Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-7 |July: 2026

Original Researcher Article

Adoption Of Ai-Enabled Fintech Services: Consumer Trust, Security, And Behavioral Intentions

Pragya Bajpayi[1], Pushpendra Pal Singh[2], Sumit Kumar[3], Dr. Ravi Kant Pathak[4], Pratima Sharma[5]
[1] Noida Institute of Engineering & Technology, Greater Noida, Uttar Pradesh, India.
Email: pragya.bajpayi13@gmail.com
[2] GL Bajaj Institute of Management, Greater Noida, Uttar Pradesh, India.
Email: pps2907@gmail.com
[3] Noida Institute of Engineering & Technology, Greater Noida, Uttar Pradesh, India.
Email: sumitkumar9084@gmail.com
[4] Sharda University, Agra, Uttar Pradesh, India.
Email: drrkpathak44@gmail.com
[5] Sharda University, Agra, Uttar Pradesh, India.
Email: pratima9sharma@gmail.com
Corresponding Author:
Pragya Bajpayi
Email: pragya.bajpayi13@gmail.com

ABSTRACT

Artificial Intelligence (AI) has revolutionized the field of financial technology (FinTech), reshaping how financial services are delivered to consumers. While AI-powered FinTech presents significant technological opportunities, consumer adoption rates are still not high enough, largely because of ongoing trust and security issues. This research builds and tests an integrated theoretical model to understand the relationship among AI system trust, perceived financial data security, and overall behavioral intention towards AI-powered FinTech services. Based on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Trust Transfer Theory, we propose a multi-dimensional model that includes cognitive trust, affective trust, system security assurance, data privacy protection and perceived risk as antecedents of adoption intentions. A cross-sectional survey was carried out on a structured questionnaire with 487 urban consumers in three metros of India (New Delhi, Mumbai and Bangalore). Structural equation modeling (SEM) using partial least squares (PLS) was used for hypothesis testing. The results show that cognitive trust ($\beta = 0.312, p < 0.001$) and perceived security assurance ($\beta = 0.278$, $p < 0.001$) have the most significant direct impacts on the behavioral intentions, whereas affective trust mainly acts as a mediator variable. The results show that perceived risk has a significant negative moderating effect on the trust-intention relationship ($\beta = -0.156$, $p < 0.01$). Moreover, the study shows that there are significant demographic differences; younger consumers (18-30-years-old) had higher risk tolerances and greater intentions of adoption than older consumers ($\beta = 0.189$, $p < 0.05$). The study advances the theory of consumer behavior by adding a dual cognitive-affective dimension to the trust construct in the context of FinTech, and offers valuable implications for practitioners aiming to boost consumer trust in AI-based financial services..

Keywords: AI-Enabled FinTech, Consumer Trust, Security Perception, Behavioral Intention, Technology Adoption, Financial Services, PLS-SEM

INTRODUCTION:

AI and financial services are converging, marking a paradigm shift in financial services consumer behavior. AI-powered FinTech can range from algorithmic wealth management, predictive credit scoring, conversational banking interfaces, to real-time fraud detection systems (Arner et al., 2020). The global AI in FinTech market is expected to grow at a compound annual growth rate (CAGR) of more than 31%, reaching USD 31.7 billion by 2028 (Statista, 2024). The growth curve is exponential, highlighting the transformative role AI can play in changing consumer financial habits.

While AI-powered FinTech solutions can offer state-of-the-art technology and operational efficiency, consumer uptake has not matched this development. There remains a persistent gap between adoption and certain groups of people who are less digitally-literate and more risk-averse (Haddad & Hornuf, 2019). However, this hesitation with AI technologies in finance is not just about newness, but also about the psychological perception of trust, security, and the intangibility of the decision-making process of such technologies (Mikalef & Pateli, 2017).

In the realm of financial service providers and AI, trust is a complex construct going beyond the classic interpersonal trust models. Consumers need to have trust in the technology itself (system trust), the financial institution that implements it (institutional trust), and the algorithm that will produce the financial outcomes (algorithmic trust) (Lankton et al., 2014). This trust equation is further complicated by the security aspect, as consumers need to balance the ease of use of AI-powered financial services with the risk their sensitive financial data may face from breaches, unauthorized access, and the potential for algorithmic exploitation.

The existing body of literature on technology adoption is extensive and well established in explaining consumer acceptance of traditional digital services but less helpful in providing guidance on the novel psychological characteristics of the financial service adoption process for AI. Davis' (1989) original Technology Acceptance Model (TAM) has been widely used to account for technology adoption in a variety of settings. Despite this, it doesn't extend to the application of AI in FinTech due to its inadequate coverage of constructs of trust and security, which are vital in financial applications (Venkatesh & Davis, 2000). Likewise, the Unified Theory of Acceptance and Use of Technology (UTAUT) takes a holistic approach that encompasses the constructs of performance expectancy, effort expectancy, social influence and facilitating conditions but does not sufficiently consider the opacity of algorithms and security concerns related to data, which are specific to AI applications in finance (Venkatesh et al., 2003).

In this study, one of the theoretical gaps is addressed by proposing an integrated framework based on the TAM, UTAUT, and Trust Transfer Theory to investigate the determinants of consumer behavioural intentions regarding AI utilization in FinTech services. Specifically, this research aims to: (1) separate the cognitive and affective components of consumer trust and assess the differential impacts of these components on behavioral intention; (2) examine the mediating and moderating relationships of perceived security and perceived risk in the relationship between trust and behavioral intention; and (3) uncover the moderating and mediating relationships of consumer demography and psychography with the relationship between trust and behavioral intention.

The rest of this paper is organized as follows. In section 2, a thorough review of theory is presented, and the research hypotheses are developed. The research methodology, such as sampling, construction of instruments, and data analysis, are described in Section 3. Empirical results are presented in Section 4, with some discussion in Section 5. The paper culminates in theoretical contributions, managerial implications, limitations and directions for further research.

2. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

2.1 Theoretical Foundations

2.1.1 Technology Acceptance Model (TAM)

Davis (1989) developed the Technology Acceptance Model (TAM), which suggests that perceived usefulness and perceived ease of use are the main factors in determining technology adoption intent. The attitude of perceived usefulness is defined as how much the individual thinks using the system would improve his/her job performance or personal outcomes, and the attitude of perceived ease of use is defined as how much the individual thinks using the system would be free of effort. TAM has been tested in many technological settings, such as e-banking, mobile payments and online financial services (Agarwal & Prasad, 1999; Pikkarainen et al., 2004).

In the case of AI-powered FinTech, perceived usefulness includes functional advantages of AI-based personalization, predictive analysis, and automated financial decision making. The model's elegance in terms of its methodology, however, has been condemned due to its narrow explanatory power in contexts where trust and security are salient (Gefen et al., 2003). The impact of system failures or data breaches can be costly and irreversible in financial services, particularly.

2.1.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) compiled eight most prevalent technology acceptance models to create UTAUT, which consists of four main technology acceptance factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy is similar to perceived usefulness in TAM, which is defined as the perceived usefulness of the technology for improving task performance. Effort expectancy refers to the ease of use, and social influence refers to the extent to which socially significant people think a consumer should use the technology. Facilitating conditions are the consumer's perceived support of the technology from an organizational and technical perspective.

Additional variables which moderate the core relationships are included in UTAUT: they are gender, age, experience, and voluntariness of use. Although UTAUT is more extensive than TAM, it does not include constructs of trust and security that are integral in the process of financial service adoption (Oliveira et al., 2016), which are crucial for the application of UTAUT to AI-enabled FinTech.

2.1.3 Trust Transfer Theory

According to TTT (Stewart, 2003; Lee et al., 2006), trust that a person has built in one context can be carried over to another context that is related to it. In the FinTech sector consumers could be moving trust from traditional financial institutions to AI-based platforms when the identity of the financial institution is disclosed. But, trust transfer does not happen on its own; it depends upon a perceived similarity between the trusted entity and the new technology, and the lack of any conflicting information that would detract from the trust transfer process (Kim et al., 2009).

The theory is especially applicable to the realm of AI-powered FinTech, where consumers might not have firsthand experience with algorithm-based systems but have well-known relationships with conventional banking or financial institutions. A grasp of the context surrounding trust transfer can guide approaches to speeding up consumer adoption of AI-powered financial services.

2.2 Conceptual Model Development

Based on the theoretical background provided above, this study provides an integrated conceptual model, which takes into account the antecedents and consequences of consumers' behavioral intentions towards AI-enabled FinTech services. According to the model, the four factors, such as cognitive trust, affective trust, perceived usefulness, and perceived security assurance, directly affect behavioral intentions. In addition, it is hypothesized that perceived risk will moderate the relationships between trust constructs and behavioral intentions, and demographic variables (age, gender, education, income) will moderate the overall model.

2.3 Hypothesis Development

Table 1: Summary of Research Hypotheses

Hypothesis	Statement	Expected Direction
H1	Cognitive trust has a positive and significant effect on consumers' behavioral intentions to adopt AI-enabled FinTech services.	Positive
H2	Affective trust has a positive and significant effect on consumers' behavioral intentions to adopt AI-enabled FinTech services.	Positive
H3	Cognitive trust mediates the relationship between affective trust and behavioral intentions toward AI-enabled FinTech services.	Positive (Indirect)
H4	Perceived security assurance has a positive and significant effect on consumers' behavioral intentions to adopt AI-enabled FinTech services.	Positive
H5	Perceived usefulness has a positive and significant effect on consumers' behavioral intentions to adopt AI-enabled FinTech services.	Positive
H6	Perceived risk negatively moderates the relationship between cognitive trust and behavioral intentions.	Negative
H7	Perceived risk negatively moderates the relationship between affective trust and behavioral intentions.	Negative
H8	Perceived risk negatively moderates the relationship between perceived usefulness and behavioral intentions.	Negative
H9	Age negatively moderates the relationship between perceived security assurance and behavioral intentions.	Negative
H10	Gender moderates the relationship between affective trust and behavioral intentions.	Moderating

2.3.1 Cognitive Trust and Behavioral Intention

Cognitive trust is the rational, knowledge-based evaluation of the competence, reliability and integrity of an AI-powered fintech platform. It is based on consumers' assessment of the technical features of the platform, the accuracy of its algorithmic results, and the stability of its results over time (McKnight et al., 2002). Cognitive trust in AI-powered financial services emerges as a result of consumers' understanding of the platform's performance, readability of algorithms, and customer support systems.

Consumers' cognitive trust of an AI powered FinTech platform fosters their confidence in the performance of the platform, the security of their financial information, and the functional benefits they anticipate. This confidence lowers psychological uncertainty about the adoption of an unfamiliar technology and heightens the chances of behavioral intention to be formed (Gefen et al. 2003). The positive association between cognitive trust and adoption intentions has been supported by empirical studies on previous adoption of e-banking and mobile payments (Kim & Prabhakar, 2004; Zhou, 2012).

2.3.2 Affective Trust and Behavioral Intention

Affective trust, unlike cognitive trust, is driven by emotional attachments and emotions of security and concern for the consumer's welfare (Lewis & Weigert, 1985). It's built one step at a time, with positive interactions that foster a sense of comfort, familiarity and emotional security with the technology and the organization behind it. For AI powered FinTech, affective trust can be developed by tailoring the messages, having chatbots that are empathetic, and feeling that the platform is truly concerned with the consumer's financial position.

Financial contexts present an interesting case of affective trust as financial decisions are emotionally charged. When consumers experience affective trust in an AI-enabled platform, they are likely to have positive attitudes toward platform adoption, in which the emotional attachment decreases the sense of risk and uncertainty and promotes the feeling of safety when engaging with the platform (Rousseau et al., 1998). Previous studies have confirmed that affective trust positively affects the intention to use online banking and digital financial services (Kim et al., 2009; Yousafzai et al., 2010).

2.3.3 Mediating Role of Cognitive Trust

The impact of affective trust on behavioral intentions might be mediated partially by cognitive trust. Once consumers form an emotional bond with an AI-powered FinTech app, they may also have more positive thoughts about the platform's functionality and reliability. Affective trust has the potential to cause a positive affect which can bias the processing of information, resulting in more positive evaluations of the platform's competence and integrity (Forgas, 1995).

The affect-as-information theory (Schwarz & Clore, 1983) implies that meditative effects on judgment and decision-making are mediated through emotional inputs. The positive emotions related to affective trust can help promote cognitive trust, which can lead to behavioral intentions in the area of AI-supported FinTech. Testing this mediation effect gives us insight into the psychological mechanisms which convert emotion into adoption behavior.

2.3.4 Perceived Security Assurance and Behavioral Intention

Perceived security assurance is a metric that captures consumers' subjective evaluation of the security controls that AI-powered FinTech platforms have put in place to effectively protect their financial and transactional data, as well as their personal information from unauthorized access, theft, or misuse. It involves confidence in the effectiveness of the encryption technologies, authentication methods, fraud detection systems, and regulatory standards (Kim et al., 2008).

Security issues are a major impediment to technology adoption in the financial services sector. When consumers feel that the AI-powered FinTech app offers strong security assurance, they are more inclined to make positive behavioral intentions, seeing a lower psychological cost in adopting the platform (Mukherjee & Nath, 2003). In the case of AI, the opacity of the algorithmic process can further contribute to concerns around data exploitation and the unauthorized use of algorithms in decision-making processes.

2.3.5 Perceived Usefulness and Behavioral Intention

Embracing AI FinTech services significantly boosts consumers' belief in the tools' ability to improve their financial management results, such as better investment returns, more efficient transaction processing, personalized financial advice, and real-time financial insights (Davis, 1989). In the case of financing, perceived usefulness is related to the functionality advantages that AI can offer, for example, predictive analysis, automatic portfolio rebalancing, and clever categorization of costs.

When consumers feel the AI-powered FinTech offering will have value, they are more likely to put in the mental and emotional effort to take action towards adoption, even if there are obstacles, such as understanding the learning curve, overcoming trust issues, or addressing security concerns. A positive correlation between perceived usefulness and behavioural intentions has been shown in numerous technology adoption studies (Venkatesh & Davis, 2000, Pikkarainen et al., 2004).

2.3.6 Moderating Role of Perceived Risk

Perceived risk is the consumer's personal appraisal of the negative outcomes that may arise with the use of AI-powered FinTech service, such as financial loss, data breaches, identity theft, algorithmic error, and loss of control over financial decisions (Bauer, 1960; Featherman & Pavlou, 2003). Financial risk, performance risk, privacy risk, security risk and psychological risk are all aspects of perceived risk in the field of financial services.

The moderating effect of perceived risk is based on risk theory which suggests that positive evaluations (e.g., trust and perceived usefulness) have less influence when the perceived risk is high (Cox, 1967). Even if consumers have high levels of trust in a platform's competence, their perception of high risk can be enough to not provide them with intentions to adopt the platform even if the advantages are high. On the other hand, in low perceived risk conditions, trust and perceived usefulness are likely to lead to behavioral intentions.

2.3.7 Demographic Moderators

Relationships within the suggested model can be different in different demographic segments. In particular, age has been shown to be a key moderator of technology adoption; younger consumers tend to have higher technology self-efficacy, lower risk aversion and more experience with digital platforms (Morris & Venkatesh, 2000). Gender differences in technology adoption have also been found, with women being more risk averse and less technology self-efficacy than men (Venkatesh & Morris, 2000). The value perceived from the AI-powered FinTech services could differ, especially based on education and income; higher education and higher income may make consumers more likely to appreciate advanced financial analytics and wealth management capabilities.

3. RESEARCH METHODOLOGY

3.1 Research Design

The research design used in this study is quantitative, which is basically a cross-sectional survey to empirically test the theoretical framework. The cross-sectional approach was chosen because it was efficient in capturing the consumer perception at a certain point in time, which is suitable for the structural relationships between the latent constructs (Creswell & Creswell, 2018). The research design is reflective and formative with reflective measures measuring the latent constructs and formative measures measuring the demographic moderators.

3.2 Sampling and Data Collection

3.2.1 Target Population and Sampling Frame

This study focuses on urban consumers in India with awareness of AI-driven FinTech products but could be new or not new to the platforms. India was chosen as the research setting because of its strong mobile penetration, a rapidly growing FinTech ecosystem, and the government's efforts to promote digital financial services with various initiatives like Digital India and Unified Payments Interface (UPI). The urban consumers segment was chosen as the target segment, since it is the main market for AI-based FinTech services, and is sufficiently digitally literate to complete the survey instrument.

A multi-stage stratified sampling method was used for framing the sample. Three metropolitan cities namely, National Capital Region (New Delhi), Mumbai and Bangalore were purposefully selected as representative cities of urban India in the first stage to cover a range of economic, cultural and technological contexts. Geographically, new Delhi is a political and administrative city with a diverse consumer base, Mumbai is a financial hub that has high financial literacy amongst its consumers, and Bangalore is a technology city with early technology adoption tendancies amongst consumers.

3.2.2 Sample Size Determination

The sample size determination method was based on the guidelines proposed by Hair et al. (2017) for partial least squares structural equation modeling (PLS-SEM). A guideline is to take at least 10 times the maximum number of formative indicators for each construct in the measurement model or 10 times the maximum number of structural paths that go to a single construct in the structural model. The proposed model has a maximum of 5 structural paths that go to the behavioral intentions, which indicates a minimum sample size of 50. To provide sufficient statistical power and to make up for the fact that some of the samples might not be available, a goal of 500 samples was set.

3.2.3 Data Collection Procedure

The data collection techniques used were online survey and offline survey. An online survey was administered through Qualtrics to panel members recruited through a professional market research firm with quotas for age, gender and income level to provide a sample that is representative. The research assistants trained in the three target cities conducted offline surveys in shopping malls, business centers, and universities. The respondents were asked the following qualifying question to check their understanding of AI-powered FinTech services, and if they did not demonstrate basic understanding, they were not included in the study.

620 questionnaires were sent out and 512 were returned, giving an initial response rate of 82.6%. Out of 487 completed questionnaires, 487 questionnaires were then included in the analysis after discarding responses with incomplete information, straight lines and responses with a high degree of missing data, giving a usable response rate of 78.5%. The sample size of 487 is larger than the required sample size, and is appropriate for conducting PLS-SEM analysis.

Table 2: Sample Demographics (N = 487)

Variable	Category	Frequency	Percentage
Gender	Male	255	52.4%
	Female	232	47.6%
Age	18-30 years	188	38.6%
	31-50 years	202	41.5%
	51+ years	97	19.9%

Education	High School	49	10.1%
	Bachelor's Degree	220	45.2%
	Postgraduate	158	32.4%
	Doctoral/Professional	60	12.3%
Monthly Household Income	Below INR 30,000	78	16.0%
	INR 30,000-50,000	125	25.7%
	INR 50,000-1,00,000	168	34.5%
	Above INR 1,00,000	116	23.8%
Prior AI-FinTech Experience	No Experience	283	58.1%
	Limited Use	124	25.5%
	Regular Use	80	16.4%

3.3 Measurement Instrument

3.3.1 Construct Operationalization

The measurement instrument is designed on the basis of the existing scales in the literature, adapted to the context of the FinTech enabled AI. The seven-point Likert scale was used for all items, and a categorical scale was used for demographic variables.

The cognitive trust (CT) scale was assessed by a 5 item scale adapted from McKnight et al. (2002) and Gefen et al. (2003). The items reflected consumers' rational evaluations of the AI-enabled FinTech platform's capabilities, reliability, predictability and integrity. The statements that are measured range from 'I believe this AI enabled FinTech platform is competent in handling financial transactions' to 'I trust the algorithmic decision-making processes used by this platform.'

Affective Trust (AT) was assessed with a four item scale modified from Lewis and Weigert (1985) and Johnson and Grayson (2005). The items reflected the emotional aspects of trust such as security, comfort and care. Some examples of sample items are ‘I feel emotionally secure when using this AI-enabled FinTech platform’ and ‘I feel that this platform actually cares about my financial well-being'.'

Perceived Security Assurance (PSA) was assessed through the six item scale taken from Kim et al. (2008) and Flavian and Guinaliu (2006). The product reflected the consumers' attitudes towards data protection, transaction security, the security of authentication and regulatory compliance. Some examples of these statements are: 'I believe my financial data is adequate protection on this platform' and 'I am confident that unauthorized access to my account will be prevented.'

The Perceived Usefulness (PU) scale was based on Davis (1989) and Venkatesh et al., (2003) and contained five items. The captured items highlighted the practical advantages of AI-powered FinTech applications, such as increased efficiency, insights into the financial landscape, and assistance in decision-making. Some of the sample items are 'Using this AI-enabled FinTech platform improves my financial management efficiency' and ‘This platform gives me financial insights which I did not have.'

The perceived risk (PR) was assessed with a 6-item scale adapted from Featherman and Pavlou (2003) and Kim et al. (2008). The items reflected the multi-dimensionality of the risk associated with the use of AI in financial services, covering financial risk, privacy risk, performance risk, and psychological risk. Some examples of sample items are: 'I am concerned about the possibility of financial loss because of algorithmic error' and 'I worry that my personal financial information could be misused.'

Behavioral Intention (BI) was assessed with a four item scale adapted from Venkatesh et al. (2003) and Taylor and Todd (1995). The items captured consumers' willingness to use, recommend, and continue using AI enabled FinTech services. Questions are such as ‘I plan on using this AI-powered financial technology platform for my financial transactions' and ‘I would recommend this financial technology platform to my friends and family.'

3.3.2 Control Variables

The following control variables were added to the model to adjust for the possible confounding effects: age, gender, and race. AI-based FinTech services experience was assessed by asking one question with the frequency of use scale ranging from 1 = Never to 5 = Very Frequently. The instrument to measure technology self-efficacy was adopted from Compeau and Higgins (1995) which comprised three items. Financial literacy was assessed using Lusardi and Mitchell's (2011) five-item scale.

3.4 Pilot Testing and Instrument Refinement

A pilot study was done with 50 respondents before the main study to measure the clarity, reliability, and validity of the measurement instrument. Ten people were interviewed using cognitive interviews to help identify confusing or unclear items. On the basis of feedback from the pilots, some minor wording changes were made to three items to improve clarity. The Cronbach alpha value for all the constructs was found to be above the recommended 0.70, which suggests that the constructs were reliable in terms of internal consistency (Nunnally, 1978).

3.5 Data Analysis Techniques

3.5.1 Partial Least Squares Structural Equation Modeling (PLS-SEM)

Since the PLS-SEM was more suitable for the prediction of the outcome variables, more capable of handling reflective and formative measurement models, and more robust in dealing with non-normal data distribution, it was chosen as the main method for analyzing the data (Hair et al., 2017). SmartPLS 4.0 software was used for model estimation. The analysis was executed in two phases: (1) assessment of the measurement model (reliability, convergent and discriminant validity) and (2) assessment of the structural model (path coefficients, coefficient of determination (R-squared), effect size (f-squared) and predictive relevance (Q-squared)).

3.5.2 Measurement Model Assessment

The composite reliability (CR) and Cronbach's alpha were used to test the internal consistency reliability. Average variance extracted (AVE) was used to measure convergent validity and the value of 0.50 was considered as a criterion suggested by Fornell and Larcker (1981). Discriminant validity was checked through the Fornell-Larcker criterion, the cross-loadings matrix and the heterotrait-monotrait (HTMT) ratio of correlations below the value of 0.85 is considered acceptable discriminant validity (Henseler et al., 2015).

3.5.3 Structural Model Assessment

Bootstrapping (with 5000 resamples) was used to estimate the standard error of the structural model and the t-statistics for testing hypotheses. Path significance was tested at the 0.05, 0.01 and 0.001 levels. The endogenous constructs were scored as having weak, moderate, and substantial explanatory power when R-squared was found to be equal to 0.25, 0.50, and 0.75, respectively (Cohen, 1988). The practical importance of each path was determined using effect sizes (f-squared) of 0.02, 0.15, and 0.35, indicating the presence of a small, moderate, and large effect, respectively. Stone-Geisser's Q-squared was calculated for the blindfolding procedure to determine predictive relevance (where Q-squared > 0).

3.5.4 Mediation and Moderation Analysis

The product of coefficients approach and bootstrapped confidence intervals (Preacher & Hayes, 2008) was used to test mediation effects. Indirect effects were assessed with the percentile bootstrap method with 5000 resamples. The moderation effects were tested by introducing interaction terms in the structural model and testing the significance of the interaction path coefficient. The Johnson-Neyman technique was used to identify the regions of significance for significant moderation effects.

3.5.5 Multi-Group Analysis

To test the demographic moderation hypotheses (H9 and H10), multi-group analysis (MGA) was performed. The sample was divided into age groups (18-30, 31-50 and 51+ years) and gender (male and female). Measurement invariance of the composite models (MICOM) procedure was performed to assess measurement invariance and permutation tests were performed to compare the path coefficients between groups.

4. EMPIRICAL RESULTS

4.1 Sample Characteristics

Table 2 shows the demographic characteristic of the respondents who completed the questionnaire (N = 487). There was a reasonably balanced sample with respect to gender, 52.4% male and 47.6% female. The age distribution was biased towards younger consumers, with 38.6% aged between 18 and 30 years, 41.5% aged between 31 and 50 years, and 19.9% aged 51 years and over. This distribution aligns with the profile of users most likely to interact with AI-powered FinTech solutions, which is urban consumers. Most respondents had a Bachelor's degree (45.2%) or a post-graduate degree (32.4%) and 58.3% had an income of INR 50,000 and above per month in their household. Around 42% of the respondents had a previous experience with AI-powered FinTech platforms, but 58% were aware of the technology without direct experience.

4.2 Measurement Model Assessment

4.2.1 Reliability and Convergent Validity

The reliability and convergent validity statistics are shown in Table 3 for all reflective constructs. All the Cronbach alpha coefficients were between 0.824 and 0.912, which is higher than the value of 0.70. The internal consistency reliability of composite reliability scores were 0.876 to 0.932 which exceeded the 0.70 criterion. The results showed that the mean values of average variance extracted (AVE) were between 0.589 and 0.734, all of which were greater than 0.50, indicating acceptable convergent validity. All indicators had factor loadings between 0.712 and 0.923 with most being greater than 0.80, and thus represent their constructs sufficiently.

Table 3: Reliability and Convergent Validity

Construct	Items	Cronbach's alpha	CR	AVE
Cognitive Trust (CT)	5	0.891	0.918	0.691
Affective Trust (AT)	4	0.856	0.903	0.701

Perceived Security (PSA)	6	0.912	0.932	0.621
Perceived Usefulness (PU)	5	0.867	0.904	0.656
Perceived Risk (PR)	6	0.889	0.916	0.612
Behavioral Intention (BI)	4	0.824	0.876	0.589

4.2.2 Discriminant Validity

Three complementary approaches were used to evaluate discriminant validity. According to the Fornell-Larcker criterion, the square root of the AVE of each construct should be higher than the correlations of all other constructs. All constructs met this criterion. A cross-loadings matrix showed that each indicator had its highest loading on the theoretically expected construct and no cross-loadings was higher than the construct that it loaded on. Henseler et al. (2015) recommended that the heterotrait-monotrait (HTMT) ratio of correlations be calculated, and all were below the conservative threshold of 0.85. The highest HTMT value among the subscales was found between the cognitive trust and perceived security assurance, and was 0.812, which is below the threshold and shows acceptable discriminant validity.

Table 4: Discriminant Validity (HTMT Ratios)

	CT	AT	PSA	PU	PR	BI
CT	—					
AT	0.723	—				
PSA	0.812	0.678	—			
PU	0.698	0.612	0.745	—		
PR	0.456	0.389	0.523	0.412	—	
BI	0.756	0.689	0.798	0.734	0.567	—

4.3 Structural Model Assessment

4.3.1 Collinearity Assessment

Collinearity of the predictor constructs was checked by variance inflation factors (VIF) before applying the structural model. The highest VIF value was 2.87, which was observed for cognitive trust and was still well below the conservative value of 5.0 (Hair et al., 2017). Multicollinearity does not pose a problem in the structural model in this case.

4.3.2 Path Coefficients and Hypothesis Testing

Table 5 shows the path coefficients, SE, t-statistics, and significance levels of the hypothesized relationships.

Table 5: Structural Model Results (Note: *p < 0.05, **p < 0.01, ***p < 0.001)

Hypothesis	Path	Beta	SE	t-value	Decision
H1	CT → BI	0.312	0.058	5.379	Supported***
H2	AT → BI	0.156	0.062	2.516	Supported**
H4	PSA → BI	0.278	0.051	5.451	Supported***
H5	PU → BI	0.201	0.055	3.655	Supported***

The model had a significant amount of variance explained (R-squared = 0.674). Cognitive trust emerged as the strongest predictor of behavioral intentions (beta = 0.312, p < 0.001), followed by perceived security assurance (beta = 0.278, p < 0.001), perceived usefulness (beta = 0.201, p < 0.001), and affective trust (beta = 0.156, p < 0.01). H1, H2, H4 and H5 were all supported by all four direct effect hypotheses.

4.3.3 Mediation Analysis

To test the mediation hypothesis (H3), an indirect effect of affective trust on behavioral intentions via cognitive trust was examined. The total effect of affective trust on behavioral intentions was 0.289 ($p < 0.001$), comprising a direct effect of 0.156 ($p < 0.01$) and an indirect effect through cognitive trust of 0.133 ($p < 0.001$, 95% CI: [0.078, 0.198]). The ratio of the indirect effect to total effect was 0.460, which means that about 46% of the total effect of affective trust to behavioral intentions is mediated by cognitive trust. This result suggests the existence of complementary partial mediation, and that the affective trust-behavioral intention relationship is mediated strongly but not entirely by cognitive trust.

4.3.4 Moderation Analysis

The results of moderation analysis are presented in Table 6. The relationships between CT and BI (beta = -0.156; $p < 0.01$) and between PU and BI (beta = -0.098; $p < 0.05$) were significantly moderated by PR. The relationship between perceived risk and the affective trust-behavioral intention was not statistically significant, however (beta = -0.042, $p = 0.312$). Therefore, H6 and H8 were confirmed and H7 was not confirmed.

Table 6: Moderation Effects

Hypothesis	Interaction	Beta	SE	t-value	Decision
H6	CT x PR → BI	-0.156	0.048	3.250	Supported**
H7	AT x PR → BI	-0.042	0.043	0.977	Not Supported
H8	PU x PR → BI	-0.098	0.045	2.178	Supported*

Results from the Johnson-Neyman analysis of the significant moderation effects showed that the positive relationship between cognitive trust and behavioral intentions no longer holds when perceived risk was above the 5.2 on the seven-point scale. The positive relationship between perceived usefulness and behavioral intentions also becomes weaker and non-significant when the perceived risk is more than 5.8. The results suggest that the positive influence of trust and usefulness on adoption intentions can be offset by high perceived risk.

4.3.5 Multi-Group Analysis

Multi-group analysis was done to verify the demographic moderation hypotheses (H9 and H10). The sample was split into three age groups (18-30, 31-50, 51+) and two gender groups (male and female). Configural and compositional invariance was confirmed through the MICOM procedure, for which all the p-values for the permutations were > 0.05.

Table 7: Multi-Group Analysis - Age Moderation

Path	18-30 (Beta)	31-50 (Beta)	51+ (Beta)	Delta p-value
CT → BI	0.289	0.318	0.334	0.456
AT → BI	0.178	0.142	0.134	0.678
PSA → BI	0.198	0.267	0.342	0.012*
PU → BI	0.234	0.187	0.156	0.234

The perceived security assurance had a significantly greater impact on the behavioral intentions of older consumers (51+ years: beta = 0.342) than the younger consumers (18-30 years: beta = 0.198; permutation $p = 0.012$). This result aligns with H9, showing that security assurance is more important to the adoption process for older consumers who may think that they are at higher baseline risk.

Table 8: Multi-Group Analysis - Gender Moderation

Path	Male (Beta)	Female (Beta)	Delta p-value
CT → BI	0.334	0.289	0.312
AT → BI	0.112	0.198	0.034*
PSA → BI	0.267	0.289	0.567
PU → BI	0.198	0.203	0.891

The influence of affective trust on behavioral intention was statistically significant in female consumers (beta = 0.198), but not in male consumers (beta = 0.112; permutation p = 0.034). This is finding supports H10, whereby emotional relationships and sense of security are more important in females' adoption decisions.

4.3.6 Effect Sizes and Predictive Relevance

The effect sizes (fsquared) of the significant paths were cognitive trust (0.142: medium), perceived security assurance (0.138: medium), perceived usefulness (0.089: small to medium), and affective trust (0.042: small). Stone-Geisser Q-squared for behavioral intentions was 0.412, which was well above zero, suggesting good predictive relevance of the model.

4.4 Robustness Checks

Various robustness checks were performed to check the stability of the result. First, the analysis was repeated with covariance-based SEM (CB-SEM), AMOS 26.0, and the results were qualitatively similar to the results of PLS-SEM. Second, a common method bias test was performed using the full collinearity VIF approach, with all inner VIF values < 3.3, suggesting that common method bias is not a major concern (Kock, 2015). Third, the analysis was repeated in the presence of the control variables (prior experience, technology self-efficacy, financial literacy) and the direction and significance of the hypothesized relationships did not change.

5. DISCUSSION

5.1 Key Findings and Theoretical Implications

This research has several significant contributions to the understanding of the adoption of AI-powered FinTechs by consumers. The results indicate that perceived security assurance is a strong second direct predictor of behavioral intentions following the cognitive trust. This finding highlights the critical role of rational, knowledge-driven evaluations in consumers' adoption decisions for AI-powered financial platforms. What wins consumers over seems to be their trust in the reliability and trustworthiness of the algorithms and the integrity of the institution more than emotional bonds or even the utility of the platform.

The level of affective trust (beta = 0.156) is significant but relatively small, indicating that emotions have a smaller impact in the FinTech context compared to their cognitive assessment. It is contrary to some previous studies in online retailing and social media settings in which affective trust has proved to have a more pronounced influence (Johnson & Grayson, 2005). A possible explanation for this divergence is that financial decisions are more likely to involve deliberative, analytical processing, which uses more complex, slow information processing, than heuristic, affect-driven processing, which relies on simpler, more rapid information processing (Chaiken & Trope, 1999).

The results of mediation analysis indicate that cognitive trust is an important mediator between affective trust and behavioral intentions. Around 46% of the overall impact of affective trust comes through cognitive trust, indicating that emotional relationships allow for more positive rational evaluations of platform capabilities. This study contributes to the Trust Transfer Theory by showing that affective trust can facilitate cognitive trust building, in turn impacting on adoption intentions. The theoretical implication is that trust building strategies need to be directed at both the cognitive and affective aspects, but not independently of each other.

Perceived risk effects as a moderator for the relationship between cognitive trust and behavioral intention (H6 supported) as well as between perceived usefulness and behavioral intention (H8 supported) illustrates the boundary conditions of adoption drivers. Consumers' sense of high risk can undermine even high cognitive trust and perceived usefulness to create adoption intentions. The finding aligns with risk theory and extends it to the AI-supported FinTech context as it shows that risk set up as a ceiling on the conversion of positive evaluations into behavioral intentions.

The lack of a moderating effect of perceived risk on the affective trust-behavioral intention relationship is interesting (H7 did not receive support). It may be because affective trust is assumed to be a psychological process of another kind operating on a different pathway which is less vulnerable to risk perception. Emotional bonds can create a type of psychological commitment that is more difficult to be disrupted by risk perceptions, as opposed to the cognitive bond of trust and perceived usefulness, which can be The demographic moderation findings show interesting dynamics by segment. The greater security assurance among older consumers indicates that older consumers' perceptions of vulnerability make security a greater factor in their adoption decisions. This result confirmed the socioemotional selectivity theory that suggests that older adults focus on social and emotional ends and make decisions based on risk avoidance (Carstensen & Mikels, 2005). The enhanced role of affective trust among female consumers is found to be consistent with previous studies that have found that women rely more on emotional cues and relational factors when forming trust (Buchan et al., 2008).

5.2 Managerial Implications

The study's results provide actionable insights for FinTech companies, traditional financial institutions, and regulators to speed up the adoption of consumers in AI-powered financial services.

First, the idea of cognitive trust implies that FinTech platforms must communicate their technology, algorithmic process and track record of performance in a clear manner. Giving consumers the information they need on how AI algorithms work, the data they are using, and how decisions are being made can improve their cognitive trust. Algorithmic performance metrics and transparent reporting of such metrics provide trust signals that can help ease consumer uncertainty and can be verified by third-party certifications and independent audits.

Secondly, the importance of perceived security assurance suggests that platforms need to invest in easily identifiable and reliable security protocols. This involves the implementation of strong technical safeguards as well as effective communication of these safeguards to consumers. Clarity in consumer terms of security certificates, regulatory compliance disclosures and clear privacy policies should be prominently displayed and explained. The age-specific results indicating that security assurance is especially crucial to older consumers indicate that age-specific security communication strategies could be justified.

Third, based on the mediation effect of cognitive trust, it is suggested that projects aimed at building affective trust should also focus on improving cognitive evaluations. Positive emotions can be cultivated through personalized customer service, empathetic interactions with chatbots, and community-building efforts, while also showcasing their ability and reliability. A chatbot that can build affective trust and displays a high level of financial knowledge will build affective and cognitive trust simultaneously.

Finally, the moderating effect of perceived risk indicates that risk reduction should be considered as a key part of the adoption strategies. Perceived risk can be lowered and the effectiveness of trust-building and usefulness-enhancing efforts can be improved by money-back guarantees, insurance for algorithmic error, and transparent dispute resolution. Risk thresholds (perceived risk > 5.2 cancels out cognitive trust effects; perceived risk > 5.8 cancels out usefulness effects) offer clear targets for interventions to reduce risk.

Fifth, the results of the multi-group analysis indicate that different groups may require different adoption strategies, or that a one-size-fits-all approach might not be ideal. Older consumers will be more receptive to security-focused messaging while female consumers will be more receptive to relationship-oriented, emotionally resonant messaging. The younger consumers are reacting better to perceived usefulness could make it more appropriate to target them using feature-rich, innovation-focused value propositions.

5.3 Limitations and Future Research Directions

The present study has a number of restrictions which need to be recognised and taken into consideration in further research. The design is cross-sectional, which means that a cause cannot be inferred. The model assumes direction of the relationships, but there is a risk of reverse causality or mutual influence. Causal claims could be strengthened with longitudinal studies of consumer perceptions and behaviours over time.

Second, the study was done in the Indian context, and the results might not be applicable in other cultural and economic contexts. India has distinct features such as high mobile penetration, government-led digital financial inclusion policies and dynamic regulatory landscape for FinTech. Replication studies in developed markets (such as the United States, the EU) and other emerging markets (such as Southeast Asia and Africa) would increase the external validity of the results.

Third, the study was limited to urban consumers, who may have distinct characteristics than rural consumers in digital skills, financial sophistication, and access to technology. Future studies should determine if the proposed model is applicable to rural and semi-urban communities where other obstacles to FinTech adoption can exist, such as infrastructure and digital skills.

Fourth, the study did not analyse specific types of FinTech services that are powered by AI (e.g., robo-advisors, AI-powered lending platforms, conversational banking). Trust and security relations can be different for various types of services. Future studies could use a comparative design to investigate if the relative influences of cognitive trust, affective trust, and security assurance varies by service type.

Fifth, the study did not use actual adoption behaviors as outcome variables, but instead behavioral intentions. Although intentions are good predictors of behaviour, the literature on consumer behaviour shows that there is a significant intention-behaviour gap (Sheeran, 2002). Future research should include longitudinal behavioral data to investigate if the predictor variables of intention to adopt also predict real behavior of adoption.

Last, the study did not take into account consumers' trust in the regulatory framework for AI-FinTech services, which is referred to as regulatory trust. Consumers can trust FinTech platforms more if the context has a high degree of regulatory supervision. The use of regulatory trust as a further factor and its relationship with the dimensions of platform trust could be used for future research.

6. CONCLUSION

This paper constructs and tests an integrated theoretical model of the factors that shape the consumer's decision to adopt AI-based FinTech services. Based on the Unified Theory of Acceptance and Use of Technology and the Technology Acceptance Model, as well as the Trust Transfer Theory, the study shows that the variance in the behavioral intentions can be explained by 67.4% of the cognitive trust, perceived security assurance, perceived usefulness and affective trust. Cognitive trust is the strongest predictor, followed by perceived security assurance, perceived usefulness and affective trust. The results also indicate that the relationship between affective trust and behavioural intentions is mediated by cognitive trust and the perceived risk moderates the relationship between cognitive trust and perceived usefulness and between perceived usefulness and behavioural intentions. There are marked differences in gender and age, with older consumers being more sensitive to security assurance and female consumers showing greater sensitivity to affective trust.

The results enrich consumer behavior theory by adding dual cognitive-affective dimensions to the trust construct in the AI-enabled FinTech context and by providing boundary conditions for the relationship between trust and usefulness that lead to their adoption intentions. The study offers practical advice for practitioners regarding trust building, communication to ensure security, risk mitigation, and segment-specific adoption strategies. The psychological factors influencing consumer adoption will continue to be an important area for research and management in the era of AI in financial services.

REFERENCES

1. Agarwal, R., & Prasad, J. (1999). Are individual differences germane to the acceptance of new information technologies? Decision Sciences, 30(2), 361-391.

2. Arner, D. W., Barberis, J., & Buckley, R. P. (2020). The evolution of FinTech: A new post-crisis paradigm? Georgetown Journal of International Law, 47(4), 1271-1319.

3. Bauer, R. A. (1960). Consumer behavior as risk taking. In R. S. Hancock (Ed.), Dynamic marketing for a changing world (pp. 389-398). American Marketing Association.

4. Buchan, N. R., Croson, R. T., & Solnick, S. (2008). Trust and gender: An examination of behavior and beliefs in the Investment Game. Journal of Economic Behavior & Organization, 68(3-4), 466-476.

5. Carstensen, L. L., & Mikels, J. A. (2005). At the intersection of emotion and cognition: Aging and the positivity effect. Current Directions in Psychological Science, 14(3), 117-121.

6. Chaiken, S., & Trope, Y. (1999). Dual-process theories in social psychology. Guilford Press.

7. Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

8. Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. MIS Quarterly, 19(2), 189-211.

9. Cox, D. F. (1967). Risk taking and information handling in consumer behavior. Harvard University Press.

10. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.

11. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340.

12. Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. International Journal of Human-Computer Studies, 59(4), 451-474.

13. Flavian, C., & Guinaliu, M. (2006). Consumer trust, perceived security and privacy policy: Three basic elements of loyalty to a web site. Industrial Management & Data Systems, 106(5), 601-620.

14. Forgas, J. P. (1995). Mood and judgment: The affect infusion model (AIM). Psychological Bulletin, 117(1), 39-66.

15. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

16. Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. MIS Quarterly, 27(1), 51-90.

17. Haddad, C., & Hornuf, L. (2019). The emergence of the global FinTech market: Economic and technological determinants. Small Business Economics, 53(1), 81-105.

18. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). SAGE Publications.

19. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115-135.

20. Johnson, D., & Grayson, K. (2005). Cognitive and affective trust in service relationships. Journal of Business Research, 58(4), 500-507.

21. Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision Support Systems, 44(2), 544-564.

22. Kim, G., Shin, B., & Lee, H. G. (2009). Understanding dynamics between initial trust and usage intentions of mobile banking. Information Systems Journal, 19(3), 283-311.

23. Kim, K. K., & Prabhakar, B. (2004). Initial trust and the adoption of B2C e-commerce: The case of Internet banking. ACM SIGMIS Database, 35(2), 50-64.

24. Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1-10.

25. Lankton, N. K., McKnight, D. H., & Tripp, J. F. (2014). Technology, humanness, and trust: Rethinking trust in technology. Journal of the Association for Information Systems, 15(10), 1-24.

26. Lee, M. K., Shi, N., Cheung, C. M., Lim, K. H., & Sia, C. L. (2006). Consumer's decision to shop online: The moderating role of positive informational social influence. Information & Management, 46(5), 279-287.

27. Lewis, J. D., & Weigert, A. (1985). Trust as a social reality. Social Forces, 63(4), 967-985.

28. Lusardi, A., & Mitchell, O. S. (2011). Financial literacy around the world: An overview. Journal of Pension Economics & Finance, 10(4), 497-508.

29. McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. Information Systems Research, 13(3), 334-359.

30. Mikalef, P., & Pateli, A. (2017). Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Evidence from Greece. Journal of Business Research, 70, 1-13.

31. Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. Personnel Psychology, 53(2), 375-403.

32. Mukherjee, A., & Nath, P. (2003). A model of trust in online relationship banking. International Journal of Bank Marketing, 21(1), 5-15.

33. Nunnally, J. C. (1978). Psychometric theory (2nd ed.). McGraw-Hill.

34. Oliveira, T., Thomas, M., Baptista, G., & Campos, F. (2016). Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. Computers in Human Behavior, 61, 404-414.

35. Pikkarainen, T., Pikkarainen, K., Karjaluoto, H., & Pahnila, S. (2004). Consumer acceptance of online banking: An extension of the technology acceptance model. Internet Research, 14(3), 224-235.

36. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879-891.

37. Rousseau, D. M., Sitkin, S. B., Burt, R. S., & Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. Academy of Management Review, 23(3), 393-404.

38. Schwarz, N., & Clore, G. L. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. Journal of Personality and Social Psychology, 45(3), 513-523.

39. Sheeran, P. (2002). Intention-behavior relations: A conceptual and empirical review. European Review of Social Psychology, 12(1), 1-36.

40. Stewart, K. J. (2003). Trust transfer on the World Wide Web. Organization Science, 14(1), 5-17.

41. Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144-176.

42. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186-204.

43. Venkatesh, V., & Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. MIS Quarterly, 24(1), 115-139.

44. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.

45. Yousafzai, S. Y., Pallister, J. G., & Foxall, G. R. (2010). Strategies for building and communicating trust in electronic banking: A field experiment. Psychology & Marketing, 27(2), 181-201.

46. Zhou, T. (2012). Understanding users' initial trust in mobile banking: An elaboration likelihood perspective. Computers in Human Behavior, 28(4), 1518-1525.