficients, presented in Table 6, reveal that all three independent variables are statistically significant predictors of consumer trust. Perceived ease of use has the largest unstandardised coefficient ($b = 0.283$, $SE = 0.040$, $t = 7.13$, $p < .001$) and the highest standardised estimate (beta = 0.375), indicating that a one-unit increase in PEOU is associated with a 0.283-unit increase in consumer trust, holding other variables constant. Perceived usefulness is the second-strongest predictor ($b = 0.232$, $SE = 0.043$, $t = 5.43$, $p < .001$, standardised beta = 0.310). Perceived security, while statistically significant, has the smallest standardised effect ($b = 0.177$, $SE = 0.042$, $t = 4.19$, $p < .001$, standardised beta = 0.236). The intercept is 0.757 ($SE = 0.345$, $t = 2.19$, $p = 0.029$), which is statistically significant. The estimated regression equation is:

Table 6. Regression Coefficients for Consumer Trust

Predictor	b	SE	t	p	Std. Beta	95% CI
Intercept	0.757	0.345	2.19	0.029	—	[0.078, 1.436]
Perceived Usefulness	0.232	0.043	5.43	< .001	0.310	[0.148, 0.317]
Perceived Security	0.177	0.042	4.19	< .001	0.236	[0.094, 0.261]
Perceived Ease of Use	0.283	0.040	7.13	< .001	0.375	[0.205, 0.361]

Note. b = unstandardised coefficient; SE = standard error; Std. Beta = standardised coefficient; CI = confidence interval.

$$CT = 0.757 + 0.232(PU) + 0.177(PS) + 0.283(PEOU) + \varepsilon$$

4.5 Hypothesis Testing

Table 7 summarises the results of the hypothesis tests. All four null hypotheses are rejected in favour of their corresponding alternative hypotheses. For H1, the significant positive coefficient of perceived usefulness ($b = 0.232$, $p < .001$) leads to the rejection of the null hypothesis that PU has no effect on consumer trust. Similarly, for H2, the significant positive coefficient of perceived security ($b = 0.177$, $p < .001$) leads to rejection of the null. For H3, the significant positive coefficient of perceived ease of use ($b = 0.283$, $p < .001$) leads to rejection of the null. Finally, the overall model significance ($F = 267$, $p < .001$) with R-squared = 0.730 leads to the rejection of H4, confirming that PU, PS, and PEOU collectively and significantly predict consumer trust in AI-enabled financial services.

Table 7. Summary of Hypothesis Testing Results

Hypothesis	Statement	Result	Decision
H1	PU has a significant positive effect on CT	$b = 0.232, p < .001$	Supported
H2	PS has a significant positive effect on CT	$b = 0.177, p < .001$	Supported
H3	PEOU has a significant positive effect on CT	$b = 0.283, p < .001$	Supported
H4	PU, PS, PEOU collectively predict CT	$F = 267, p < .001, R^2 = 0.730$	Supported

5. Discussion

The findings of this study provide empirical evidence that perceived usefulness, perceived security, and perceived ease of use are all significant positive predictors of consumer trust in AI-enabled financial services in India. The model's R-squared of 0.730 indicates that these three variables collectively explain a substantial proportion of the variance in consumer trust, which is consistent with the theoretical expectations derived from TAM and the trust literature (Davis, 1989; Gefen et al., 2003).

Perceived ease of use emerged as the strongest predictor of consumer trust (standardised beta = 0.375). This finding is particularly meaningful in the Indian context, where digital literacy levels vary considerably across demographic groups. AI-enabled financial services that offer intuitive, effortless interfaces are more likely to inspire confidence among users who may be unfamiliar with algorithmic decision-making processes. This result aligns with the findings of Shin (2009), who reported that perceived ease of use was a significant determinant of trust in mobile payment services. It also resonates with the TAM proposition that PEOU influences both the adoption intention and the perceived usefulness of a technology (Davis, 1989; Venkatesh & Davis, 2000).

Perceived usefulness was the second-strongest predictor (standardised beta = 0.310), confirming that consumers who perceive tangible benefits from AI-enabled financial services, such as faster transactions, better recommendations, and improved financial outcomes, are more likely to trust these services. This is consistent with the extensive TAM literature demonstrating PU as a fundamental driver of technology adoption (Davis, 1989; Davis et al., 1989) and with Pavlou's (2003) finding that perceived usefulness of transaction mechanisms enhances trust in online environments.

Perceived security, while statistically significant, had the smallest standardised effect (standardised beta = 0.236) among the three predictors. This does not diminish its importance; rather, it suggests that in the current sample, the functional benefits (usefulness) and usability (ease of use) of AI-enabled financial services may play a somewhat larger role in shaping trust than security perceptions alone. This finding is broadly consistent with Luo et al. (2010), who found that while security perceptions were significant, other factors such as perceived usefulness also exerted strong influences on trust in mobile banking contexts. However, it is important to note that security concerns in AI-driven financial services are evolving rapidly, and future studies may yield different patterns as consumers become more aware of AI-specific risks such as algorithmic bias, data misuse, and adversarial attacks.

6. Conclusion

This study examined the factors influencing consumer trust in AI-enabled financial services in India, drawing on the Technology Acceptance Model and trust literature. The analysis of 300 respondents revealed that perceived usefulness, perceived security, and perceived ease of use are all significant positive predictors of consumer trust, collectively explaining 73% of the variance. Perceived ease of use was the strongest predictor, followed by perceived

usefulness and perceived security. These findings have several practical implications. Fintech providers should prioritise the development of intuitive, user-friendly interfaces that minimise the cognitive effort required to interact with AI-driven financial tools. Simultaneously, the functional value proposition of AI-enabled services should be clearly communicated to consumers, emphasising tangible benefits such as faster processing, personalised recommendations, and improved financial decision-making. Security measures, including data encryption, transparent privacy policies, and robust authentication mechanisms, should be prominently featured to reinforce consumer confidence.

The study has several limitations that must be acknowledged. First, the use of convenience sampling may limit the generalisability of the findings to the broader Indian population. Second, the cross-sectional design precludes causal inferences, as the data capture associations at a single point in time. Third, the model focuses on only three predictors of trust and does not account for other potentially influential variables such as social influence, regulatory awareness, or prior experience with AI systems. Fourth, self-reported measures may be subject to response bias. Future research could address these limitations by employing longitudinal designs, probability sampling, and extended models that incorporate additional constructs such as algorithmic transparency, regulatory trust, and cultural factors specific to the Indian context.

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