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Modeling User Behaviour for AI-Driven
Financial Decision Systems: A Mixed-Methods
Investigation of Mutual-Fund Innovation
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Abstract

Though the digital financial services ecosystem in India is rapidly adopting AI-enabled delivery, mutual fund adoption among educated, salaried people remains disproportionate, raising two questions: why are mutual funds being adopted, and what should be prioritised when designing advances in robo-advisory? By presenting digital investment platforms as a systematic innovation in the Indian fintech ecosystem (after Unified Payments Interface and the Account Aggregator framework), we propose a user-behaviour model of AI-based financial decision-making and examine the key factors influencing mutual-fund adoption among academic institutions of Indian central universities. The paper follows the diffusion of innovations approach to interpretation and operationalises it with an extended Theory of Planned Behaviour, where attitude, subjective norms, fintech self-efficacy, financial literacy, and religiosity are theorised as predictors of intention to adopt, and fintech self-efficacy mediates the attitude–intention relationship. It integrates three bodies of research (behavioural modelling [PLS-SEM], importance-based prioritisation [IPMA], and invention design [TRIZ]) into one fintech-adoption research pipeline; inculcates an innovation-specialised self-efficacy construct within the Rogers–Ajzen synthesis; and illustrates how an empirical user behaviour model can be transformed into a prioritised, design-ready blueprint of AI robo-advisors in India. A sample of 412 academicians from 24 central universities (September 2024–February 2025) was used to apply the three-stage design. Support for 9 out of 10 hypotheses and the model's ability to explain 43.8% of the variation in investment intention were achieved. The top adoption antecedents included subjective norms (importance weight = 0.272), attitude (0.256), financial literacy (0.231), fintech self-efficacy (0.201), and religiosity (0.040). The target design-leverage, though, was fintech self-efficacy: it performed worst and was the only antecedent that modulated the attitude–intention relationship significantly ($\beta = 0.114$). The four design contradictions the expert panel retained were resolved using five TRIZ inventive principles, yielding a prioritised design blueprint for next-generation robo-advisory platforms.

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1. Introduction

A decade of systematic innovations in the digital financial services ecosystem has completely reshaped the manner in which investments are undertaken in India, leveraging artificial intelligence (AI)-based recommendation engines to convert raw know-your-customer (KYC) forms and risk-profile data into personalised investment baskets—Unified Payments Interface (UPI), the Account Aggregator (AA) framework, the Securities and Exchange Board of India (SEBI)–Reserve Bank of India (RBI) regulatory sandbox, and the advent of a new generation of robo-advisory platforms, such as Groww, Zerodha Coin, Kuvera, and ET Money (RBI, 2024). As the Indian mutual-fund segment size has increased to Indian Rupee (INR) 60 trillion in March 2025 (Association of Mutual Funds in India, 2025) as compared to INR 5.6 trillion in 2014, the adoption has been patchy, with only about 45 million unique mutual-fund investors in a country of more than 1.4 billion people—fewer than 1 in 30—which indicates there is much further to run on the innovation-adoption curve, especially among the educated, earning populations.

In this paper, we consider one such user group—professionally homogeneous academic users at central universities in India—and model their behavioural intention to invest in mutual funds through an AI-based mutual-fund decision system. The adoption of a digital investment platform represents the uptake of a systematic innovation. We conceptualized this process using the classical diffusion of innovations (DOI) framework, complemented by modern technology adoption models, to examine five user-side antecedents: relative advantage (attitude), normative influence (subjective norms), an innovation-specific competence belief (fintech self-efficacy), knowledge base (financial literacy), and cultural or value orientation (religiosity). We retained the behavioural backbone of the theory of planned behaviour (TPB), which has been applied widely to explain the intentions to finance (Ajzen, 1991; Akhtar & Das, 2019; Raut, 2020), and extended it in three ways typical of systematic-innovation research: (i) we substituted generic perceived behavioural control with fintech self-efficacy as a behavioural antecedent of the innovation outcome; (ii) we introduced financial literacy and religiosity as an enabling and a cultural antecedent, respectively; and (iii) we did not treat the model as an end in itself but rather as providing the input to a downstream innovation-prioritisation and inventive-design process (importance–performance map analysis [IPMA] + Theory of Inventive Problem Solving [TRIZ]).

This research study addresses three research questions (RQs): RQ1: Are there any joint effects of attitude, subjective

norms, fintech self-efficacy, financial literacy, and religiosity on the intention of central-university academicians to invest in mutual funds via digital platforms? RQ2: Which innovation-adoption antecedents hold the most weight when the behavioural model is expressed at the level of construction based on importance–performance? RQ3: What are the design contradictions identified for robo-advisory platforms targeting this user group, and how can these be overcome by the TRIZ principles of invention?

The article contributes to the field of systematic innovation studies in three ways. At the conceptual level, it introduces a Rogers–Ajzen formulation adapted to the Indian context of fintech products and services and validates the implications for innovation-specific self-efficacy on the attitude–intention continuum. Methodologically, it presents a three-phase mixed-methods pipeline, from user modelling in behavioural information to a prioritised design-derived model used as a target for AI-based financial decision systems. Practically, it has design implications for next-generation robo-advisory interfaces for Indian scholarly users, in line with the policy agenda of the National Strategy of Financial Education.

The paper is organised as follows: Section 2 presents a literature review covering innovation adoption, extended TPB, and fintech self-efficacy. The conceptual framework and hypotheses are provided in Section 3. The mixed-methods research design is described in Section 4. The results of partial least squares structural equation modelling (PLS-SEM), IPMA, and TRIZ are reported in Section 5. Section 6 is devoted to theoretical and design implications, limitations, and future research directions, including the extension of the patent landscape, while Section 7 concludes the study.

2. Literature review

2.1. Innovation in financial-services platforms and architectures

According to the DOI theory, there are five attributes of innovation (relative advantage, compatibility, complexity, trialability, and observability) and five stages of adoption (knowledge, persuasion, decision, implementation, and confirmation). These constructs were synthesised by Venkatesh *et al.* (2003), who formulated the unified theory of acceptance and use of technology (UTAUT). More recent studies on introducing systematic innovation into a financial services business build on these themes to highlight personalisation through AI, algorithmic robo-advice, and platform-mediated trust signals (Frame *et al.*, 2019; Panos & Wilson, 2020). The Indian digital financial services UPI–AA model has been considered one of the most innovative and architecturally sound national fintech models over the last 10 years (RBI, 2024).

2.2. The theory of planned behaviour as a model of user behaviour

The TPB has been continually applied to the study of human intention, including in financial markets participation (Akhtar & Das, 2019; Raut, 2020), retirement planning (Bongini & Cucinelli, 2019), and Islamic financial products (Albaity & Rahman, 2019; Che Hassan *et al.*, 2024). The classical three factors of attitude, subjective norms, and perceived behavioural control are important in predicting behavioural intention, and intention is important in predicting behaviour. According to this framing, attitude is linked to the relative-advantage consideration by the user, subjective norms relate to the interpersonal-influence channel, while behavioural control is interpreted as a person's ability to use the innovation, i.e., in a digital-platform context, as fintech self-efficacy. We want to make clear that the DOI framework attributes are not operationalised as distinct measurement scales, nor are they directly tested, to avoid any ambiguity with regard to the role of the framework in question. DOI is employed as merely a hypothetical prism driving and interpreting the TPB constructs that are directly measured: attitude is perceived as relative advantage and compatibility of the innovation, fintech self-efficacy as an innovation-specific belief that reflects the complexity and ease of use of the platform, subjective norms as the interpersonal channel of persuasion, and religiosity as a cultural-fit layer. There is no estimation of relative-advantage, compatibility, or complexity constructs, and no relative-advantage attributes are observed in the measurement or structural model. Everything in the model is a TPB-based construct, which is empirically measured, and DOI is merely used to frame and explain them.

2.3. Fintech self-efficacy in the adoption of innovation

Self-efficacy, according to Bandura (1977), is a person's perception of their planning and execution skills required to achieve a goal. The construct has been applied to other domains of the digital environment, such as information and communication technology learning (Anouze & Alamro, 2020), mobile devices (Singh & Srivastava, 2020), and financial self-efficacy (Mindra & Moya, 2017).

2.4. Financial literacy and religiosity as adoption-relevant factors

Lusardi & Mitchell (2014) conceptualised the Big Three of financial literacy: knowledge of compound interest, inflation, and risk diversification. The evidence on the relationship between financial literacy and the stock market, or financial literacy and mutual fund engagement, is well developed in the Indian context (Agarwalla *et al.*,

2015; Janor *et al.*, 2016). Religiosity, as the internalisation of religious values, beliefs, and practices (Worthington *et al.*, 2003), is a culturally salient factor in India, as 99.7% of the population is religious (Census of India, 2011; Pew Research Center, 2021). The research literature has been mixed, with some indicating a direct effect of religiosity on investment (Duqi & Al-Tamimi, 2019; Newaz *et al.*, 2016), others showing a mediated effect of religiosity on investment (Che Hassan *et al.*, 2024; Souiden & Rani, 2015). We included the two constructs as the proximal and distant cultural inputs in our model.

2.5. Importance–performance map analysis and Theory of Inventive Problem Solving in systematic innovation study

A popular follow-up approach in PLS-SEM that includes both the importance of a construct—the standardised total effect of a construct on a target endogenous variable (i.e., score) on a 0–100 scale and the performance, or the mean value, of an indicator—is IPMA (Ringle & Sarstedt, 2016). It is increasingly used to evaluate technologies and prioritise fintech products, identifying the constructs that can provide the greatest leverage for improving the product. TRIZ (Altshuller, 1996) has 40 principles of inventive problem-solving that were originally developed in the field of mechanical engineering, but have been applied to service- and digital-product design (Chechurin & Borgianni, 2016). Although each of these three methods is relatively well-established, we are unaware of any previous fintech-adoption studies that integrate all three—behavioural modelling (PLS-SEM), importance-based prioritisation (IPMA), and inventive design (TRIZ)—into a single pipeline. Thus, we propose this integration as a methodological aspect of the study rather than arguing that any of the three approaches, or a combination of them, is innovative. The proposed contribution is to systematic innovation research, not to financial-behaviour research per se: the pipeline would turn a descriptive explanation of who adopts and why into a prioritised, contraposition-based design requirement, in which the binding constraints on the AI-advisory artefact are prioritised by importance ranking (IPMA) and then addressed by inventive principles (TRIZ).

3. Conceptual framework and hypotheses

The concept is illustrated in Figure 1. The systematic innovation in the investment intention of mutual funds can be characterised as follows: five direct antecedents (attitude, subjective norm, fintech self-efficacy, financial literacy, and religiosity), two mediation channels (attitude and subjective norm), and a moderation channel (fintech self-efficacy enhancing the relationship between attitude and intention).

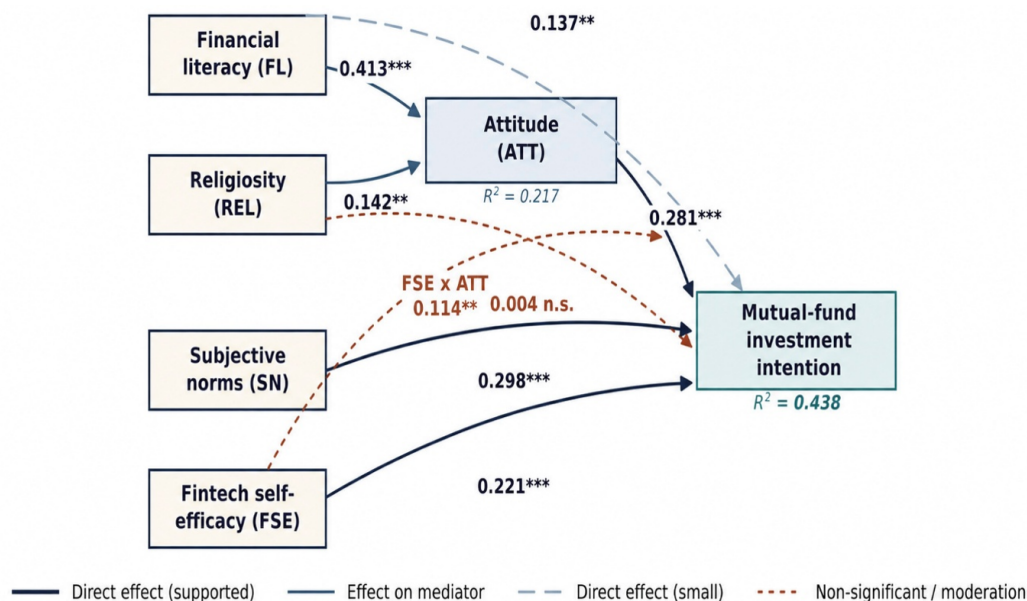


Figure 1. Conceptual framework: User-behaviour model for artificial intelligence-driven financial decision systems. Path coefficients shown are partial least squares structural equation modelling (PLS-SEM) estimates from $n = 412$ (see Section 5). Notes: ** $p < 0.01$, *** $p < 0.001$, n.s. = not significant.

3.1. Direct effects

The hypotheses for direct effects are as follows:

- H1: There is a positive relationship between attitude and intention to invest in mutual funds.
- H2: The subjective norms have a positive and significant impact on the investment intention of mutual funds.
- H3: Fintech self-efficacy positively relates to commitment to invest in mutual funds.
- H4: Financial literacy is positively and significantly related to investing in mutual funds.
- H5: Financial literacy and attitude towards mutual-fund investment have a significant positive relationship.
- H6: There is a positive relationship between religion and attitude towards investment in mutual funds.
- H7: The more religious the individuals are, the more likely they are to have intentions to invest in mutual funds.

3.2. Mediation effects

The hypotheses for mediation effects are as follows:

- H8: There is a mediating role of attitude between financial literacy and intention to invest in mutual funds.
- H9: Attitude mediates the relationship between religiosity and investment intention towards mutual funds.

3.3. Moderation effect

The hypothesis for the moderation effect is as follows:

- H10: Fintech self-efficacy positively moderates the attitude–intention relationship, such that the relationship is stronger at higher levels of fintech self-efficacy.

4. Mixed-methods research design

The research employed a mixed-methods methodology (Figure 2), comprising a quantitative behavioural model (PLS-SEM), a quantitative method of priority ranking (IPMA), and a qualitative method of inventive design (TRIZ). Stage 1 establishes a behavioural foundation, Stage 2 provides a systematic-innovation priority ranking, and Stage 3 scales the priority ranking onto the design contradiction and inventive principles.

4.1. Stage 1: Partial least squares structural equation modelling (behavioural modelling)

4.1.1. Research design

A quantitative cross-sectional design was adopted. This aligns with behavioural-finance studies that focus on capturing attitudes, perceptions, and intentions at a single point in time (Akhtar and Das, 2019; Che Hassan *et al.*, 2024; Raut, 2020).

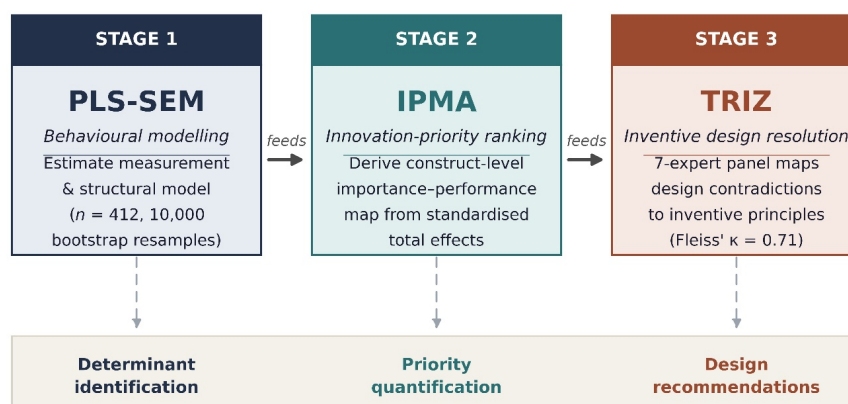


Figure 2. Three-stage mixed-methods design integrating PLS-SEM, IPMA, and TRIZ

Abbreviations: IPMA: Importance–performance map analysis; PLS-SEM: Partial least squares structural equation modelling; TRIZ: Theory of Inventive Problem Solving.

4.1.2. Data gathering, sampling, and non-response evaluation

The sample included a list of 56 central universities in 27 states and union territories within India, including Assistant, Associate, and Full Professors of the teaching faculty. The purposive and random-combination sampling used in the study consisted of two stages. To achieve geographical and disciplinary diversity, 24 universities were randomly selected from this frame in the first stage; in the second stage, random sampling was conducted among the faculty at the selected universities. The respondent selection criteria were (i) full-time academic, (ii) used at least one digital financial-services platform (UPI, internet banking, or a digital investment application), and (iii) had at least one year of work experience. The data collection period was from September 2024 to February 2025. Following screening and data-quality checks, 412 of the 443 initial responses were retained, resulting in a 93.0% usable response rate.

The Armstrong & Overton (1977) wave comparison method was used to determine the non-response bias, comparing the first 25% of the respondents with the last 25% of the respondents on all demographic variables and means of the constructs and there was no significant difference ($p < 0.05$), which indicates that the non-response bias does not seem to be in a position to invalidate the validity of the findings. We also observed two sample limitations: the sample tends to be skewed towards the mid-career faculty, which is aligned with the sample of retail mutual fund investors in India, but it does not allow for generalisation to very young (under 25) and very senior (over 70) segments; and the above-60 sample is small,

which might not allow for findings on perceived control and complexity to be fully representative across those segments. These are reported in Section 6.

4.1.3. Ethics and informed consent

The study was approved by the Mittal School of Business, Mittal Ethics Committee of Research Involving Human Participants, Phagwara, India (approval number: LPU/10.2/SC/2024/029/250305/0048), and was adhered to the Declaration of Helsinki (World Medical Association, 2013) and the Indian Council of Medical Research (ICMR) National Ethical Guidelines of Biomedical and Health Research Involving Human Participants. All participants provided electronic informed consent prior to participation and were informed of the study's objective, the voluntary nature of participation, the right to withdraw at any time without consequences, the anonymity of responses, and the safe treatment of information, as well as the absence of participation incentives. We did not retain any personally identifying information and anonymised the responses prior to analysis, storing them on an encrypted institutional hard drive, in compliance with the Digital Personal Data Protection Act 2023. No vulnerable groups were involved, no pictures of biological samples were involved, and no recognisable pictures were used; all the participants were full-time adult academicians and at minimal risk.

Each multi-item measure was a modification of previously accepted measures. Intention to invest and attitude towards investment (across five items and four items, respectively) were adapted from Lai (2019) and Akhtar & Das (2019). The fintech self-efficacy items (five items) were adapted from Aziz *et al.* (2019) and reworded

to fit the context of mutual funds in India. The subjective norm (four items) was adapted from Amin (2016). Financial literacy (six items) was based on the Lusardi–Mitchell core battery with questions relevant to India. Religiosity (6 items, increased to 10 during refinement) was adapted from Worthington *et al.* (2003). The exogenous variables were assessed on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), and the endogenous variable was assessed on a seven-point scale as specified by Podsakoff *et al.* (2012) to deflate scale-anchor differences and common methodological variance. Construct blocks were randomly ordered, and respondent anonymity was ensured by informing respondents of this in the first phase of the instrument.

4.2. Stage 2: Importance–performance map analysis (innovation-priority ranking)

In Stage 2, to determine the construct-level priority levels of the five antecedents of innovation-adoption obtained in Stage 1, an IPMA (Ringle & Sarstedt, 2016) was conducted. The IPMA included two additional items (not in a standard PLS-SEM output): (i) the significance of a predictor construct, or its standardised summed effect on the target endogenous variable (investment intention); and (ii) the performance of a construct, or its average indicator score scaled to a 0–100 metric. After result normalization, the performance score of every construct was calculated as the unstandardised mean of the latent variables as:

$$Performance = \frac{Mean - Min scale}{Max scale - Min scale} \times 100 \quad (1)$$

where min scale and max scale are the lowest and highest values, respectively, on the measurement scale (here 1 and 5), so that readers can replicate the reported performance scores based on the indicators' underlying data. The priorities in a four-quadrant priority map were determined by performance on the vertical axis and importance on the horizontal axis. In the quadrant of high importance, low performance, the major areas that should be worked on and improved were identified.

It is important to be very clear that IPMA is not Saaty's (1980) analytic hierarchy process (AHP). None of these steps were implemented in IPMA: AHP requires hierarchical decomposition, pairwise comparisons on a 1–9 scale by experts, calculation of priorities using eigenvalues, and verification of the consistency ratio. The importance weights were directly derived from the standardised total effects of the PLS-SEM and were thus not used in the independent and pairwise elicitation process. One of the

possible future research directions identified in Section 6 is a true expert-pairwise AHP study, utilised to triangulate the priority ranking provided by the IPMA.

4.3. Stage 3: Theory of Inventive Problem Solving (inventive design resolution)

In Stage 3, a transparent four-step process with a panel of domain experts was used to apply TRIZ contradiction analysis (Altshuller, 1996) on the design tensions indicated by the PLS-SEM and IPMA.

Step 1 involves an expert panel. The three criteria that seven domain experts used in the process of purposive sampling included: (i) over five years of work experience in the financial field; (ii) experience with both behavioural finance and AI-based advising solutions; and (iii) the ability to participate in a two-round structured elicitation. The panel consisted of three academic scholars who studied behavioural finance/finance technology, two practitioners working in AI-driven advisory firms established in India, and two SEBI-registered mutual fund distributors with 5–15 years of experience in retail advisory advice. No financial interest, including the platforms used in investigating their contradictions, involved any of the experts.

Step 2 involves identifying contradictions in the text (Round 1). Each expert was briefed individually on the IPMA result and the TRIZ framework and asked to identify candidate technical contradictions (parameters that improve one construct and degrade another construct) and physical contradictions (parameters that take two values that are inconsistent with each other). There were 19 candidate contradictions generated.

Step 3 involves consolidation (Round 2). G. K. narrowed the list of similar candidates to 11 contradictions, and both authors deliberated and agreed on the candidates in a moderated joint session. Four of these contradictions remained, as the others were abandoned, with recorded reasons why they were no longer relevant or illegitimate as contradictions in AI-driven advisory design. There was substantial agreement among the raters, with a Fleiss' $\kappa = 0.71$.

Step 4 involves identifying creative ideals. The contradictions were independently assessed by both authors, using the Altshuller contradiction matrix to identify candidate inventive principles, and conflicts were resolved through collaborative review, reconsultation of Altshuller documented examples, and, when necessary, by both authors. The four design directions identified in Section 5.6 were created by synthesising the inventive principles chosen across the remaining contradictions.

5. Results

5.1. Multivariate normality and common-method variance

Three separate tests were used to assess common-method variance (CMV) on a procedural basis (through the use of varying scale anchors, anonymity, and item-order randomisation) and statistically. First, Harman's one-factor test reported a variance less than 50%, suggesting that CMV was not a substantial threat. Second, the inner variance inflation factor (VIF) of the full-collinearity test (Kock, 2015) was less than 3.3, a conservative figure that indicates the procedures did not substantially bloat the structural relationships. Third, an unmeasured latent method factor was added as a predictor of all indicators. Following Liang *et al.* (2007), after controlling for the method factor, all substantive factors had significant factor loadings, and the amount of variance they explained was significantly less than that of the substantive factors. The three tests indicate that CMV is unlikely to have a material effect on the findings. The Mardia multivariate-normality test (WebPower) reported a skewness of 11.624 ($p < 0.001$) and a kurtosis of 102.873 ($p < 0.001$), which is larger than 3 and 20, respectively, confirming that the model is non-normal and justifying the use of variance-based PLS-SEM instead of covariance-based SEM.

5.2. Respondent profile

Details for the 412 respondents on the demographic, occupational profile, and age bands are presented in Table 1.

5.3. Stage 1: Partial least squares structural equation modelling measurement model

The degree of reliability of indicators, internal consistency reliability, and convergent validity was evaluated. Outer loadings of items FL1, REL1, REL2, REL5, and REL10 were less than the 0.60 retention criterion; hence, they were removed during refinement. The remaining items had a minimum outer loading of 0.652 and a maximum of 0.929 on their constructs. All construct scores exceeded the convergent-validity threshold (Cronbach's alpha 0.70, composite 0.80, and average variance extracted 0.50). No indicator-level multicollinearity was identified, as all VIFs fell below the conservative value of 3.3 (outer VIF). The results are tabulated in Table 2.

The heterotrait-monotrait ratio (HTMT) of correlations (Henseler *et al.*, 2015) was used to determine the discriminant validity. The values of all HTMTs were lower than the conservative level of 0.85, implying that all constructs are empirically different (Table 3). Cross-loadings also helped establish that each indicator loads more on its respective construct than any other.

Table 1. Details for the 412 respondents

Category	Sub-category	<i>n</i>	%
Gender	Male	242	58.7
	Female	170	41.3
Age group	Below 30 years	31	7.5
	30–40 years	147	35.7
	41–50 years	84	20.4
	51–60 years	118	28.6
	Above 60 years	32	7.8
Designation	Assistant Professor	197	47.8
	Associate Professor	118	28.6
	Professor	97	23.5
Highest qualification	Master's degree	21	5.1
	M.Phil.	28	6.8
	Ph.D.	313	76.0
	Post-doctorate	50	12.1
Discipline	Sciences and Engineering	139	33.7
	Social Sciences and Humanities	168	40.8
	Commerce and Management	73	17.7
	Law, Education, and other	32	7.8
Religion	Hindu	287	69.7
	Muslim	48	11.7
	Sikh	33	8.0
	Christian	24	5.8
	Other/No religion	20	4.9
Mutual fund holder	Yes	256	62.1
	No	156	37.9

5.4. Stage 1: Partial least squares structural equation modelling structural model

The structural model was estimated using PLS-SEM bootstrapping with 10,000 replications. Table 4 presents the results of hypothesis testing. Nine out of 10 hypothesised relationships were supported. Attitude ($\beta = 0.281$, $t = 4.218$, $p < 0.001$), subjective norms ($\beta = 0.298$, $t = 5.034$, $p < 0.001$), fintech self-efficacy ($\beta = 0.221$, $t = 4.687$, $p < 0.001$), and financial literacy ($\beta = 0.137$, $t = 2.893$, $p = 0.002$) each exerted a significant positive direct effect on investment intention, supporting H1–H4. The strongest path in the model was financial literacy $\rightarrow$ attitude ($\beta = 0.413$, $t = 7.612$, $p < 0.001$), supporting H5. Religiosity had a small significant positive effect on attitude ($\beta = 0.142$, $t = 2.971$, $p = 0.002$), supporting H6, but a non-significant direct effect on intention ($\beta = 0.004$, $t = 0.121$, $p = 0.452$),

Table 2. Indicator reliability, internal-consistency reliability, and convergent validity

Construct	Item	Outer loading	Composite reliability	Cronbach's α	AVE
Financial literacy (FL)	FL2	0.731	0.872	0.808	0.578
	FL3	0.802			
	FL4	0.778			
	FL5	0.694			
	FL6	0.751			
Religiosity (REL)	REL3	0.774	0.879	0.834	0.541
	REL4	0.762			
	REL6	0.703			
	REL7	0.728			
	REL8	0.652			
Fintech self-efficacy (FSE)	REL9	0.769			
	FSE1	0.851	0.924	0.897	0.708
	FSE2	0.836			
	FSE3	0.759			
	FSE4	0.881			
Subjective norms (SN)	FSE5	0.846			
	SN1	0.842	0.881	0.819	0.650
	SN2	0.821			
	SN3	0.793			
Attitude (ATT)	SN4	0.747			
	ATT1	0.886	0.947	0.926	0.816
	ATT2	0.904			
	ATT3	0.921			
Investment intention (INTENT)	ATT4	0.871			
	INTENT1	0.879	0.962	0.949	0.831
	INTENT2	0.918			
	INTENT3	0.892			
	INTENT4	0.929			
	INTENT5	0.914			

Note: Items FL1, REL1, REL2, REL5, and REL10 were removed due to outer loadings below 0.60.

Abbreviation: AVE: Average variance extracted.

Table 3. Heterotrait–monotrait ratio (HTMT) of correlations

Construct	FL	REL	FSE	ATT	SN
Financial literacy (FL)	–				
Religiosity (REL)	0.341	–			
Fintech self-efficacy (FSE)	0.452	0.218	–		
Attitude (ATT)	0.518	0.293	0.276	–	
Subjective norms (SN)	0.529	0.327	0.262	0.683	–
Investment intention (INTENT)	0.491	0.249	0.418	0.564	0.628

Note: All HTMT values are below 0.85, supporting discriminant validity (Henseler *et al.*, 2015).

Table 4. Hypothesis-testing results

Hypothesis	Path	β	SD	<i>t</i> -value	<i>p</i> -value	BCI LL	BCI UL	Decision
H1	ATT → INTENT	0.281	0.067	4.218	<0.001	0.157	0.401	Supported
H2	SN → INTENT	0.298	0.059	5.034	<0.001	0.187	0.408	Supported
H3	FSE → INTENT	0.221	0.047	4.687	<0.001	0.139	0.305	Supported
H4	FL → INTENT	0.137	0.047	2.893	0.002	0.058	0.218	Supported
H5	FL → ATT	0.413	0.054	7.612	<0.001	0.319	0.498	Supported
H6	REL → ATT	0.142	0.048	2.971	0.002	0.061	0.221	Supported
H7	REL → INTENT	0.004	0.034	0.121	0.452	−0.062	0.071	Not supported
H8	FL → ATT → INTENT	0.116	0.029	3.998	<0.001	0.066	0.175	Supported
H9	REL → ATT → INTENT	0.040	0.017	2.341	0.010	0.014	0.077	Supported
H10	ATT × FSE → INTENT	0.114	0.046	2.488	0.006	0.041	0.193	Supported

Notes: β = Standardised path coefficient; BCI = 95% bias-corrected confidence interval; bootstrap with 10,000 resamples. $R^2(\text{INTENT}) = 0.438$; $R^2(\text{ATT}) = 0.217$.

Abbreviations: ATT: Attitude; FL: Financial literacy; FSE: Fintech self-efficacy; INTENT: Investment intention; LL: Lower limit; REL: Religiosity; SN: Subjective norms; UL: Upper limit.

so H7 was not supported. Both mediation hypotheses were proven: the relation between financial literacy and intent was mediated by attitude (H8: $\beta = 0.116$, $p = 0.001$), and between financial literacy and religiosity (H9: $\beta = 0.040$, $p = 0.010$). The following results confirm the moderation hypothesis, as fintech self-efficacy significantly positively moderated the attitude–intention relationship (H10: $\beta = 0.114$, $t = 2.488$, $p = 0.006$; Figure 3).

The model accounted for 43.8% of the variance in the investment intention ($R^2 = 0.438$) and the attitude variance ($R^2 = 0.217$), greater than the medium effect that Cohen (1988) defined. Predictive relevance was strong: $Q^2(\text{INTENT}) = 0.362$ and $Q^2(\text{ATT}) = 0.196$. The effect sizes (f^2) of the structural paths were interpreted according to Cohen's (1988) criteria (small = 0.02, medium = 0.15, and large = 0.35). The effects ranged from small

(religiosity → intention) to medium and large (financial literacy → attitude), consistent with the corresponding path coefficients. The model demonstrated good fit, with a standardised root-mean-square residual below the 0.08 threshold (Hu & Bentler, 1999) and a normed fit index value higher than 0.90. In addition, both d_ULS and d_G were within their 95% bootstrap confidence interval, indicating no significant model misfit.

Table 5 presents the predictive evaluation based on PLSpredict using 10-fold cross-validation. The PLS-SEM model yielded lower root-mean-squared error (RMSE) values than the linear model benchmark for all five indicators of investment intention (mean $\Delta\text{RMSE} = -0.029$), and all Q^2 predict values exceeded zero, suggesting that the model over-predicts the naïve linear model.

Table 5. PLSpredict assessment of out-of-sample predictive power

Indicator	PLS-SEM RMSE	LM RMSE	ΔRMSE	Q^2 predict
INTENT1	0.929	0.963	−0.034	0.211
INTENT2	0.902	0.934	−0.032	0.237
INTENT3	1.071	1.099	−0.028	0.184
INTENT4	0.971	0.999	−0.028	0.252
INTENT5	1.032	1.057	−0.025	0.221

Note: The PLS-SEM RMSE is lower than the LM benchmark across all five indicators.

Abbreviations: INTENT: Investment intention; LM: Linear model; PLS-SEM: Partial least squares structural equation modelling; RMSE: Root-mean-squared error.

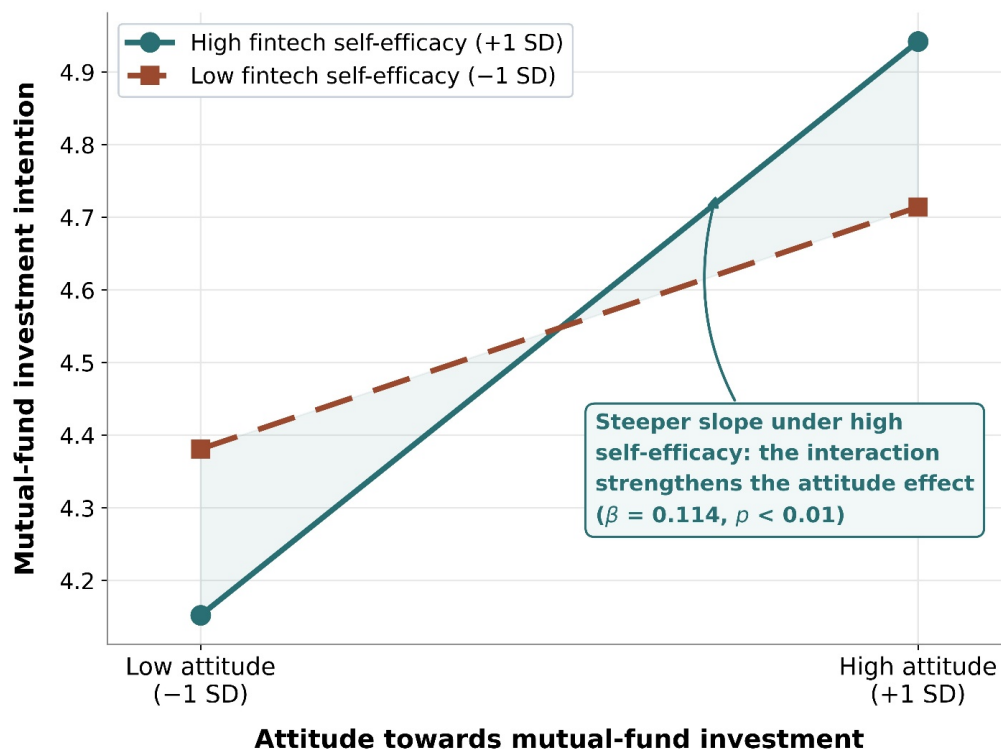


Figure 3. Simple slope visualisation of the H10 moderation effect. The attitude–intention relationship is steeper for academicians with high fintech self-efficacy.

5.5. Stage 2: Importance–performance map analysis priority ranking

Based on the IPMA process, construct-level importance weights were obtained from the standardised total effect of antecedent on investment intention determined in Stage 1. Total effects were the summation of the direct effect of each antecedent on intention and the indirect effect of the antecedent on intention through its attitude. In line with conventional IPMA, the impact weight of fintech self-efficacy was only based on its direct effect; the interaction (moderation) coefficient of the attitude–intention path ($\beta = 0.114$) was a product-term effect rather than a total effect. As such, it was not cumulated to the impact weight, but was instead reported as an individual qualitative, design-relevant finding. The basic calculations are in Table 6, and the ranking of the importance with the rescaled performance values is plotted in Figure 4.

Subjective norms reported the highest importance rating (0.272), followed by attitude (0.256), financial literacy (0.231), fintech self-efficacy (0.201), and religiosity (0.040), which was last due to the non-significant direct effect and non-significant mediated effect. The importance weight alone, however, does not determine which of the

five actionable design levers is most actionable: fintech self-efficacy had a relatively small importance weight and the lowest performance score among the antecedents, while also exerting a distinct reinforcing effect on the attitude–intention channel. Therefore, fintech self-efficacy was identified as the highest-leverage design target of systematic innovation, since interventions that enhance the fintech self-efficacy of users can simultaneously target the construct with the greatest headroom for improvement and enhance the effect of attitude on intention. This finding directly informs the design of AI-based robo-advisory systems.

5.6. Stage 3: Theory of Inventive Problem Solving contradiction analysis

A visualisation of the IPMA priorities and PLS-SEM coefficients onto the robo-advisory platform design options raised four conflicting design considerations (the four contradictions that the expert panel retained in Section 4.3). The contradictions and the creative principles chosen to solve them are summarised in Figure 5.

Contradiction C1 (ease of use vs. depth of information) was aligned with Inventive Principle 24 (Intermediary).

Table 6. Importance–performance map analysis construct-level importance ranking for innovation-adoption antecedents

Innovation-adoption antecedent	Direct effect on INTENT	Indirect effect (via ATT)	Total effect	Importance weight
Fintech self-efficacy (FSE)	0.221	0.000	0.221	0.201
Subjective norms (SN)	0.298	0.000	0.298	0.272
Attitude (ATT)	0.281	0.000	0.281	0.256
Financial literacy (FL)	0.137	0.116	0.253	0.231
Religiosity (REL)	0.004 (n.s.)	0.040	0.044	0.040
Sum	–	–	1.097	1.000

Notes: Importance weights are derived from PLS-SEM standardised total effects via the IPMA procedure. n.s. = non-significant individual path retained at zero for total-effect purposes only where direction of effect is preserved. For fintech self-efficacy, the importance weight is based on its direct effect only; the moderating effect on the attitude–intention path ($\beta = 0.114$) is a product-term interaction rather than an additive total-effect component and is therefore reported separately rather than added to the importance weight, in line with standard IPMA practice. Abbreviations: INTENT: Investment intention; PLS-SEM: Partial least squares structural equation modelling.

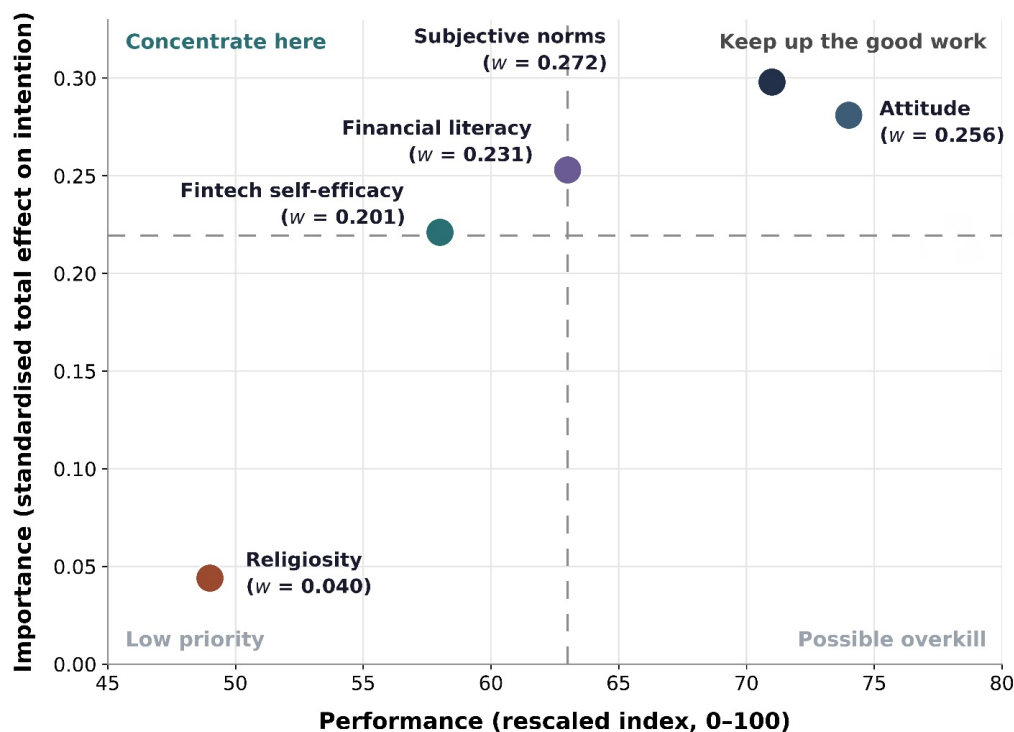


Figure 4. Importance–performance map for innovation-adoption antecedents. Importance is the standardised total effect on intention; performance is the rescaled construct score (0–100). Subjective norms and attitude carry the largest importance weights (w), whereas fintech self-efficacy combines roughly average importance with the lowest performance score of the five antecedents, placing it in the high-priority “concentrate here” region and identifying it as the principal design-leverage target.

It was addressed through AI-based explainer agents that gradually provide information according to users' assessed financial literacy levels. Contradiction C2 (universal user experience vs. customization of religious and cultural needs) was addressed using configurable modules, including Shariah-compliant, environmental, social, and governance (ESG), and sector-specific filter modules that can be activated when needed, corresponding to Inventive Principle 15 (Dynamics). Contradiction C3 (autonomy in digital decision-making vs. the need for social approval) was mapped to Inventive Principles 2 (Taking Out) and 25 (Self-Service) and resolved through embedded peer-investor signals, academically and community-validated reviews, and AI-enhanced reviews. Contradiction C4 (low-cost mass provision vs. quality of individualized service) was mapped to Inventive Principle 35 (Parameter Changes) and addressed through tiered AI personalization, comprising a free version with a rule-based interface and a premium version with a machine-learning-based personalized interface.

6. Discussion

A combination of the PLS-SEM, IPMA, and TRIZ scores yielded a systematic-innovation score of mutual-fund adoption within the sampled user population. The interpretation of the principal findings against previous evidence (Section 6.1) is followed by the positioning of the results within the fintech-adoption literature (Section 6.2), the emerging AI-adoption literature (Section 6.3), the behavioural-finance theory (Section 6.4), and the discussion of how far the results may be expected to apply outside of the academic sample (Section 6.5).

6.1. Principal findings

First, fintech self-efficacy holds its value not in terms of its importance but as a design lever. Despite having the smallest standardised total effect among the five antecedents (weight = 0.201), it had a large direct effect on intention, had the lowest performance score, and was the only antecedent with a path-strengthening (moderating)

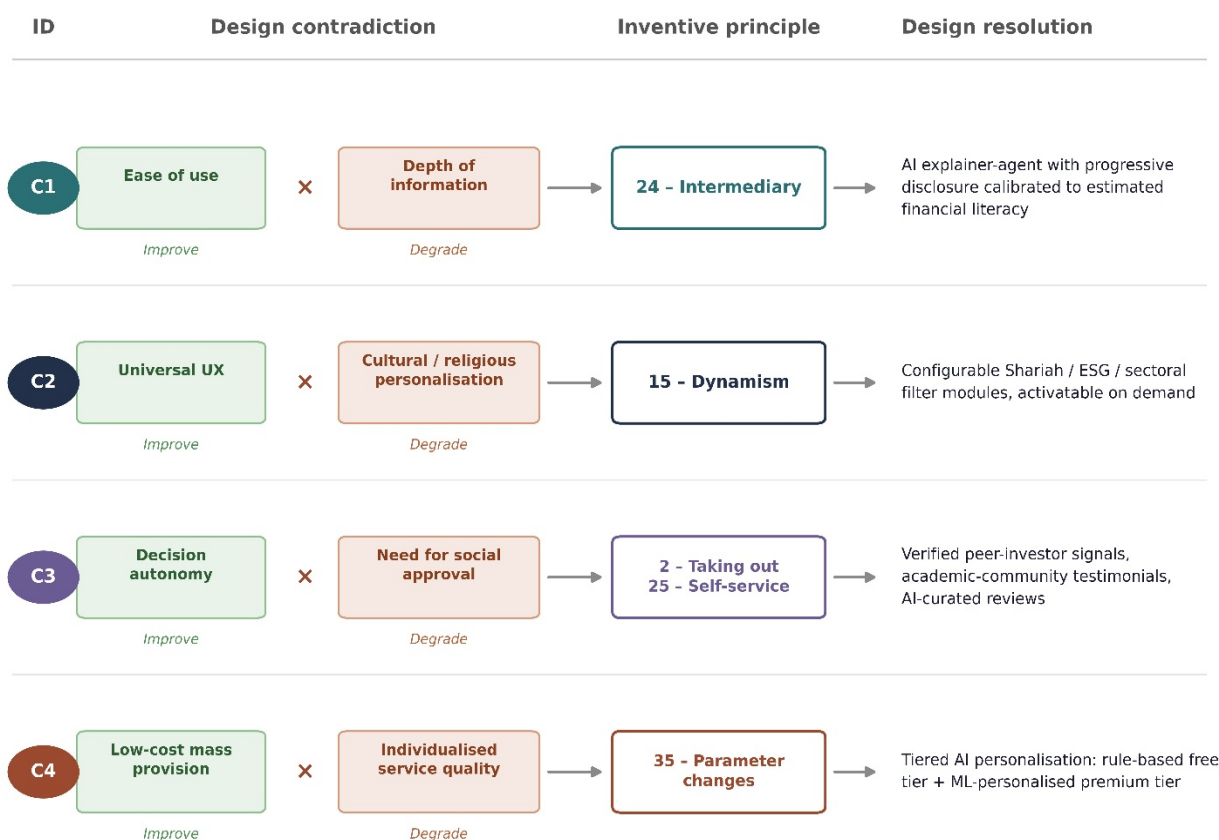


Figure 5. Theory of Inventive Problem Solving contradiction analysis for mutual-fund robo-advisory platform design. Four contradictions are mapped to inventive principles 2, 15, 24, 25, and 35. Note: Inventives drawn from Altshuller's (1996) 40 principles; contradictions retained by a seven-expert panel (Section 4.3).

Abbreviation: AI: Artificial intelligence; ML: Machine learning; ESG: Environmental, social, and governance; UX: User experience.

effect on the attitude–intention relationship ($\beta = 0.114$). It thus provides the most significant improvement headroom in terms of importance performance and emerges as the priority design target as opposed to the antecedent with the largest single importance weight. This finding extends the results of Che Hassan *et al.* (2024) on Islamic unit trusts in Malaysia to the mainstream mutual-fund setting and to a highly digitally literate population of academic researchers, among whom confidence in using financial-technology applications may still vary. The broader implication is that, within the full digital adoption domains, innovation-specific competence constructs may serve as alternatives to generic self-efficacy constructs in capability-based systematic innovation research.

Second, the subjective-norms construct, which demonstrated the highest direct effect in the model (0.298), is consistent with findings in the behavioural finance literature that social influence is one of the main drivers of diffusion of digital financial services among Indian academic workers (Raut, 2020). This finding aligns with the interpersonal-channel hypothesis. This discovery directly contributes to platform design via TRIZ contradiction C3 and its resolution, including peer ratings, verified commentaries, and AI-edited reviews.

Third, the finding on religiosity suggests that the influence of religiosity on the decision to adopt religious products in this general (non-Islamic-product) Indian mutual-fund sample is culturally mediated; that is, religiosity influences intention indirectly through attitude rather than directly. The non-significant direct religiosity–intention path, combined with the significant religiosity–attitude path, implies that, in this sample of digitally literate academicians, religiosity is acting as a value orientation that shapes the overall assessment of mutual-fund investment rather than playing a causal role in intention. This finding contrasts with previous studies demonstrating a direct religiosity effect (Duqi & Al-Tamimi, 2019; Newaz *et al.*, 2016) but is consistent with research supporting a mediated effect (Che Hassan *et al.*, 2024; Souiden & Rani, 2015). This subtle yet identifiable heterogeneity in preferences is reflected at the design level through the TRIZ solution of configurable Shariah-compliant, ESG, and sector-specific filter modules.

Two additional findings are noteworthy. Financial literacy exerted both direct and indirect effects on investment intention, with a strong direct effect and a large indirect effect via attitude. Thus, it had a cumulative effect comparable to that of the other cognitive antecedents. This two-pronged route suggests that, within the group of digitally literate academicians, financial literacy not only

cultivates a positive view of mutual-fund investment but also directly enables the intention to invest. This finding aligns with previous reports indicating that financial knowledge is both an attitude antecedent and a capability that reduces the perceived cost of action (Lusardi & Mitchell, 2014). Furthermore, the considerable moderation of the attitude–intention relationship by fintech self-efficacy suggests that positive attitudes are more effectively translated into investment intentions when users possess greater confidence in using digital financial platforms. Therefore, financial literacy and fintech self-efficacy represent complementary capabilities, consistent with social-cognitive explanations, which suggest that positive appraisals are more likely to result in behavioural enactment when individuals possess sufficient self-efficacy (Bandura, 1977). These two effects explain why enhancing fintech self-efficacy represents a high-leverage design target: increasing self-efficacy can directly strengthen investment intention while amplifying the effect of interventions aimed at improving attitudes, although fintech self-efficacy does not have the highest importance weight among the five antecedents.

6.2. Comparison to previous fintech-adoption research

The patterns of effects presented here can be compared with three threads of previous fintech-adoption studies. Akhtar & Das (2019) discovered that attitude was the primary antecedent of investment intention among Indian stock market investors in the TPB framework, with social influence serving as a secondary influencer. In the current sample, however, subjective norms ($\beta = 0.298$) were marginally stronger than attitude ($\beta = 0.281$). One possible explanation is that the adoption of mutual funds through robo-advisory is a less-involved and more delegable investment decision than direct equity trading; therefore, peer cues may play a more prominent role, particularly within dense professional communities where peers' behaviours are highly visible. Similar results were reported by Raut (2020): financial literacy and social influence co-determine individual investment decisions. Our decomposition further clarifies this image by demonstrating that financial literacy operates through a two-way pathway (directly and indirectly through attitude), a relationship that cannot be identified using single-path TPB specifications.

Within the technology acceptance literature, UTAUT-based research identifies effort expectancy and facilitating conditions as external factors to technology adoption (Venkatesh *et al.*, 2003), while e-banking and mobile banking studies note that ease of use and self-efficacy affect usage intention (Anouze & Alamro, 2020; Singh

& Srivastava, 2020). These externally defined usability conditions are redefined by our findings as an internal, innovation-specific competence belief: fintech self-efficacy not only predicts intention similarly to traditional ease-of-use-related factors but also strengthens the translation of attitude into intention. Lastly, the moderation finding replicates the results of Che Hassan *et al.* (2024) across different product types (mainstream vs. Islamic unit trusts), institutional contexts (India vs. Malaysia), and sampling frames. This supports the argument that the moderating role of fintech self-efficacy is a strong, generalisable attribute of digital-investment adoption rather than a study-specific effect.

6.3. Implication to the artificial intelligence-adoption literature

The essence of robo-advisor adoption is the delegation of part of an individual's financial decision-making process to an algorithmic agent. As of now, the literature on AI adoption has focused on technological attributes, such as accuracy, transparency, and trust in algorithmic advice (Frame *et al.*, 2019; Panos & Wilson, 2020). The current results redirect part of the explanatory focus towards the user side: the intention to adopt AI-based systems is determined not only by trust in the technology but also by how users' confidence in their ability to interact with, supervise, and, where needed, override the system. Of particular use in this sense is the significant H10 moderation. Positive attitudes toward AI-mediated investments are translated into adoption intention when users possess strong competence beliefs; when such beliefs are weak, even users who assess the innovation positively may remain reluctant to adopt it. Therefore, explainability, progressive disclosure, and in-platform micro-learning should be viewed not merely as regulatory or ethical desiderations but as behavioural requirements for adoption, as reflected in the TRIZ contradiction C1 resolution through an AI explainer agent acting as an intermediary.

These findings have two theoretical implications for AI adoption models. First, innovation-specific self-efficacy should be modelled alongside, but not subsumed within, trust and performance-expectancy constructs, as it represents a self-referential belief ("can I work with this system?"), whereas trust reflects a belief about the system ("will it work?"). Second, as the attitude–intention relationship is strengthened by self-efficacy, AI-adoption specifications that estimate only additive effects may underestimate the behavioural importance of capability-building interventions. Interaction effects between evaluative and competence-related constructs should be routinely included in future AI-adoption specifications.

6.4. Implications on behavioural-finance theory

There are three behavioural finance conversations to which the findings address. First, the pre-eminence of subjective norms supports social-interaction and peer-effect explanations of retail investor behaviour (Raut & Das, 2017). In a world of information overload, investors may develop cognitive economisation by using the observed adoption behaviour of trusted peers as informational heuristics. This heuristic reliance may be further enhanced in collectivist environments and dense professional networks. Second, the two-way pathway of financial literacy challenges the knowledge-deficit perspective proposed by Lusardi and Mitchell (2014). Financial literacy enhances investment participation by shaping evaluations through the attitude-mediated pathway and by directly reducing the perceived costs and risks of action. Knowledge-only policy in financial education addresses only one of the two channels; the findings indicate that combining knowledge-oriented interventions with capability-building interventions (i.e., self-efficacy) may generate greater behavioural benefits. Third, the religiosity findings can be reconciled with a value–attitude–behaviour gradient, in which highly rated cultural values influence evaluations rather than directly determining behaviour. Together with the fintech self-efficacy moderation, these findings provide a behavioural account for the well-known attitude–behaviour gap in retail investing: favourable evaluations do not translate into action when users lack sufficient competence beliefs to execute the intended behaviour (Bandura, 1977).

6.5. Generalisability beyond the academic sample

It is important to note that generalisability outside of the academic sample cannot be assumed. Because the sample consists of academicians from Indian central universities, one might ask to what extent the results can be extended to other investor groups. Three arguments support the potential transferability of the findings, although two boundary conditions should also be acknowledged. First, population-general mechanisms were tested in the model, rather than sample-specific constructs. Population-specific theories (such as TPB, social-cognitive theory, DOI), whose relationships are core to each other, have been replicated in heterogeneous populations of retail investors in India and elsewhere (Akhtar & Das, 2019; Che Hassan *et al.*, 2024; Raut, 2020). The relative magnitude of the paths, rather than their existence or direction, is sample-dependent.

Second, central-university scholars possess all the economically relevant attributes of the wider population of robo-advisory platforms: salaried, digitally connected urban professionals with a consistent formal income, regular use of UPI and internet banking, and exposure to workplace retirement products. This sample, on these

dimensions relevant to adoption, may resemble other salaried professionals, including private-sector employees, bank officers, information technology workers, and public-sector managers. Therefore, the proposed design implications are likely to be applicable to broader salaried populations, although some calibration may be required.

Third, in cases where the sample is non-representative, one can predict the direction in which the bias may result. In most cases, such bias tends to enhance instead of undermine practical conclusions. The high and homogeneous educational level of the sample limits the range of financial literacy, which statistically dilutes its effects. In the general investing population, where the range of literacy differences is much larger, the financial-literacy influence is likely to be underestimated. Similarly, because fintech self-efficacy is the lowest-performing antecedent even among digitally literate academicians, the performance gap identified through IPMA may be even greater among less digitally experienced investor groups. The subjective-norms effect, already the strongest path, may not be weakened in non-academic populations, as the high level of social influence has been consistently observed in Indian and other collectivist samples of retail investors (Raut & Das, 2017). Nevertheless, two boundary conditions exist. Investors with volatile or informal earnings (the self-employed, gig workers) have liquidity constraints, making income stability rather than the modelled antecedents the primary barrier to adoption. Meanwhile, first-time rural users may be constrained by convenience factors (e.g., access to devices, internet connectivity, vernacular-language interfaces) that are not captured in the current model. For these segments, the framework should be extended to incorporate trust and facilitating-condition constructs, and the resulting design priorities may differ. In Section 6.9, formal replication in non-academic samples is identified as a priority for future research.

6.6. Theoretical implications

The study makes three theoretical contributions. First, it shows that a synthesis of an innovation-specific self-efficacy could be used to create a coherent model of user behaviour in the context of digital financial services. Second, it shows that PLS-SEM standardised total effects could be transformed into an innovation-priority ranking (IPMA), without requiring independent pairwise elicitation. Third, it demonstrates that behavioural empirical results can inform a defensible TRIZ-based design synthesis, linking quantitative user-behaviour modelling with systematic-design methodology. These contributions are based on a much simpler framework, the integration of which the study makes explicit. The DOI perspective is adopted not as a distinct set of measured constructs but as a logic of

organisation that re-interprets the antecedents of the TPB in an innovation-adoption context. Attitude is re-read as the perceived relative advantage and compatibility of the innovation; perceived behavioural control is re-specified as innovation-specific fintech self-efficacy, reflecting the complexity and trialability of the digital platform; and subjective norms are retained as the social-system channel through which an innovation diffuses. In this framework, DOI expands the explanatory coverage of TPB in two aspects. It provides an innovation-focused reason for why every TPB antecedent ought to be relevant to a new digital financial service. Additionally, it inspires the incorporation of constructs (e.g., fintech self-efficacy as a mediator, and financial literacy and religiosity as enabling and cultural conditions) that are not included in a cognitively bare TPB conception. The added difference to the innovation-adoption theory is then to demonstrate that, in a completely digital adoption domain, it is an innovation-specific competence belief, rather than generic perceived control, that plays a central role in shaping adoption behaviour. Fintech self-efficacy not only enhances adoption intention but also strengthens the translation of attitude into intention, thereby extending the TPB-DOI framework toward the operationalisation of AI-based financial services.

6.7. Practical implications

The findings of the empirical study and the IPMA-TRIZ priority outputs offer tangible guidelines to various practitioner groups. The highest-leverage design priority (resolution C1) is the integration of AI-based adaptive disclosure that tailors information to users' estimated financial literacy levels, together with in-platform micro-learning modules that continually increase fintech self-efficacy. As fintech self-efficacy is both a low-performing construct and a moderator of the attitude-intention relationship, improving this capability is expected to yield the greatest return on design effort. In the case of asset management companies, the strong subjective-norms effect suggests that investor acquisition strategies should emphasize social proof, including peer testimonials, community endorsements, and verified user experiences. The indirect religiosity effect indicates that platforms should provide configurable investment filters (e.g., Shariah-compliant, ESG, and sector-specific screening options) to accommodate the diverse preferences of religiously heterogeneous investors. The findings inform regulators by highlighting the importance of explainability and tiered personalisation in the development of AI governance frameworks for financial advisory services. Financial advisers and distributors may use these insights to facilitate clients' acceptance of AI-assisted investment

recommendations during advisory interactions. A tiered AI personalisation strategy (resolution C4), consisting of a free rule-based service and a premium machine-learning-based personalised service, represents a practical design blueprint that could be implemented within the AA data-sharing architecture and the SEBI investment-adviser regulatory framework.

6.8. Policy implications

The results are in accordance with the objectives of the National Strategy on Financial Education 2020–2025 on the developmental focus on financial literacy and digital skills training. The policy implication, according to the IPMA results, seems rather evident: incorporating short and modular self-efficacy teaching activities to strengthen fintech self-efficacy into faculty-development programmes regulated by the University Grants Commission may be a cheaper means of promoting adoption among this user group than providing additional financial-literacy programmes alone. For example, optional 45-minute modules on digital financial skills and fintech self-efficacy could be offered as part of compulsory continuing professional development programmes.

6.9. Limitations and future directions

This study has several limitations that suggest directions for future research. First, the cross-sectional design cannot be used to infer causality. Longitudinal or panel designs that allow repeated measurements would provide stronger evidence regarding the directionality of the user-behaviour relationships. Second, the sample was limited to academics from central universities in India. Although Section 6.5 presents mechanism-based reasons supporting the potential transferability of the findings to broader populations of salaried, digitally connected retail investors, and identifies boundary conditions for informal-income and first-time rural investors, the proposed design blueprint should be validated through formal replication in non-academic samples. Future studies should therefore examine private-sector salaried professionals, self-employed investors, and first-time rural users, while also conducting measurement-invariance testing across population subsets. Third, religiosity was conceptualised as a pooled variable, and the available data did not allow conducting a formal multigroup comparison (PLS-MGA) of the religiosity–attitude correlation across religious groups. The Sikh ($n = 33$) and Christian ($n = 24$) subgroups were too small to support reliable PLS path estimation or measurement invariance of composite models (MICOM)-based measurement-invariance testing. Accordingly, the religiosity findings should be interpreted only at the pooled-sample level. Future studies using larger, faith-stratified

samples should investigate whether the religiosity–attitude relationship varies across Hindu, Muslim, Sikh, and Christian subpopulations. Fourth, the upstream PLS-SEM did not obtain the IPMA importance weights. A real expert-pairwise AHP would have re-triangulated the rankings achieved in this case by eliciting expert pairs of stakeholders in the fintech and academic sectors. Fifth, TRIZ is still conceptual even though it is currently bound to an expert-panel-based protocol. Future studies can bring together the capabilities of the platform and designers to actualise the identified TRIZ principles. Finally, a patent-landscape analysis of Indian robo-advisory and AI-based financial decision-making systems would supplement the existing ubiquitous user-behaviour-modelling conceptualisation with a technology-evolution view. Such work could draw upon the systematic-innovation tradition, using the Indian patent database and the Pension Fund Regulatory and Development Authority (PFRDA)/SEBI sandbox filings.

7. Conclusion

This paper reported a mixed-methods study (PLS-SEM + IPMA + TRIZ) of mutual-fund innovation adoption among academics from central universities in India. Test outcomes revealed that 9 out of the 10 hypotheses were supported, 43.8% of the variance in the investment intention was explained, fintech self-efficacy emerged as the highest-leverage design target (due to its lowest performance score among the five antecedents and the significant moderating effect on the attitude intention relationship), and 4 design implications of the robo-advisory derived from TRIZ contradiction analysis using 5 inventive principles. The integrated PLS-SEM–IPMA–TRIZ workflow provides a convenient methodological template for future studies of systematic innovation, although we do not claim to have originated this integrated approach.

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Conflict of interest

All authors have declared that there are no competing financial or non-financial interests.

Author contributions

Conceptualization: Gulshan Kumar, Babli Dhiman

Data curation: Gulshan Kumar

Formal analysis: Gulshan Kumar, Babli Dhiman
Investigation: Gulshan Kumar, Babli Dhiman
Methodology: Gulshan Kumar, Babli Dhiman
Supervision: Babli Dhiman
Validation: Gulshan Kumar, Babli Dhiman
Visualization: Gulshan Kumar
Writing–original draft: Gulshan Kumar
Writing–review & editing: Gulshan Kumar, Babli Dhiman
All authors have read and approved the final version of the manuscript.

Ethics approval and consent to participate

All participants agreed to the study and provided written informed consent, and ethics approval was obtained. This study was undertaken in compliance with the Declaration of Helsinki and the ICMR National Ethical Guidelines for Biomedical and Health Research Involving Human Participants (2017) and approved by the Institutional Research Ethics Committee of Mittal School of Business, Lovely Professional University, Phagwara, India (ethics approval number: LPU/10.2/SC/2024/029/250305/0048, code no. CRT206; ethics approval date: 05-Mar-2025). No vulnerable group, biological samples, or identifiable images were involved, and all participants were full-time adult academicians and were presented with no more than minimal risk. Electronic informed consent was obtained using a Participant Information Sheet, which included information about the purpose of the study, that the study was voluntary, that they could terminate their participation at any time, that their anonymity would be preserved, that their data would be handled, and that there were no incentives for participation.

Consent for publication

There was no retention of personally identifying information. Responses were anonymized prior to analysis and stored on an encrypted institutional drive, in compliance with the Digital Personal Data Protection Act, 2023.

Availability of data

The authors will share anonymized data supporting the conclusions of this study on reasonable academic demand, subject to a data sharing agreement which will ensure participant confidentiality. Upon acceptance, a de-identified dataset will be made public in a repository.

Further disclosure

In limited language editing, the application of generative AI is merely used to enhance or correct fragments of text. It has not been used in the study design, data analysis or

interpretation. The authors have full responsibility for the content of the manuscript.

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