

Behavioral Biases and FinTech Adoption Intention Among Young Adults: A Structural Equation Modeling Study in the Indian Context

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Abstract. India has developed one of the fastest-growing FinTech markets in the world through the expansion of digital financial services delivered via smartphones. Although the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) dominate the adoption literature, few studies have examined the psychological drivers of FinTech adoption. This study investigated the impact of four behavioral biases, namely overconfidence (OC), herd behavior (HB), present bias (PB), and loss aversion (LA), on FinTech adoption intention (FAI) among university students in India. Drawing on Kahneman's dual-process theory and prospect theory, a five-point Likert-type survey was administered to 148 respondents at Anurag University, Hyderabad. Confirmatory factor analysis (CFA) was first used to test construct reliability and validity, followed by path analysis with structural equation modeling (SEM). The measurement model showed good fit (comparative fit index [CFI] = 0.940, Tucker-Lewis index [TLI] = 0.928, root mean square error of approximation [RMSEA] = 0.062), good internal reliability (Cronbach's α = 0.766 to 0.850; composite reliability [CR] = 0.765 to 0.852), and average variance extracted (AVE) values of 0.486 to 0.655; the AVE of herd behavior (0.486) fell below the 0.50 threshold for convergent validity. All heterotrait-monotrait (HTMT) ratios were below 0.85, but discriminant validity for loss aversion was marginal under the Fornell-Larcker criterion. In the structural model, present bias (β = 0.370, p = 0.004) and loss aversion (β = 0.499, p = 0.001) were significant predictors of adoption intention, and overconfidence (β = 0.216, p = 0.038) also had a significant influence, whereas herd behavior (β = -0.204, p = 0.054) was not a significant predictor. The model explained 74.1% of the variance in FinTech adoption intention (R^2 = 0.741). The results challenge purely utilitarian adoption models and offer implications for FinTech product designers, financial educators, and regulators.

Keywords. FinTech adoption; behavioral biases; structural equation modeling; confirmatory factor analysis; behavioral finance; young adults; India; prospect theory

I. INTRODUCTION

Over the last ten years, FinTech in India has grown rapidly with the spread of smartphones and affordable wireless internet, supported by government initiatives such as the Unified Payments Interface (UPI) and Jan Dhan Yojana. UPI was projected to process more than 13,000 crore transactions in 2023-24, while FinTech platforms such as Zerodha, Groww, and Paytm Money are enabling retail investors to enter the market [1], [2]. The leading demographic driving this change is the "digital natives" aged 18 to 28, who use mobile apps to make payments, save money, invest, and borrow.

The technology acceptance model (TAM) [3] and the unified theory of acceptance and use of technology (UTAUT) [4] are the main conceptual frameworks in this area. Both place heavy emphasis on perceived usefulness (PU) and perceived ease of use (PEU) but do not consider the psychological factors that influence adoption. Research in behavioral finance, by contrast, has shown that financial decision-making is shaped by cognitive biases, which cause

systematic deviations from rational decision-making [5], [6]. This is especially true in fast-paced digital environments, where most processing occurs as System 1 activity.

No previous study has examined the simultaneous effect of overconfidence, herd behavior, present bias, and loss aversion on FinTech adoption by college students in India using a multi-bias structural framework validated by confirmatory factor analysis (CFA) and structural equation modeling (SEM). This study fills that gap with such a framework and offers recommendations for FinTech companies, educators, and policymakers.

II. REVIEW OF LITERATURE

A. FinTech Adoption and Behavioral Finance

Cognitive biases influence a person's decision-making and challenge the traditional economic concept of the rational actor, a challenge that arose from behavioral finance theory [5], [6]. One such theory, dual-process theory, holds that individuals often rely on their intuitive thinking system

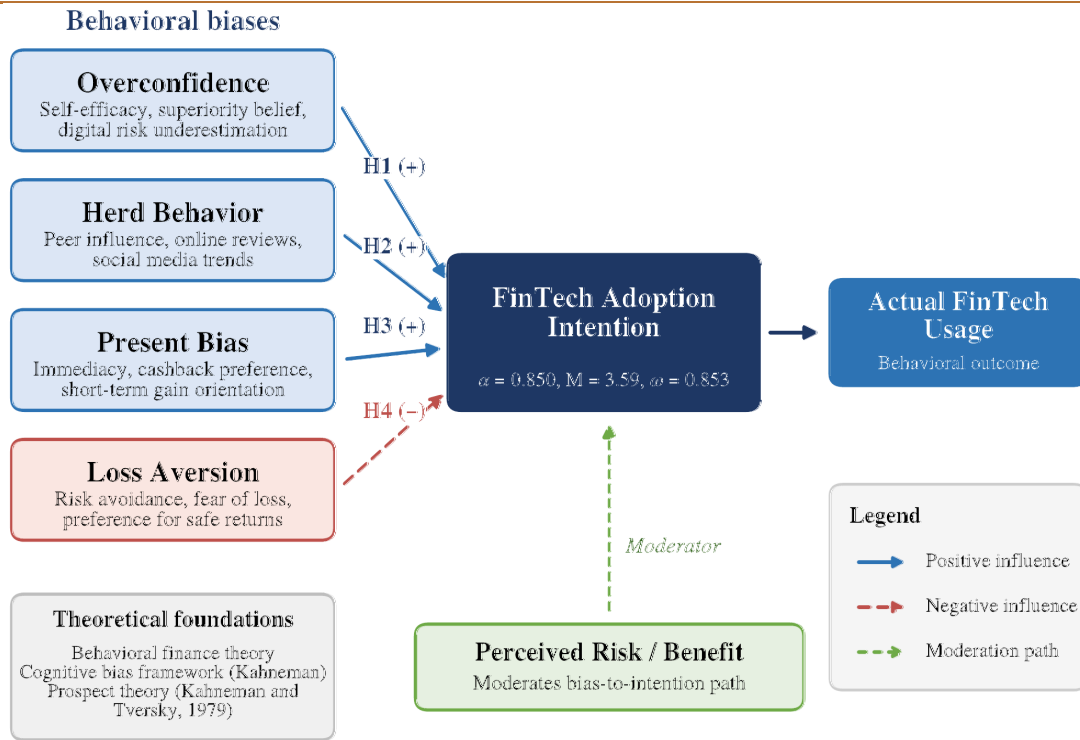


Fig. 1. Conceptual framework: behavioral biases and FinTech adoption intention.

(System 1) when they interact with the fast, easy-to-use interfaces of FinTech platforms, and decisions made intuitively leave individuals more vulnerable to cognitive biases.

Among the behavioral biases that may drive FinTech use, overconfidence has proven to be a major determinant of risk perception and has increased FinTech use among younger investors [7], [8]. The tendency to imitate others when making investment decisions (herd behavior) is driven by the influence of social media [9], [10]. Similarly, present bias may lead individuals to prefer immediate financial incentives, such as instant cashback rewards, over cash received later [11], [12]. Finally, loss aversion may deter individuals from adopting FinTech when they perceive the financial risk to be greater than the reward [13], [14].

B. Research Gap and Hypotheses

Few studies have analyzed overconfidence, herd behavior, present bias, and loss aversion together in relation to young adults' intention to adopt FinTech products in India. The following hypotheses were therefore tested (Fig. 1).

H1: Overconfidence has a positive effect on the intention to adopt FinTech.

H2: Herd behavior has a positive effect on the intention to adopt FinTech.

H3: Present bias has a positive effect on the intention to adopt FinTech.

H4: Loss aversion has a negative effect on the intention to adopt FinTech.

III. OBJECTIVES

The study had two objectives: (i) to examine the impact of overconfidence, herd behavior, present bias, and loss aversion on FinTech adoption intention among the students of

Anurag University; and (ii) to suggest practical recommendations for FinTech firms, educators, and policymakers based on the role of behavioral biases in digital financial adoption.

IV. RESEARCH METHODOLOGY

This study used a quantitative cross-sectional survey design. The target sample was students enrolled at Anurag University, Hyderabad, and data were collected from late November 2025 to early January 2026. A two-stage analytical approach was used: CFA to validate the measurement model, followed by SEM to test the hypothesized relationships.

The target population consisted of engineering and management students aged 18 to 28 years. A convenience-purposive sampling approach yielded 148 valid responses ($n = 148$), fairly evenly split between male (77, 52.0%) and female (71, 48.0%) respondents, and between undergraduate (50.7%) and graduate (49.3%) education levels.

Data were collected with a structured five-point Likert-type questionnaire measuring overconfidence (OC, five items), herd behavior (HB, four items), present bias (PB, four items), loss aversion (LA, three items), and FinTech adoption intention (FAI, three items). The items were adapted from previously validated instruments, and the scales were used in a pilot study.

SEM was performed with maximum likelihood estimation in semopy (v2.3.11). CFA was used to assess factor loadings, average variance extracted (AVE), composite reliability (CR), and discriminant validity through the hetero-trait-monotrait ratio (HTMT), and model fit was assessed with the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and χ^2/df . Harman's single-factor test showed that the single-factor model fit significantly worse than the five-factor model, suggesting that common method variance is not a

serious threat [15]. However, the use of a single data source and a cross-sectional design still limit this study, and future studies should use procedural remedies such as temporal separation of measures.

V. RESULTS

A. Descriptive Statistics and Reliability

Cronbach's α ranged from 0.766 (LA) to 0.850 (FAI), all above the 0.70 threshold [16] (Table 1). FAI recorded the highest mean ($M = 3.590$, $SD = 1.267$). Herd behavior had the lowest mean ($M = 2.689$), indicating that peer imitation is less prominent than the other biases.

TABLE 1. DESCRIPTIVE STATISTICS, RELIABILITY, AVE, AND COMPOSITE RELIABILITY

Construct	Items	Mean	SD	α	AVE	CR
Overconfidence (OC)	5	3.241	1.213	0.830	0.541	0.852
Herd behavior (HB)	4	2.689	1.271	0.773	0.486	0.786
Present bias (PB)	4	3.211	1.204	0.824	0.546	0.827
Loss aversion (LA)	3	3.284	1.250	0.766	0.524	0.765
FinTech adoption intention (FAI)	3	3.590	1.267	0.850	0.655	0.850

Note: $n = 148$ for every construct. α = Cronbach's alpha; AVE = average variance extracted; CR = composite reliability.

B. Exploratory Factor Analysis

An exploratory factor analysis (EFA) was carried out before the CFA to examine the factor structure of the 19-item scale. The Kaiser-Meyer-Olkin (KMO) measure of 0.887 ("meritorious" [17]) and Bartlett's test of sphericity ($\chi^2 = 2864$, $df = 171$, $p < 0.001$) confirmed that the data were suitable for factor extraction. Minimum residual extraction with oblimin rotation yielded a four-factor solution consistent with the theoretical structure. The FAI items loaded on F1 ($\lambda = 0.626$ to 0.810) together with two loss aversion items (Q21 and Q22); overconfidence loaded on F2 ($\lambda = 0.679$ to 0.857), herd behavior on F3 ($\lambda = 0.640$ to 0.810), and present bias on F4 ($\lambda = 0.528$ to 0.687). Table 2 presents these results.

C. Confirmatory Factor Analysis

Table 3 shows that all indicator loadings were significant ($p < 0.001$), and most exceeded 0.60. AVE ranged from 0.486 (HB) to 0.655 (FAI). The AVE of HB (0.486) falls marginally below 0.50 [18], but its CR of 0.786 and significant loadings justify retaining the construct [19]. All CR values (0.765 to 0.852) exceeded 0.70.

D. Discriminant Validity

Table 4 presents the HTMT matrix [20]. All off-diagonal entries are below the 0.85 threshold (the maximum is 0.730, for PB-FAI), so the HTMT criterion was met. Under the Fornell-Larcker criterion [18], the square root of the AVE on the diagonal exceeds the off-diagonal values for OC, HB, PB, and FAI, but for LA the diagonal value (0.724) is slightly below the LA-FAI value (0.727), so discriminant validity for LA is marginal.

E. Model Fit

Table 5 shows $\chi^2/df = 1.564$ (< 3.0), CFI = 0.940 and TLI = 0.928 (≥ 0.90), and RMSEA = 0.062 (≤ 0.08). The

TABLE 2. ROTATED FACTOR LOADINGS (OBLIMIN ROTATION, MINIMUM RESIDUAL EXTRACTION)

Item	F1	F2	F3	F4	Uniq.
Q26: Plan to explore more FinTech platforms	0.810				0.373
Q25: Intend to continue using digital financial services	0.805				0.238
Q24: Regularly use FinTech apps for transactions	0.626				0.460
Q22: Prefer safe returns over uncertain profits	0.545				0.418
Q21: Avoid financial apps involving high risk	0.495				0.567
Q9: Confident making financial decisions without advice		0.857			0.210
Q11: Financially smarter than peers		0.792			0.383
Q10: Manage investments through digital platforms		0.679			0.356
Q15: Online reviews affect adoption decisions			0.810		0.349
Q16: Peer recommendations influence adoption			0.684		0.418
Q14: Social media trends influence app trials			0.640		0.504
Q19: Quick access to money via digital platforms				0.687	0.354
Q18: Focus on short-term gains over savings				0.589	0.521
Q17: Prefer services with immediate benefits or rewards				0.528	0.454

Note: Loadings below 0.30 suppressed. F1 = FinTech adoption intention and loss aversion (co-loaded); F2 = overconfidence; F3 = herd behavior; F4 = present bias; Uniq. = uniqueness. KMO = 0.887; Bartlett's $\chi^2 = 2864$, $df = 171$, $p < 0.001$.

normed fit index (NFI, 0.854) and goodness-of-fit index (GFI, 0.854) approach 0.90, which is acceptable given $n = 148$. The model shows acceptable-to-good fit.

F. Structural Model Results and Hypothesis Testing

The structural model explained 74.1% of the variance in FAI ($R^2 = 0.741$). Table 6 gives the path coefficients and hypothesis decisions.

H1 was supported ($\beta = 0.216$, $p = 0.038$), suggesting that overconfidence reduces the perceived risk of adoption. H3 was supported ($\beta = 0.370$, $p = 0.004$), indicating that present bias, through a preference for immediate rewards and cashback, motivates consumers to adopt FinTech platforms. H2 was not supported ($\beta = -0.204$, $p = 0.054$), suggesting that herd behavior may create caution toward adopting FinTech platforms. Loss aversion showed a significant positive relationship with adoption intention ($\beta = 0.499$, $p = 0.001$), contrary to the negative effect proposed in H4.

VI. DISCUSSION

The model accounted for 74.1% of the variance in FinTech adoption intention ($R^2 = 0.741$), which is much higher than values reported in TAM- and UTAUT-based studies ($R^2 = 0.40$ to 0.60) [1], [2]. The results imply that behavioral finance variables capture psychological dimensions of technology adoption beyond utilitarian frameworks; however, the cross-sectional design does not allow causal relationships to be determined.

TABLE 3. CFA STANDARDIZED LOADINGS, AVE, AND COMPOSITE RELIABILITY

Construct / item	Loading	<i>p</i>	AVE	CR
Overconfidence (OC)			0.541	0.852
Q8: Good knowledge of digital financial products	0.743	(ref.)		
Q9: Confident making financial decisions without advice	0.844	< 0.001		
Q10: Can manage investments through digital platforms	0.782	< 0.001		
Q11: Financially smarter than peers	0.768	< 0.001		
Q12: Rarely worry about mistakes in financial apps	0.490	< 0.001		
Herd behavior (HB)			0.486	0.786
Q13: Use financial apps because friends use them	0.477	(ref.)		
Q14: Social media trends influence app trials	0.734	< 0.001		
Q15: Online reviews affect adoption decisions	0.767	< 0.001		
Q16: Peer recommendations influence app adoption	0.768	< 0.001		
Present bias (PB)			0.546	0.827
Q17: Prefer services with immediate benefits or rewards	0.751	(ref.)		
Q18: Focus on short-term gains over savings	0.647	< 0.001		
Q19: Quick access to money via digital platforms	0.787	< 0.001		
Q20: Cashbacks encourage FinTech app usage	0.762	< 0.001		
Loss aversion (LA)			0.524	0.765
Q21: Avoid financial apps involving high risk	0.698	(ref.)		
Q22: Prefer safe returns over uncertain profits	0.833	< 0.001		
Q23: Hesitate to try new apps for fear of loss	0.626	< 0.001		
FinTech adoption intention (FAI)			0.655	0.850
Q24: Regularly use FinTech apps for transactions	0.768	(ref.)		
Q25: Intend to continue using digital financial services	0.884	< 0.001		
Q26: Plan to explore more FinTech platforms	0.769	< 0.001		

Note: Loading = standardized loading; (ref.) = reference indicator. All estimated loadings significant at $p < 0.001$.

TABLE 4. HTMT DISCRIMINANT VALIDITY MATRIX ($\sqrt{\text{AVE}}$ ON DIAGONAL)

	OC	HB	PB	LA	FAI
OC	0.736				
HB	0.349	0.697			
PB	0.633	0.613	0.739		
LA	0.637	0.627	0.700	0.724	
FAI	0.707	0.371	0.730	0.727	0.809

Note: Diagonal = $\sqrt{\text{AVE}}$; off-diagonal = HTMT ratios. All values < 0.85.

TABLE 5. STRUCTURAL MODEL FIT INDICES

Index	Value	Assessment
χ^2/df	1.564	Acceptable
CFI	0.940	Good fit
TLI	0.928	Good fit
NFI	0.854	Acceptable
RMSEA	0.062	Good fit
GFI	0.854	Acceptable

TABLE 6. STRUCTURAL PATH COEFFICIENTS AND HYPOTHESIS TESTING

H	Path	β (std)	SE	<i>z</i>	<i>p</i>	Decision
H1	OC → FAI	0.216	0.134	2.074	0.038	Supported*
H2	HB → FAI	-0.204	0.171	-1.923	0.054	Not supported
H3	PB → FAI	0.370	0.147	2.917	0.004	Supported**
H4	LA → FAI	0.499	0.160	3.307	0.001	Not supported**

Note: β (std) = standardized path coefficient; * $p < 0.05$; ** $p < 0.01$. SE and *z* refer to the unstandardized estimates. Source: primary data analyzed with semopy 2.3.11 in Python.

Contrary to the hypothesis, loss aversion was positively related to FinTech adoption intention. In the Indian context, this may reflect the perceived safety of the government-supported UPI system compared with informal and cash-based systems.

Present bias was a strong predictor of adoption intention ($\beta = 0.370$), the largest effect among the supported hypotheses, reflecting the appeal of immediate gratification such as cashback rewards or rapid access to cash. Overconfidence was also significant ($\beta = 0.216$), although its influence was considerably smaller; it appears to act mainly as a cognitive device that lowers perceived risk and therefore the barriers to adoption. Herd behavior did not significantly predict FinTech adoption in this group of analytically oriented users (university students, 50.7% undergraduate and 49.3% graduate), suggesting that social influence plays a minimal role in their adoption of FinTech products.

VII. IMPLICATIONS

FinTech user interface design should integrate nudging techniques, such as default saving options, graphics showing goal attainment, and transparent communication of risk, which can counter present bias and overconfidence in one's decision-making ability [21]. Self-assessment tools during onboarding, together with simulated portfolios, would help loss-averse users make better decisions about adopting digital financial technology.

VIII. LIMITATIONS

The study has several limitations that should be considered when interpreting the findings. First, the sample was limited

to students of Anurag University in Hyderabad, India; all participants were aged 18 to 28 years and digitally literate, which greatly limits generalization to working professionals, rural users, and non-student populations. Second, because the study was cross-sectional, causal relationships cannot be inferred: although SEM supports the relationships among the variables, it cannot establish whether one variable preceded another. Third, the use of self-reported data raises the possibility of common method variance, although a post hoc Harman's single-factor CFA showed that common method variance alone does not account for the covariance structure among the variables (CFI = 0.611, RMSEA = 0.174). Fourth, herd behavior showed the weakest psychometric properties (AVE = 0.486; Q13 loading = 0.477), and loss aversion, which was unexpectedly positively related to adoption intention ($\beta = 0.499$), co-loaded with the FAI items in the EFA; both scales need further item development and examination. Finally, no multigroup analysis by gender or education level was performed, so the study offers no insight into subgroup differences, and no alternative theoretical models such as TAM or UTAUT were tested, so only high-level R^2 comparisons with existing studies are possible.

IX. CONCLUSION

This study examined how four behavioral biases (overconfidence, herd behavior, present bias, and loss aversion) influenced the intention to use FinTech among 148 students at a university in Hyderabad, India. CFA and SEM showed that the model had acceptable fit (CFI = 0.940, RMSEA = 0.062), and reliability was established for all constructs; convergent validity was below the 0.50 AVE threshold for herd behavior (AVE = 0.486), and discriminant validity for loss aversion was marginal. Present bias ($\beta = 0.370$) and loss aversion ($\beta = 0.499$) were the most significant predictors, overconfidence ($\beta = 0.216$) was a significant but weaker predictor, and herd behavior was not significant. The model explained 74.1% of the variance in adoption intention, indicating greater explanatory power than previous TAM- and UTAUT-based models.

Future research should use larger samples from multiple sites and professional backgrounds, test multigroup invariance by gender and educational attainment, adopt longitudinal designs, refine the herd behavior and loss aversion scales, and compare the present framework with TAM and UTAUT models in a competing-model design to establish an empirical benchmark.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception and preparation of this work and approved the final version of the manuscript.

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DECLARATION OF GENERATIVE AI USE

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript. The authors take full responsibility for the content of the publication.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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