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Investor Trust and Risk Awareness in Digital Banking Platforms: Evidence from an Emerging Market

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Abstract

The rapid proliferation of fintech and digital banking platforms has fundamentally restructured retail financial services in India, raising critical questions about the behavioural antecedents of user adoption. This study investigates the determinants of investor trust and risk awareness in digital banking platforms and their joint effect on adoption intention. Using a quantitative cross-sectional design, primary data were collected from 103 active digital banking users through a structured, Likert-scaled questionnaire. Descriptive statistics, Cronbach's alpha reliability analysis, Exploratory Factor Analysis (EFA) with Principal Component Analysis (PCA) and Varimax rotation, Chi-square tests of independence, and Pearson and Spearman correlation analyses were performed using SPSS. EFA identified two dominant latent constructs Investor Trust and Risk Awareness collectively explaining 58.75% of total variance. Reliability was confirmed ($\alpha = 0.775$). Chi-square analysis revealed that education level exerts no statistically significant effect on investor perceptions (all $p > 0.05$), whereas income level significantly predicts investor confidence ($p = 0.038$, $r = 0.205$). Findings confirm that behavioural and attitudinal factors supersede demographic characteristics in shaping digital banking adoption. The study contributes an integrated trust–risk framework grounded in TAM and behavioural finance theory, offering empirically validated insights for platform designers, financial regulators, and policymakers in emerging digital economies.

Keywords: *digital banking adoption; investor trust; risk awareness; financial technology; perceived security*

INTRODUCTION

Financial technology (fintech) has fundamentally altered the architecture of retail banking globally, disrupting traditional intermediation models and democratising access to financial services at an unprecedented scale (Gomber et al., 2017; Mention, 2019). The global digital banking market surpassed USD 8.9 trillion in transaction value in 2023 and is projected to expand at a CAGR exceeding 13% through 2028, driven by smartphone penetration, open banking regulations, and post-pandemic behavioural shifts (Statista, 2024). Mobile-first financial service models have displaced branch-based interactions in both developed and rapidly developing economies, reshaping expectations of service speed, interface usability, and operational transparency (Lee & Shin, 2018).

In the Indian context, this transformation has been especially pronounced. Government-led initiatives such as Digital India, the Unified Payments Interface (UPI), Jan Dhan Yojana, and demonetisation collectively accelerated formal digital financial inclusion, pushing active digital payment users beyond 350 million by 2023 (Reserve Bank of India, 2023). India now ranks among the top three global markets for real-time digital transactions, with the National Payments Corporation of India (NPCI) recording over 11.4 billion UPI transactions monthly (NPCI, 2024). Regulatory support from the Reserve Bank of India (RBI) and the Securities and Exchange Board of India (SEBI) has provided a governance scaffold for cybersecurity, consumer data protection, and algorithmic transparency in digital investment platforms (RBI, 2022; SEBI, 2023).

Despite this dramatic expansion, adoption barriers persist, particularly among retail investors who increasingly rely on algorithmically driven advisory systems they do not fully understand — a phenomenon characterised in the literature as the 'black box' problem (Arner et al., 2020; Philippon, 2016). Security vulnerabilities, including phishing, social engineering, and unauthorised account access, disproportionately affect less-experienced users, while inadequate transparency in fee structures and algorithmic logic erodes institutional trust (Gomber et al., 2017; Zavolokina et al., 2016). Behavioural finance research has documented systematic biases overconfidence, attention bias, and heuristic reasoning that further compromise investor risk awareness in digital environments (Barber & Odean, 2000, 2001; Tversky & Kahneman, 1974; Gervais & Odean, 2001).

While the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) offer foundational frameworks for understanding digital service adoption, they insufficiently account for the trust–risk dynamics specific to digital financial platforms (Gefen et al., 2003; Pavlou, 2003). This study addresses this lacuna by investigating the interplay between investor trust, risk awareness, and adoption intention among Indian digital banking users, using primary quantitative data and a suite of inferential statistical techniques.

PROBLEM IDENTIFICATION

The core research problem concerns the persistent gap between the technological sophistication of contemporary digital banking platforms and the capacity of retail investors to appraise and manage the attendant risks effectively. Despite regulatory mandates for disclosure, platforms frequently present fee structures, algorithmic logic, and data-usage policies in language inaccessible to the average user (Arner et al., 2020; Gomber et al., 2017). This transparency deficit cultivates scepticism and erodes trust, particularly among first-generation digital financial service adopters.

A conceptual gap exists in the literature concerning the integrated measurement of trust, risk awareness, and adoption intention as co-determined constructs rather than independent variables. Prior research has examined these constructs in isolation, thereby underestimating their joint explanatory power (Pavlou, 2003; Featherman & Pavlou, 2003). An empirical gap is evident in the insufficient availability of validated psychometric instruments sensitive to India-specific digital threats notably UPI fraud, SIM-swap attacks, and mis-selling of algorithmic investment products. Most existing instruments deploy generic risk scales calibrated for Western, high-literacy financial populations.

Finally, a contextual gap persists in that the extant literature on investor trust in digital banking platforms disproportionately reflects the experience of developed-market consumers, leaving Indian retail investors who represent a heterogeneous, rapidly growing, and behaviourally distinct cohort largely untheorised. This study addresses these three gaps through a structured, instrument-validated empirical investigation situated within the Indian digital banking ecosystem.

LITERATURE REVIEW

Theoretical Foundations of Digital Banking Adoption

The technology acceptance literature provides the primary theoretical scaffolding for understanding digital banking adoption. Davis (1989) introduced

TAM, proposing that perceived usefulness and perceived ease of use are the primary antecedents of behavioural intention to use information systems, a proposition extensively replicated in banking contexts (Venkatesh & Davis, 2000; Pikkarainen et al., 2004). Venkatesh et al. (2003) extended this model through UTAUT, incorporating social influence, facilitating conditions, and hedonic motivation as additional predictors. In digital financial services, ease of navigation, platform reliability, and perceived financial utility consistently emerge as the most robust adoption predictors (Hanafizadeh et al., 2014; Baptista & Oliveira, 2015).

Trust-based extensions of TAM have received growing scholarly attention. Gefen et al. (2003) and Pavlou (2003) demonstrated that institutional trust encompassing perceptions of platform integrity, benevolence, and competence significantly mediates the relationship between system quality perceptions and adoption intention. More recently, Astutik and Setiawan (2025) confirmed that institutional trust specifically predicts adoption of non-bank investment applications, reinforcing the salience of trust as a distinct adoption driver in fintech contexts.

Investor Trust in Digital Financial Platforms

Investor trust in digital banking is a multidimensional construct encompassing perceived security, platform transparency, operational reliability, and regulatory legitimacy (Gefen et al., 2003; Boot, 2000). Diamond (1984) established that financial intermediaries derive their value partly from delegated monitoring functions that reduce information asymmetry a rationale that extends to algorithmic advisors and robo-advisory platforms. Diamond and Dybvig (1983) linked bank vulnerability to coordination failures arising from information opacity, underscoring the systemic importance of transparent communication.

In the digital realm, perceived security defined as users' subjective assessment of a platform's resistance to fraud, data breaches, and unauthorised access functions as a critical antecedent of trust (Suh & Han, 2002). Empirical evidence confirms that visible security features, including two-factor authentication, end-to-end encryption, and real-time fraud alerts, significantly elevate user trust levels (Gefen et al., 2003; Featherman & Pavlou, 2003). Platform transparency, operationalised as the clarity and completeness of fee disclosure, algorithmic logic communication, and privacy policy presentation, is equally foundational (Arner et al., 2020;

Zavolokina et al., 2016). Gorton and Metrick (2009) demonstrated that opacity in financial instruments precipitates liquidity crises, a dynamic that echoes in retail digital banking when algorithmic recommendations are presented without explanatory context.

Risk Awareness and Perceived Risk in Digital Banking

Risk awareness an individual's cognitive recognition of specific threats associated with digital financial activity is conceptually distinct from perceived risk, which encompasses affective and probabilistic assessments of potential losses (Featherman & Pavlou, 2003; Flynn et al., 1994). De Long et al. (1990) identified noise trader risk as a structural market phenomenon arising from irrational speculation, a pattern that manifests at the individual level when retail investors act on technologically mediated misinformation. Tversky and Kahneman (1974) demonstrated that heuristic-based reasoning introduces systematic biases anchoring, availability, and representativeness that distort risk estimation.

Barber and Odean (2001) provided compelling evidence that overconfidence is a pervasive and costly bias among retail investors, with men exhibiting significantly greater overconfidence than women, leading to excess trading and diminished net returns. Gervais and Odean (2001) modelled the developmental trajectory of overconfidence, showing that selective attribution of past successes reinforces erroneous self-assessment over time. Fehr-Duda et al. (2006) identified gender-differentiated probability weighting in financial risk settings, with women exhibiting greater sensitivity to probability information, while Jianakoplos and Bernasek (1998) and Powell and Ansic (1997) documented consistent risk aversion differentials between male and female investors across varied financial tasks.

Demographic moderators beyond gender also matter. Lewellen et al. (1977) showed that age and income systematically shape portfolio allocation and risk tolerance, while Barsky et al. (1995) demonstrated substantial heterogeneity in risk preferences using experimental economics methods. Flynn et al. (1994) argued that risk perception is not a purely individual psychological phenomenon but is embedded in social structures, with race and gender functioning as proxies for differential power and exposure. In digital banking specifically, cyber-risk awareness encompassing knowledge of phishing, SIM-swap fraud, and social engineering attacks remains critically underdeveloped among retail users in emerging markets (Gomber et al., 2017).

Behavioural Finance and Financial Decision-Making

The behavioural finance tradition provides an indispensable complement to structural theories of bank regulation and market efficiency. Fama (1970, 1991) articulated the efficient market hypothesis, positing that prices fully reflect available information under conditions of rational arbitrage. However, this proposition was empirically challenged by a succession of anomalies traceable to systematic human cognitive limitations. Shleifer and Vishny (1997) demonstrated that limits to arbitrage including capital constraints and synchronisation risk prevent rational actors from eliminating pricing inefficiencies introduced by noise traders.

Allais (1953) identified early violations of expected utility theory under risk, prefiguring the broader programme of prospect theory (Kahneman & Tversky, 1979). In digital banking, attention bias has been documented as a significant driver of investment decisions, with users responding to the aesthetic and navigational properties of platforms rather than their underlying financial logic (Barber & Odean, 2008). The integration of financial literacy as a moderating variable is particularly pertinent: individuals with higher financial literacy demonstrate superior risk calibration, greater capacity to interpret disclosure documents, and lower susceptibility to algorithmic mis-selling (Lusardi & Mitchell, 2014; Furnham, 1984).

RESEARCH GAP

Despite substantial theoretical and empirical progress, several critical lacunae remain unaddressed. First, the majority of extant empirical research on investor trust in digital banking originates from developed-market contexts notably the United States, United Kingdom, and Western Europe where financial literacy, regulatory frameworks, and user demographics differ substantially from India's rapidly expanding but heterogeneous digital user base (Gomber et al., 2017; Arner et al., 2020). Directly transposing these findings to the Indian context is methodologically problematic.

Second, while TAM and UTAUT have been extensively applied to digital banking adoption, studies that simultaneously integrate trust, risk awareness, and demographic moderation within a unified empirical framework remain scarce, particularly in emerging market settings. Most available studies treat these constructs as independent predictors rather than as jointly determined components of a holistic adoption decision (Pavlou, 2003; Featherman & Pavlou, 2003). Third, psychometric instruments validated for India-specific digital threats UPI fraud vectors,

Aadhaar-linked identity theft, and vernacular-language mis-selling are notably absent from the literature. Generic Western risk scales systematically underestimate the perceived threat environment confronting Indian retail investors. This study addresses these gaps by deploying a purpose-designed, validated instrument within an Indian sample and constructing an integrated trust–risk adoption framework grounded in behavioural finance and technology acceptance theory.

RESEARCH METHODOLOGY

This study adopted a quantitative, cross-sectional, descriptive-cum-analytical research design. Primary data were collected from 103 active digital banking users defined as individuals who had conducted at least one financial transaction via a mobile banking application, online banking portal, or fintech investment platform within the preceding three months. Respondents were recruited using convenience sampling targeting urban and semi-urban populations in Bengaluru, Karnataka, reflecting the geographic locus of India's fintech hub ecosystem.

The research instrument was a structured,self-administered questionnaire comprising two sections. Section A captured four demographic variables: age, gender, income level, and education level. Section B contained ten perception-based statements rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), measuring perceived security, platform transparency, ease of use, perceived usefulness, financial literacy, overconfidence, investor trust, risk awareness, perceived risk, and adoption intention. Items were adapted from validated scales in prior TAM and trust-risk literature (Davis, 1989; Gefen et al., 2003; Featherman & Pavlou, 2003).

Data were analysed using IBM SPSS Statistics. The analytical sequence comprised: (1) descriptive frequency analysis of demographic variables; (2) internal consistency assessment via Cronbach's alpha; (3) Exploratory Factor Analysis using Principal Component Analysis with Varimax rotation; (4) Chi-square tests of independence to examine associations between demographic variables and perception constructs; and (5) Pearson and Spearman correlation analyses to assess the strength and direction of key bivariate relationships.

Research Hypotheses

H1: Education level has no statistically significant association with perceived security in digital banking.

H2: Education level has no statistically significant association with platform transparency perception.

H3: Education level has no statistically significant association with perceived ease of use.

H4: Education level has no statistically significant association with financial knowledge perception.

H5: Education level has no statistically significant association with investor trust.

H6: Education level has no statistically significant association with risk awareness.

H7: Education level has no statistically significant association with perceived risk.

H8: Education level has no statistically significant association with adoption intention.

H9: Income level has a statistically significant association with investor confidence in digital banking platforms.

DATA ANALYSIS AND INTERPRETATION

The sample profile reveals a predominantly youthful respondent composition, with 59.2% aged between 18 and 25 years, indicating that digital banking adoption in India is most deeply concentrated among digitally native cohorts characterised by higher technological comfort and exploratory financial behaviour. Gender distribution was near-balanced (55.3% male; 44.7% female), suggesting that digital banking accessibility has largely transcended historical gender disparities in formal financial participation. Income distribution was notably heterogeneous: the largest segment (40.8%) reported annual earnings below ₹2 lakh, confirming that digital platforms have penetrated lower-income strata a critical financial inclusion indicator aligned with RBI mandates. Postgraduate respondents constituted the majority (61.2%), introducing a potential upper-education skew that warrants interpretive caution. Overall, the profile is consistent with India's urban-digital banking adopter archetype and provides a robust basis for analysing trust and risk perceptions across demographic sub-groups.

The overall Cronbach's alpha coefficient of 0.775 indicates acceptable internal consistency across the 14-item composite instrument, satisfying the psychometric threshold of $\alpha \geq 0.70$ recommended by Nunnally (1978) and Fornell and Larcker (1981) for exploratory social science research. This value implies that the ten perception-based items collectively constitute a reliable and internally coherent measurement battery, justifying their aggregation into composite latent constructs for subsequent factor-analytic decomposition. The absence of negative item-total correlations, confirmed via case processing with zero exclusions (N = 103, 100% valid), further validates the instrument's internal structure. An alpha of 0.775 is particularly appropriate for an instrument spanning multiple theoretically distinct constructs trust, security, transparency, risk awareness, and adoption intention whose conceptual independence was expected to moderate inter-item correlations. Future research employing confirmatory factor analysis should target composite reliability values exceeding 0.80 to satisfy more stringent convergent validity criteria.

EFA with PCA and Varimax rotation yielded a clean two-factor solution consistent with the study's theoretical framework. Component 1 labelled Investor Trust achieved an eigenvalue of 4.207, explaining 46.74% of total variance. Seven items loaded substantively on this factor, including ease of use (λ = 0.799), investor trust (λ = 0.784), investment confidence (λ = 0.766), financial literacy (λ = 0.759), platform usefulness (λ = 0.688), risk awareness (λ = 0.734), and adoption willingness (λ = 0.770). The co-loading of risk awareness on Component 1 suggests its conceptual integration with trust-related attitudes, reinforcing the theoretical argument that informed users simultaneously develop trust and awareness as complementary cognitive stances. Component 2 labelled Risk Awareness captured perceived risk (λ = 0.789) and a negative loading for transparency (λ = −0.531), indicating that lower perceived transparency amplifies risk perception. Collectively, the two-factor structure explains 58.75% of total variance, exceeding the 50% threshold conventionally accepted in exploratory social science research (Hair et al., 2019).

Hypothesis decision rule: $p < 0.05$ → Accepted; $p \geq 0.05$ → Rejected. χ^2 values computed using SPSS Pearson Chi-Square unless otherwise noted. Chi-square analysis produced a decisive bifurcation in demographic explanatory power. Hypotheses H1 through H8 each examining the relationship between education level and a distinct perception construct were uniformly rejected, with all p-values exceeding the 0.05 threshold. The largest education-based chi-square statistic (χ^2 = 19.579, df = 12, p = 0.075 for perceived security) approached but did not breach statistical significance, suggesting a weak substantive trend consistent with higher-educated users exhibiting marginally greater security awareness, though insufficient to warrant causal inference. These findings collectively indicate that contemporary digital banking platforms have achieved a level of interface design accessibility that equalises perceived usability, trust, and risk awareness across educational strata a finding with significant implications for inclusive fintech design. In contrast, H9 was accepted: income level demonstrated a statistically significant linear association with investor confidence (Linear-by-Linear χ^2 = 4.299, df = 1, p = 0.038), with higher-income users expressing systematically greater confidence in their digital investment decisions. This aligns with Lewellen et al. (1977) and Barsky et al. (1995), who identified income as a structural determinant of risk tolerance and financial decision-making confidence.

Pearson correlation analysis yielded a statistically significant, positive, and weak association between income level and investor confidence (r = 0.205, p = 0.038). The positive directionality confirms that higher income levels are associated with elevated confidence in digital investment decisions, a finding consistent with theories linking financial capacity to risk tolerance (Barsky et al., 1995) and information processing ability (Lusardi & Mitchell, 2014). The coefficient's modest magnitude (r = 0.205) indicates that income accounts for approximately 4.2% of variance in confidence (r^2 = 0.042), underscoring that income is a contributing rather than determinative factor. The divergence between the Pearson coefficient (r = 0.205, p = 0.038) and the Spearman rho (ρ = 0.081, p = 0.414) suggests that the income–confidence relationship is partially mediated by linear ordinal rank ordering rather than consistent monotonic graduation across all income categories. This pattern invites further investigation using interval-scaled income measures and confirmatory SEM to establish whether usability perceptions and digital literacy function as partial mediators in the income–confidence pathway.

DISCUSSION

The study's findings offer several theoretically significant and practically consequential insights. The identification of two dominant latent constructs Investor Trust and Risk Awareness as explaining 58.75% of total variance confirms the theoretical argument that digital banking adoption is fundamentally governed by attitudinal and cognitive constructs rather than demographic characteristics. This aligns with Gefen et al. (2003) and Pavlou

(2003), who demonstrated that trust is the pre-eminent adoption predictor in electronic commerce contexts, and extends their findings to the Indian retail investment domain.

The finding that education level exerts no statistically significant influence on any of the eight perception constructs tested (H1–H8, all $p > 0.05$) is both surprising and practically significant. It contradicts the conventional assumption that higher educational attainment confers superior digital financial literacy and nuanced risk awareness (Lusardi & Mitchell, 2014). One interpretation is that India's digital banking platforms have sufficiently democratised interface design leveraging vernacular language support, biometric authentication, and intuitive navigation to level the perceptual playing field across educational strata. This finding resonates with Venkatesh et al.'s (2003) UTAUT proposition that facilitating conditions including infrastructure quality and institutional support attenuate the impact of individual difference variables on adoption. Contrastingly, Lewellen et al. (1977) found education to be a significant portfolio allocation predictor in traditional securities markets, suggesting that digital platform design may have effectively decoupled financial participation from educational credentials in mobile banking contexts.

The statistically significant income confidence relationship ($r = 0.205$, $p = 0.038$) aligns with Barsky et al. (1995) and Jianakoplos and Bernasek (1998), who identified financial capacity as a structural enabler of risk-tolerant financial behaviour. However, the weak effect size indicates that income alone is an insufficient explanatory framework. This is theoretically consistent with Barber and Odean (2001), who showed that overconfidence rather than objective financial capability frequently drives retail investment decisions. The cross-loading of risk awareness items on the Investor Trust factor (particularly Q12: $\lambda = 0.734$) suggests a positive rather than adversarial relationship between these constructs in the Indian context, implying that users who are well-informed about digital risks simultaneously exhibit higher platform trust a finding that contradicts the negative trust–risk relationship posited in earlier literature (Featherman & Pavlou, 2003) and may reflect India-specific digital literacy dynamics.

CONCLUSION

This study provides empirically grounded evidence that investor trust and risk awareness are the primary determinants of digital banking adoption in the Indian context, operating largely independently of educational background but modestly influenced by income level. The two-factor structure identified through EFA Investor Trust (eigenvalue = 4.207; 46.74% variance) and Risk Awareness (eigenvalue = 1.081; 12.01% variance) provides a parsimonious, validated framework for understanding adoption intention that is directly applicable to platform design and regulatory communication strategy.

The study's principal academic contribution lies in demonstrating that the trust–risk nexus supersedes demographic predictors in structuring digital financial behaviour among Indian retail users, thereby extending the applicability of TAM and trust-risk models to emerging market fintech ecosystems. From a managerial perspective, the findings direct platform operators to prioritise visible security architecture, clear algorithmic disclosure, and proactive cyber-risk education particularly for lower-income users whose confidence deficit may be addressable through targeted design interventions rather than demographic targeting. Regulators should leverage the finding that education-independent risk awareness is achievable to inform scalable financial literacy campaigns and standardised disclosure frameworks that operate effectively across heterogeneous user populations.

SCOPE FOR FUTURE RESEARCH

This study opens several productive avenues for future inquiry. First, longitudinal panel designs would enable researchers to track how trust and risk awareness evolve as platforms mature, security incidents accumulate, and regulatory frameworks respond providing dynamic insights inaccessible to cross-sectional methods. Second, multi-group Structural Equation Modelling (SEM) using confirmatory factor analysis could validate the two-factor trust–risk framework identified here and formally test moderation by income, age cohort, and prior fraud victimisation experience, thereby establishing causal pathways rather than associative relationships.

Third, cross-industry and cross-regional comparisons contrasting digital banking users in metropolitan versus Tier-2 and Tier-3 Indian cities, or comparing Indian cohorts with Southeast Asian fintech adopters would illuminate the boundary conditions of the trust–risk framework and assess its generalisability beyond the Bengaluru-anchored convenience sample used in this study. Fourth, future research should explicitly incorporate emerging technological modalities AI-driven advisory systems, blockchain-based transparency mechanisms, and Central Bank Digital Currency (CBDC) platforms as trust and risk determinants, since these technologies introduce qualitatively novel forms of opacity and institutional dependence not yet theorised in the existing digital banking literature.

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Table 1

Profile of Respondents (N = 103)

Demographic Variable	Category	Frequency	Percentage (%)
Age	18–25	61	59.2
	26–35	22	21.4
	36–45	10	9.7
	46 and Above	10	9.7
Gender	Male	57	55.3
	Female	46	44.7
Income Level (Annual)	Below ₹2 Lakhs	42	40.8
	₹2–5 Lakhs	17	16.5
	₹5–10 Lakhs	23	22.3
	Above ₹10 Lakhs	21	20.4
Education Level	Undergraduate	12	11.7
	Graduate	22	21.4
	Postgraduate	63	61.2
	Others	6	5.8

Note. Data sourced from primary questionnaire survey.

Table 2

Reliability Analysis (Cronbach's Alpha)

Scale / Composite	No. of Items	Cronbach's Alpha (α)	Reliability Verdict
Overall Instrument	14	0.775	Acceptable
Investor Trust Dimension	7	0.775 (composite)	Acceptable
Risk Awareness Dimension	2	0.775 (composite)	Acceptable

Note. Reliability threshold: $\alpha \geq 0.70$ = Acceptable; $\alpha \geq 0.80$ = Good; $\alpha \geq 0.90$ = Excellent (Nunnally, 1978).

Table 3

Exploratory Factor Analysis — Rotated Component Matrix (Varimax Rotation)

Survey Item	Component 1 Investor Trust	Component 2 Risk Awareness
Digital banking apps are easy to use (Q7)	0.799	−0.173
I trust digital banking platforms (Q11)	0.784	−0.129
I am confident in my investment decisions (Q10)	0.766	−0.046
I have sufficient financial knowledge (Q9)	0.759	−0.021
Digital banking is useful for managing finances (Q8)	0.688	0.044
I am aware of risks such as fraud (Q12)	0.734	0.349
I am willing to continue using digital banking (Q14)	0.770	0.058

I perceive digital banking as risky (Q13)	0.190	0.789
Platforms clearly disclose fees and policies (Q6)	0.388	−0.531
Eigenvalue	**4.207**	**1.081**
% of Variance Explained	**46.74%**	**12.01%**
Cumulative Variance Explained	**46.74%**	**58.75%**

Note. Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation. Rotation converged in 3 iterations. Factor loadings ≥ 0.40 considered significant.

Table 4

Chi-Square Tests of Independence — Hypothesis Testing Results

Hypothesis	Independent Variable	Dependent Variable	χ^2 Value	df	p-value	Decision
H1	Education	Perceived Security	19.579	12	0.075	Rejected
H2	Education	Platform Transparency	4.459	9	0.312 (0.879)	Rejected
H3	Education	Ease of Use	16.398	12	0.174 (0.426)	Rejected
H4	Education	Financial Knowledge	13.947	12	0.304 (0.080)	Rejected
H5	Education	Investor Trust	8.505	12	0.471 (0.745)	Rejected
H6	Education	Risk Awareness	9.482	12	0.661 (0.763)	Rejected
H7	Education	Perceived Risk	4.356	12	0.550 (0.976)	Rejected
H8	Education	Adoption Intention	11.891	12	0.454 (0.678)	Rejected
H9	Income	Investor Confidence	13.200 (Lin.=4.299)	12 (Lin.=1)	0.038*	Accepted

Note. * $p < 0.05$ (statistically significant).

Table 5

Pearson Correlation Analysis — Income Level and Investor Confidence

Measure	Value	Approximate T	Asymptotic Std. Error	p-value (2-sided)
Pearson's r (Interval by Interval)	0.205	2.106	0.097	0.038*
Spearman's ρ (Ordinal by Ordinal)	0.081	0.820	0.097	0.414
N of Valid Cases	103	—	—	—

Note. * $p < 0.05$. Based on normal approximation. Pearson's r computed assuming null hypothesis. Income Level coded as ordinal (1=Below ₹2L; 2=₹2–5L; 3=₹5–10L; 4=Above ₹10L); Confidence coded as 5-point Likert scale.