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TRUST IN AI, BEHAVIOURAL NUDGING, AND INVESTOR OVERSIGHT IN RETAIL INVESTOR DECISION-MAKING: EVIDENCE FROM INDIA

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AI-powered investment platforms have fundamentally altered how retail investors in India access and act on financial information. Despite rapid platform adoption the psychological mechanisms through which AI recommendations, platform embedded behavioural nudges and perceived regulatory oversight shape investor decision-making remain poorly understood especially in emerging market contexts. This study addresses that gap by examining the direct and mediated pathways through which these three antecedents influence investment behaviour, operating through trust in AI and cognitive bias as dual mediating mechanisms.

Drawing on the Technology Acceptance Model, Nudge Theory, Prospect Theory, and Trust-in-Automation literature, this study develops and tests an integrated structural model. Primary data were collected via a structured survey of 276 retail investors actively using digital investment platforms in India. Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to assess the measurement model and test eight hypotheses, including two mediation relationships, using bias-corrected bootstrapping with 5,000 subsamples.

Five of six direct hypotheses were supported, with behavioural nudging emerging as the most powerful predictor of cognitive bias activation ($\beta = 0.492$, $p < 0.001$, $f^2 = 0.324$) — a medium effect that substantially exceeds the influence of AI recommendation quality. Both mediation hypotheses were confirmed: trust partially mediates the path from AI recommendation quality to investment behaviour (indirect $\beta = 0.041$, $p = 0.036$), while cognitive bias partially mediates the path from behavioural nudging to investment behaviour (indirect $\beta = 0.070$, $p = 0.034$). The study's most significant finding is the non-support of H4: perceived investor oversight enhanced trust in AI ($\beta = 0.180$, $p = 0.002$) but did not reduce bias susceptibility ($\beta = 0.103$, $p = 0.096$). This dissociation indicates that oversight functions as a legitimacy signal rather than a debiasing mechanism — investors feel more confident using AI-assisted platforms under visible regulation, but are not more rational in their decision-making.

This is among the first studies to simultaneously operationalise AI recommendation quality, behavioural nudging, and perceived investor oversight as antecedents within a unified structural model, validated on Indian retail investor data. The oversight-bias dissociation also has direct implications for regulators: disclosure-oriented frameworks may build investor confidence without improving decision quality, suggesting the need for behavioural design standards alongside transparency mandates.

KEYWORDS: *AI in finance, Retail investor behaviour, Behavioural nudging, Trust in AI, Cognitive bias, Digital investment platforms, Robo advisory platforms, PLS-SEM, India, Investor oversight, FinTech regulation*

1. INTRODUCTION

Retail Investors in India have embraced AI as an aspect of making financial decisions. Today we see that AI is taking up the shape of recommendations on stocks in Zerodha, recommendations on portfolios in Groww, or chatbots answering investment questions to a large number of young investors. These platforms have become very accessible to the growth of smartphones and cheap internet, and it has exposed investment tools to individuals who previously lacked access to financial advisors.

In 2024, more than 90 million retail investors were registered at the National Stock Exchange, with many of them being first-time investors, aged under 35, who depend on AI-based mobile platforms as guides in their investments (Fatima and Chakraborty, 2024; Mohapatra et al., 2025).

These platforms however are not just a source of information. The user experience is designed to include features such as push notifications on trending stocks, indicators of what other users are buying, gamified rewards based on daily trading, and default portfolio settings, all of which have the potential to impact investor behaviour. The psychological impact of these characteristics on the retail investors has not been examined thoroughly (Back, Morana and Spann, 2023; Rakovic and Inal, 2023).

The studies of the relation between investors and algorithmic recommendations are also inconsistent. There are studies indicating that after a single error, investors immediately lose confidence in algorithms and switch to human judgment despite their poorer performance, a phenomenon known as algorithm aversion (Diet Vorst, Simmons and Massey, 2014). The reverse is true in others where investors over-follow algorithmic recommendations especially in fields that they are inexperienced in, known as algorithm appreciation (Logg, Minson and Moore, 2019). One of the questions that is answered in this research is how young retail investors gain trust in AI and how it influences their choices.

Another aspect that has been studied insufficiently is investor oversight - how much individual investors would actively review and challenge AI-assisted decisions. While regulators like SEBI have raised concerns about the impact of AI on retail investors, there is little empirical evidence on whether perceived oversight changes investor behaviour at the individual level (Mohapatra et al., 2025). This paper takes a look at that question and concludes that even though perceived oversight enhances trust in AI, it does not decrease investor bias.

The paper is based on Technology Acceptance Model (Davis, 1989), Nudge Theory (Thaler and Sunstein, 2008), Prospect Theory (Kahneman and Tversky, 1979) and the Trust-in-Automation literature (Logg et al., 2019) and applies an integrated model to the data of 276 retail investors in India by using the PLS- SEM. Section 2 provides literature review and formulates hypotheses; Section 3 outlines the conceptual framework; Section 4 outlines the methodology; Section 5 outlines the results; Section 6 and 7 outlines findings and implications; Section 8 outlines limitations and future research; Section 9 provides a conclusion.

2. LITERATURE REVIEW

2.1 Investment Recommendations and Robo-Advisors based on AI.

Such studies on AI-based investment platforms have increased significantly, but most have concentrated on adoption, and not on behavioural results. Research results indicate that trust, perceived usefulness, and transparency are the key factors behind robo-advisor adoption by retail investors (Fatima and Chakraborty, 2024; Singh and Kumar, 2025; Mohapatra et al., 2025), and perceived risk, anxiety, and lack of transparency drive resistance (Gupta, Sehgal and Sharma, 2024) In the Indian context in particular, usefulness and trust are more motivating on younger investors than older groups and anxiety is more discouraging of adoption in more experienced users (Fatima and Chakraborty, 2024).

In addition to adoption, there is less literature that investigates the real impact of AI platforms on investor psychology. Kulkarni, Patil and Pramod (2025) discovered that personalisation, interactivity and interpretability of the algorithms of robo-advisor minimised the loss aversion and overconfidence in Indian investors, but the structural assurance itself did not have a big influence on bias. In a nine-month longitudinal study, Trinh et al. (2025) discovered that the level of trust towards AI advisors have non-linear patterns and that disclosure of system limitations contributed to the rightful reliance greatly However Eichler and Schwab (2024) warned that robo-advisors can cause the overconfidence of unskilled users and cannot recreate the affective aspects of human advisory relationships.

Two conflicting tendencies also characterize the connection between algorithmic advice and investors. The appreciation of algorithms, including the tendency to take algorithmic advice over human advice, especially in areas where there are obvious accuracy criteria, was reported by Logg, Minson and Moore (2019). The opposite was proved by Dietvorst, Simmons and Massey (2014): human beings are ready to quickly reject accurate algorithms, despite the fact that human variants perform poorly after one observable mistake The Consumer Technology Vulnerability concept was proposed by Wang et al. (2026), demonstrating that the feeling of powerlessness can lead to an upsurge in the level of dependency on AI due to the same powerlessness which is concerning as it does not empower users but makes them dependent. On the same basis, account-level trading data in a natural experiment in Italy by Even-Tov et al. (2025) showed that investors diversified more with AI access and tried new assets, with the highest impact on low-income and inexperienced investors, the same group being studied in this study Morana and Spann (2023) experimentally demonstrated that the addition of human-like design features to robo-advisor names, avatars, conversational interfaces, enhanced the disposition effect and minimised advice-seeking behaviour, leading to worse investor outcomes. Synthesising 83 papers, Namyslo, Jung and Sturm (2025) found that choice architecture and nudging are accepted design tools in robo-advisor systems and that poorly designed nudges undermine trust and over-automation is detrimental.

2.2 Nudging in Behaviour on Financial Platforms and Dark Patterns.

The nudge theory by Thaler and Sunstein (2008) gives the theoretical framework of interpreting how the design of platforms informs investor behaviour. According to Cai (2019), digital AI platforms have increased the reach of nudges many times over, providing the ability to affect millions of investors, but also making it highly likely that commercially-driven platforms will apply these instruments as sludge - friction created to exploit users instead of protecting them.

The empirical literature determines default, salience, and framing as the most effective types of nudges consistently in financial situations (Gajewski et al., 2024; Neuss and Zielke, 2022). Specifically, defaults have a transformative impact on savings and investment participation, but peer-norm nudges have counterproductive effects amongst lower-income/lower-literacy users. Vasas (2021) discovered that nudges boost search and switching by two to three percentage points on average, and that structural nudges (nudges which decrease administrative friction) outperform informational ones by far.

Dark patterns are the extreme of nudges that are manipulative. Auditing 26 Norwegian investment apps, Rakovic and Inal (2023) discovered that the use of hidden fees, coerced participation, gamification, and social proof signals to motivate speculative trading were common design practices in non-bank fintech platforms but less so in bank-related platforms. Andrade et al. (2025) discovered the same trends in the UK CFD trading apps, where risk warnings were often hidden, disclosures were often hidden and educational material was framed to view trading losses as an individual skill failure. Pancholi and Shukla (2024) demonstrated that gamification features such as points, badges, trading streaks are more likely to enhance engagement and cause overtrading and much ethical concern.

Notably, nudges do not necessarily work their magic. Hettler et al. (2025) discovered that default and scarcity-warning nudges drastically decreased user trust in an experiment on a simulated platform, where the users perceived these to be manipulative. Van den Akker and Sunstein (2025) discovered that the attitude towards financial nudges was neutral to positive, yet younger and less financially literate users were the most open to manipulation (this group was the most accessible, and the most susceptible to manipulation).

2.3 Retail Investment Decision Behavioural Biases.

The Prospect Theory (Kahneman and Tversky, 1979) is still the pillar in understanding the process of risk processing by retail investors. The main propositions of its core, which is that people consider the outcomes against a reference point, are more sensitive to losses than reflecting the same gain, and that probability weights are systematically distorted, are the source of well-documented patterns in investor behaviour, such as the disposition effect, overtrading driven by overconfidence, anchoring, and herding.

Gupta (2025) discovered in the Indian setting that overconfidence, herding, anchoring, and loss aversion are the most prevalent biases among retail investors, and that fintech apps are increasing all of them with real-time alerts, gamification, and social trading functionalities. The most frequent traders were younger investors, and they were the most vulnerable to risk-taking, which is caused by FOMO. Using machine learning on combined trading and survey data, Gupta and Rao (2025) discovered that 43-percent of their sample had loss aversion and that AI tools do indeed have real potential to reveal bias in real-time, but they also warned about the ethical issues of such a capability being used to exploit investors instead of protecting them.

Sayeed and Kapoor (2025) discovered that the disposition effect and home bias can be diminished by robo-advisors with the correct design, however, emotional and cognitive biases can still be present even in algorithmically-supported settings. Researching 233 Gen-Z equity investors in India, Shriya and Velmurugan (2025) discovered that intention to use AI-enabled platforms was a good predictor of investment decision-making, and the path coefficient of 0.78 indicated a close relationship between platform engagement and investment behaviour among this cohort.

2.4 Investor Oversight, Ethics and Regulation.

Governance of AI-based financial advice has become a topic of growing interest, but little empirical data is available at the level of individual investors. Baker and Dellaert (2018) suggested a regulatory system that is constructed around honesty, competence, and suitability, suggesting that regulators require technical abilities to audit algorithms, choice architectures, and underlying data. In a comparison of seven jurisdictions, Gurrea-Martinez and Wan (2021) identified that most regulators continued to use the traditional licensing frameworks to AI advisory services in most cases without the specialised ability to audit algorithmic systems in a good manner.

On the ethics front, Brueggen et al. (2024) have created a six-domain framework, such as autonomy, explainability, transparency, fairness, harm prevention, and accountability, and came to the conclusion that compliance rules are not enough. Kofman (2025) suggested a system of ethics-licensing and scorecard whereby the published gateway scores would enhance market responsibility and investor confidence. The two papers view oversight as a process-level concept, as opposed to a view held by investors themselves.

In the individual level aspect of oversight, minimal empirical information has been discussed. In a pre-registered study (n=810 participants) by Mei et al. (2025), buck passing, or the propensity to defer decisions to others, was a strong predictor of AI reliance, and that younger and less educated participants exhibited the greatest buckpassing propensities, indicating a higher risk of blind reliance on AI. Users who were more vigilant were more critical of AI explanations and did not trust them less, citing a lack of association between scrutiny and actual decision behaviour similar to the current study on oversight and bias.

2.5 Research Gaps

This review gives rise to three gaps. First, although AI adoption and portfolio performance have been well researched, psychological processes connecting AI recommendation exposure to investment behaviour via the mediating influence of trust and bias activation as mediating mechanisms have not been experimented as an integrated structural equation, especially in a new market. Second, behavioural nudging studies in finance have been done mostly in the Western context of retirement and savings; little empirical support has been done regarding how AI-based nudges work with cognitive bias among young retail investors in India. Third, investor oversight has been addressed virtually as an institutional or regulatory notion. It has not been previously operationalised as an individual-level behavioural construct and simultaneously tested on its effects on trust and bias susceptibility in a single framework. The current research fills all three gaps with the help of PLS-SEM on survey data of 276 Indian retail investors.

3. CONCEPTUAL FRAMEWORK AND THEORY.

3.1 Theoretical Underpinnings

This paper combines four theoretical frameworks to elaborate on how AI-based investment platforms, behavioural nudges and perceived investor oversight influence retail investment choices. All the frameworks explain a unique route in the model and when combined, they offer the theoretical reasoning behind the structural associations examined in this paper.

Technology Acceptance Model (Davis, 1989) believes that ease of use and perceived usefulness are the crucial factors of technology adoption and usage. When applied to AI investing platforms, this paper builds on the fundamental premise of TAM logic by considering trust more as an active process than as a mere result of adoption, based on the perceived quality of AI advice and the credibility of a platform regulatory context. This extension is in line with the adoption of TAM in the robo-advisor literature, where trust has continued to be the most important predictor of adoption intention among Indian retail investors (Fatima and Chakraborty, 2024; Singh and Kumar, 2025).

According to Nudge Theory (Thaler and Sunstein, 2008), choice settings can be systematically used to direct behaviour without limiting choices and altering incentives. In the case of digital investment platforms, this framework can be used to describe how the following design elements push notifications, default portfolio configurations, personalised prompts, social proof cues can be used to trigger heuristic processing and establish the situation that encourages biased decisions. More importantly, the same mechanisms may operate on a spectrum between true choice architecture and intentional manipulation, based on the commercial motives of the platform (Cai, 2019).

Prospect Theory (Kahneman and Tversky, 1979) showed that individuals judge the results in comparison to a reference point, are between two times more sensitive to losses than to identical gains and that the probability weights are predicted to be distorted in certain predictable ways. These trends form the basis of typical retail investor biases such as herding, the disposition effect, and anchoring. Prospect Theory suggests that nudges that capitalize on these biases - such as scarcity framing, social proof, or loss-highlighted alerts - will increase, but not rectify, any prior bias tendency in the context of AI platforms.

Literature on Trust-in-Automation (Lee and See, 2004; Logg et al., 2019) focuses on the situations when individuals correctly tune trust in automated systems. It posits trust as a mediating factor between inputs to the system and the behaviour of the user that is influenced by perceived reliability, transparency and congruence between system goals and user interests. More importantly, this framework recognizes under-trust and over-trust as potential threats: algorithm aversion causes investors to forego correct systems following one failure (Dietvorst et al., 2014), whereas algorithm appreciation makes people blindly trust algorithmic advice (Logg et al., 2019). Both are suboptimal and both results are possible in case of young, inexperienced retail investors that are exposed to AI platforms the first time.

3.2 Conceptual Model

This research paper presents a structural model, which comprises of three exogenous variables: AI Recommendation Quality (AR), Behavioural Nudging Influence (BN), and Perceived Investor Oversight (IO), two mediating variables: Trust in AI Systems (TA) and Behavioural Bias Tendencies (BB), and one endogenous variable: Investment Decision Behaviour (ID).

According to the model, the quality of AI recommendations and perceived oversight have an indirect impact on investment behaviour, via their own effect on trust. Behavioural nudges influence investment behaviour indirectly, through their activation of cognitive bias. It is also postulated that perceived oversight will decrease the bias vulnerability by making the decisions more reflective but this correlation is not established in the results empirically which is presented further in Section 6.

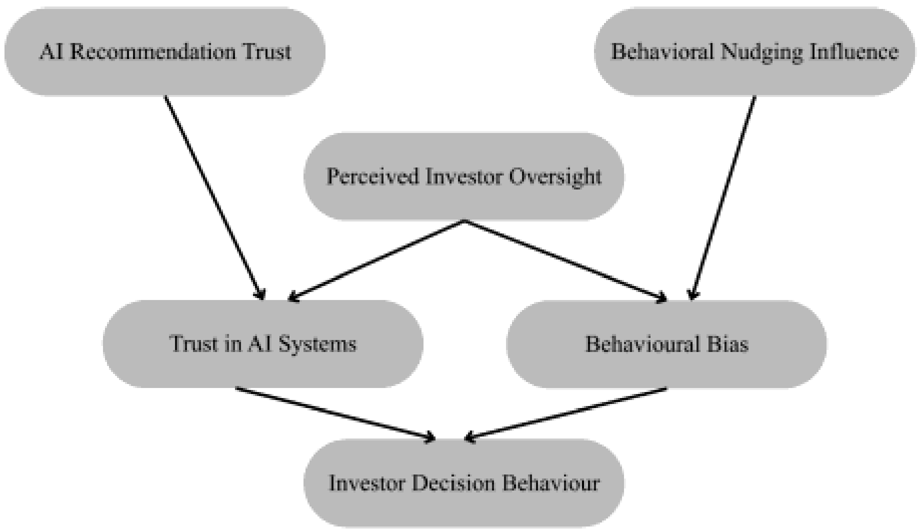

Image 3.1: Conceptual Framework

3.3 Hypothesis Development

AI Recommendations and Trust

Investors who perceive AI-generated recommendations as accurate and objective, and informative are more likely to develop trust in the platform as a whole. Within TAM, perceived usefulness shapes attitudes toward a system, and in the context of AI advisory platforms, the quality and perceived objectivity of recommendations is the primary signal through which usefulness is judged. The Trust-in-Automation literature further supports this, with perceived competence identified as a key driver of initial trust formation (Trinh et al., 2025).

H1: AI Recommendation Quality is positively associated with Trust in AI Systems

Behavioural Nudging and Bias

Platform- embedded nudges are expected to activate heuristic processing and amplify cognitive bias tendencies. Nudge Theory predicts that environmental design cues trigger automatic, System 1 thinking. According to the Prospect Theory investors predisposed to loss aversion and herding are particularly sensitive to nudges using social proof, scarcity framing, and default effects. This nudging to bias pathway is supported empirically by Rakovic and Inal (2023), Pancholi and Shukla (2024), and Cai (2019).

H2: Behavioural Nudging Influence is positively associated with Behavioural Bias Tendencies

Oversight and Trust

Investors who perceive meaningful regulatory and platform level protections to be in place in the platform with risk disclosures, algorithmic transparency, investor protection mechanisms are more likely to trust AI systems. The Trust-in-Automation framework finds transparency and institutional credibility as foundational conditions for appropriate trust calibration. This aligns with evidence from the regulatory literature showing that perceived oversight strengthens investor confidence in automated systems (Baker and Dellaert, 2018; Kofman, 2025).

H3: Perceived Investor Oversight is positively associated with Trust in AI Systems

Oversight and Bias

Oversight mechanisms are theoretically expected to promote more deliberate, reflective decision-making, reducing susceptibility to herding, anchoring, and loss-aversion driven choices. Van den Akker and Sunstein (2025) found that reflective nudges reduced perceptions of manipulation and Mei et al. (2025) showed that vigilant decision-making styles were associated with more critical engagement with AI outputs.

H4: Perceived Investor Oversight is negatively associated with Behavioural Bias Tendencies

Trust and Investment Decisions

Investors who trust AI platforms are more likely to engage actively with recommendations, use platform tools, and take decisions on AI-generated advice. This pathway is central to both TAM and the Trust-in-Automation framework. Empirically, trust has been found to fully mediate the relationship between platform design features and investment behaviour (Trinh et al., 2025; Fatima and Chakraborty, 2024).

H5: Trust in AI Systems is positively associated with Investment Decision Behaviour

Bias and Investment Decisions

Investors with stronger bias tendencies — herding, loss aversion, anchoring, sensitivity to market signals — are expected to make more reactive and emotionally driven investment decisions. Prospect Theory provides the foundational basis for this relationship, and it holds even in AI-assisted environments where automated recommendations are available (Kulkarni, Patil and Pramod, 2025; Sayeed and Kapoor, 2025).

H6: Behavioural Bias Tendencies are positively associated with Investment Decision Behaviour

Mediation: Trust

AI recommendations are not expected to directly determine investment decisions. Rather, they work by building platform trust, which then facilitates AI-assisted decision-making behaviour. This indirect pathway follows the trust-mediation logic within TAM and is empirically supported by Gupta (2025) and Trinh et al. (2025), both of whom found trust to fully mediate the link between design quality and investor behaviour.

H7: Trust in AI Systems mediates the relationship between AI Recommendation Quality and Investment Decision Behaviour

Mediation: Bias

Platform nudges are not expected to directly produce investment outcomes. Instead, they influence decisions by activating or amplifying cognitive biases, which then shape behaviour. This indirect pathway combines the predictions of Nudge Theory and Prospect Theory, and is supported by the empirical evidence on how platform design features translate into bias-driven investment choices (Cai, 2019; Pancholi and Shukla, 2024).

H8: Behavioural Bias Tendencies mediate the relationship between Behavioural Nudging Influence and Investment Decision Behaviour

4. RESEARCH METHODOLOGY

4.1 Research Design

This study uses a quantitative, cross-sectional research design. The data were gathered using a structured survey that was given to retail investors in India, who regularly use the digital investment platforms. The data were analysed using partial Least Squares Structural Equation Modelling (PLS-SEM) because it is suitable to test the model with several constructs and mediation paths, moderately large samples, and does not assume that data are normally distributed (Hair et al., 2019). The analysis was done in two steps, with the measurement model evaluated in the first step, followed by testing the structural relationships.

4.2 Population, Sampling, and Data collection.

The sample population was retail investors in India who actively utilize AI-enabled or digitally assisted investment platforms. The study does not have a formal sampling frame of this population, so the convenience sampling method was applied, similar to other studies in the Indian retail investing setting (Fatima and Chakraborty, 2024; Mohapatra et al., 2025). The questionnaire in the form of an online survey was implemented in the social media, investor forums, and professional networks between February and March 2026. They were interviewed to verify that the respondent actively uses mobile trading applications or robo-advisory programs and participation was voluntary and informed consent was provided before the completion of the interview.While convenience sampling limits generalisability, it is appropriate for exploratory structural models in emerging fintech contexts where no sampling frame exists (Fatima and Chakraborty, 2024).

The end result was 276 valid responses. This is at least ten observations per indicator, which is suggested as the minimum threshold in PLS-SEM (Hair et al., 2019) and can be compared with the sample size of other studies of this category (Kulkarni, Patil and Pramod, 2025; Singh and Kumar, 2025).

4.3 Sample Profile

The sample mostly was young, educated and active digitally. More than half (52.5) of the respondents were between the ages of 18 and 25, and the next 29.0% were between 26 and 35, which implies over 81.0% of the respondents were less than 36 years old. The sample was 57.6% male and 42.4% female. The majority of the respondents (78.3) were postgraduate holders. As regards to investment experience, 54.7% of them had invested one to three years and 36.6% had invested less than one year, which means that the sample is composed mainly of relatively new investors. The most popular investment channel among the respondents was mobile trading platforms, which were used by 61.6% of the respondents and the rest were robo-advisory or broker platforms.

Table 1: Sample Profile (n = 276)

Variable	Category	Frequency	Percentage (%)
Age	18–25 years	145	52.5
	26–35 years	80	29.0
	36–45 years	36	13.0
	46 years and above	15	5.4
Gender	Male	159	57.6
	Female	117	42.4
Education	Undergraduate	37	13.4
	Postgraduate	216	78.3
	Professional Course	20	7.2
	Others	3	1.1
Investment Experience	Less than 1 year	101	36.6
	1–3 years	151	54.7
	3–5 years	14	5.1
	More than 5 years	10	3.6
Primary Platform	Mobile Trading	170	61.6
	Robo-Advisory	39	14.1
	Broker Platforms	40	14.5
	Others	27	9.8

4.4 Measurement of Constructs

Six latent constructs are measured in the study: AI Recommendation Quality (AR), Behavioural Nudging Influence (BN), Perceived Investor Oversight (IO), Trust in AI Systems (TA), Behavioural Bias Tendencies (BB), and Investment Decision Behaviour (ID). Reflective indicators were adapted to the existing scales in the literature and operationalised as measure on a five-point Likert scale (Strongly Disagree=1; Strongly Agree=5). Items were contextualised to the Indian AI-assisted investing setting. All the constructs were measured using five items, except AI Recommendation Quality, whose one item was dropped during refinement of the measurement model because its outer loading was below the acceptable threshold of 0.70 (Hair et al., 2019), leaving the construct with four items.

4.5 Preliminary Analysis

Prior to testing the structural model, an initial testing in IBM SPSS was done to verify data appropriateness. Kaiser-Meyer-Olkin was 0.841, which is much higher than the recommended value of 0.60, which implies that the sampling was sufficient. The Test of Sphericity by Bartlett was significant (2 = 3261.288, 435, p = 0.001), which implies that factor analysis was suitable. The result of the Principal Component Analysis using Varimax rotation identified six components in line with the theoretical constructs and accounted 61.52% of the total variance which is good in behavioural research. The alpha values of the six constructs were between 0.809 to 0.854 and all above the required alpha value of 0.70 which indicates sufficient internal consistency.

Table 2: Preliminary Reliability Analysis (Cronbach's Alpha)

Construct	Cronbach's Alpha	No. of Items
AI Recommendation Quality	0.809	5
Behavioural Nudging Influence	0.834	5
Perceived Investor Oversight	0.853	5
Trust in AI Systems	0.854	5
Behavioural Bias Tendencies	0.836	5
Investment Decision Behaviour	0.835	5

4.6 Common Method Bias
Given that all the data were gathered on one source through a self-report survey, Harman single factor test was used to determine common method bias. The initial unrotated factor accounted 26.3% of total variance, which is far less than the 50% mark that would indicate a problematic common method factor (Podsakoff et al., 2003). Common method bias is thus not viewed as a major weakness to the validity of the findings although the cross-sectional self-report design is a weakness as observed in Section 8.

4.7 PLS-SEM Analysis
The data were also analysed with SmartPLS 4 according to the two-step analysis procedure suggested by Hair et al. (2019). The initial measure was to assess the measurement model, such as the reliability of the indicators based on the outer loadings, internal consistency, based on Cronbach alpha and rho A and composite reliability, convergent and discriminant validity based on the Average Variance Extracted (AVE) and Fornell-Larcker ratio. The second step was to estimate the structural model, path coefficients, hypothesis testing, bootstrapping with 5000 subsamples, coefficient of determination (R^2), effect sizes (f^2), and mediation analysis, which was based on indirect effect bias-corrected confidence intervals.

5. DATA ANALYSIS AND RESULTS
5.1 Preliminary Analysis
Before testing the structural model, preliminary checks were run in IBM SPSS to confirm the data were suitable for analysis. The Kaiser-Meyer-Olkin measure was 0.841, above the recommended threshold of 0.60, and Bartlett's Test of Sphericity was significant ($\chi^2 = 3261.288$, df = 435, $p < 0.001$), confirming that factor analysis was appropriate. Principal Component Analysis with Varimax rotation identified six components aligned with the theoretical constructs explaining 61.52% of total variance Harman's single factor test showed that the first unrotated component accounted for 26.3% of variance, well below the 50% threshold, indicating that common method bias is not a significant concern (Podsakoff et al., 2003)

5.2 Measurement Model
5.2.1 Indicator Reliability
All indicator outer loadings exceeded 0.70 which ranged from 0.735 to 0.858. One item from AI Recommendation Quality (AR2) was removed during model refinement due to an insufficient loading which left a four-item scale for that construct. The remaining loadings are reported in Table 3.

Table 3: Indicator Outer Loadings

Construct	Indicator	Loading
AI Recommendation Quality	AR1	0.759
	AR3	0.831
	AR4	0.756
	AR5	0.804
Behavioural Nudging	BN1	0.810
	BN2	0.796
	BN3	0.774
	BN4	0.751
	BN5	0.742
Behavioural Bias	BB1	0.778
	BB2	0.781
	BB3	0.754
	BB4	0.763
	BB5	0.808
Trust in AI	TA1	0.829
	TA2	0.808
	TA3	0.765
	TA4	0.775
	TA5	0.795
Investment Decision	ID1	0.740
	ID2	0.742
	ID3	0.858
	ID4	0.793
	ID5	0.735

Investor Oversight	IO1	0.807
	IO2	0.765
	IO3	0.815
	IO4	0.792
	IO5	0.788

5.2.2 Internal Consistency and Convergent Validity

Cronbach's alpha rho_A, and composite reliability values all exceeded 0.70 across all six constructs. And the AVE values exceeded 0.50 for all constructs, confirming that each construct captures more than half the variance in its indicators. Results are reported in Table 4.

Table 4: Reliability and Convergent Validity

Construct	Cronbach's Alpha	rho_A	CR	AVE
AI Recommendation Quality	0.798	0.806	0.868	0.622
Behavioural Nudging	0.834	0.841	0.883	0.601
Behavioural Bias	0.836	0.839	0.884	0.604
Investment Decision	0.836	0.877	0.882	0.601
Investor Oversight	0.854	0.861	0.895	0.630
Trust in AI	0.855	0.865	0.895	0.631

5.2.3 Discriminant Validity

Discriminant validity was assessed using the Fornell-Larcker criterion and HTMT ratios. For the Fornell-Larcker criterion, the square root of each construct's AVE exceeded its correlations with all other constructs, confirming that each construct is empirically distinct. Results are in Table 5.

Table 5: Fornell-Larcker Criterion (diagonal = √AVE)

Construct	AR	BN	BB	ID	IO	TA
AI Recommendation Quality	**0.788**					
Behavioural Nudging	0.063	**0.775**				
Behavioural Bias	0.111	0.491	**0.777**			
Investment Decision	0.083	0.131	0.161	**0.775**		
Investor Oversight	0.100	−0.005	0.100	0.074	**0.794**	
Trust in AI	0.278	0.073	0.115	0.174	0.206	**0.795**

All HTMT values ranged from 0.070 to 0.581, well below the 0.85 threshold, confirming discriminant validity across all construct pairs (Table 6).

Table 6: HTMT Ratio Matrix

Construct Pair	HTMT
Behavioural Bias ↔ AI Recommendation Quality	0.140
Behavioural Bias ↔ Behavioural Nudging	0.581
Investment Decision ↔ AI Recommendation Quality	0.106
Investment Decision ↔ Behavioural Nudging	0.156
Investment Decision ↔ Behavioural Bias	0.177
Investor Oversight ↔ AI Recommendation Quality	0.121
Investor Oversight ↔ Behavioural Nudging	0.070
Investor Oversight ↔ Behavioural Bias	0.123
Investor Oversight ↔ Investment Decision	0.095
Trust in AI ↔ AI Recommendation Quality	0.325
Trust in AI ↔ Behavioural Nudging	0.108
Trust in AI ↔ Behavioural Bias	0.137
Trust in AI ↔ Investment Decision	0.200
Trust in AI ↔ Investor Oversight	0.231
Behavioural Nudging ↔ AI Recommendation Quality	0.108

5.3 Structural Model

The structural model was tested using bootstrapping with 5,000 subsamples. All VIF values were below 3.3, confirming no multicollinearity issues.

5.3.1 Hypothesis Testing

Five of six direct hypotheses were supported. Behavioural nudging had the strongest effect in the model ($\beta = 0.492$, $p < 0.001$). The one unsupported hypothesis — H4, that perceived oversight reduces bias tendencies — is the study's most notable finding and is discussed in detail in Section 6.

Table 7: Hypothesis Testing Results

Hypothesis	Relationship	β	t-value	p-value	Result
H1	AI Recommendations → Trust in AI	0.260	4.704	0.000	Supported
H2	Behavioural Nudging → Behavioural Bias	0.492	10.863	0.000	Supported
H3	Investor Oversight → Trust in AI	0.180	3.173	0.002	Supported
H4	Investor Oversight → Behavioural Bias	0.103	1.667	0.096	Not Supported
H5	Trust in AI → Investment Decision	0.157	2.519	0.012	Supported
H6	Behavioural Bias → Investment Decision	0.143	2.242	0.025	Supported

5.3.2 Effect Sizes

Table 8: Effect Sizes (f^2)

Path	f^2	Interpretation
Behavioural Nudging → Behavioural Bias	0.324	Medium
AI Recommendations → Trust in AI	0.075	Small
Investor Oversight → Trust in AI	0.036	Small
Investor Oversight → Behavioural Bias	0.014	Small
Trust in AI → Investment Decision	0.026	Small
Behavioural Bias → Investment Decision	0.021	Small

Behavioural nudging had the only medium effect size in the model, reinforcing its role as the dominant driver of bias activation.

5.3.3 Mediation Analysis

Both mediation hypotheses were tested using bootstrapped indirect effects with 95% bias-corrected confidence intervals. Both were statistically significant, supporting H7 and H8. As both the direct and indirect effects are significant, both mediations are partial.

Table 9: Mediation Results

Mediation Path	Indirect β	t-value	p-value	95% CI
AR → Trust in AI → Investment Decision (H7)	0.041	2.098	0.036	[0.003, 0.079]
BN → Behavioural Bias → Investment Decision (H8)	0.070	2.121	0.034	[0.006, 0.135]

5.3.4 Model Explanatory Power

Table 10: R^2 Values

Construct	R^2	R^2 Adjusted
Behavioural Bias	0.252	0.247
Trust in AI	0.109	0.103
Investment Decision Behaviour	0.050	0.043

The model explains 25.2% of variance in behavioural bias, 10.9% in trust in AI, and 5.0% in investment decision behaviour. The relatively low R^2 for investment decision behaviour is not unexpected because investment decisions are influenced by several external factors beyond platform-related variables, including financial literacy, income, market conditions, risk tolerance, personality traits, and prior investment experience. This is consistent with behavioural finance research, where investment behaviour is shaped by many factors outside any single model. This aligns with Mohapatra et al.(2025) and Shriya and Velmurugan (2025) where platform level variables similarly explained modest variance in investment behaviour which reflects the multi determined nature of financial decisions.

5.3.5 Model Fit

The SRMR was 0.057, below the 0.08 threshold, indicating acceptable model fit. The NFI was 0.831 which approaches the 0.90 benchmark which is acceptable for complex behavioral models with multiple constructs (Hair et al,.2019).

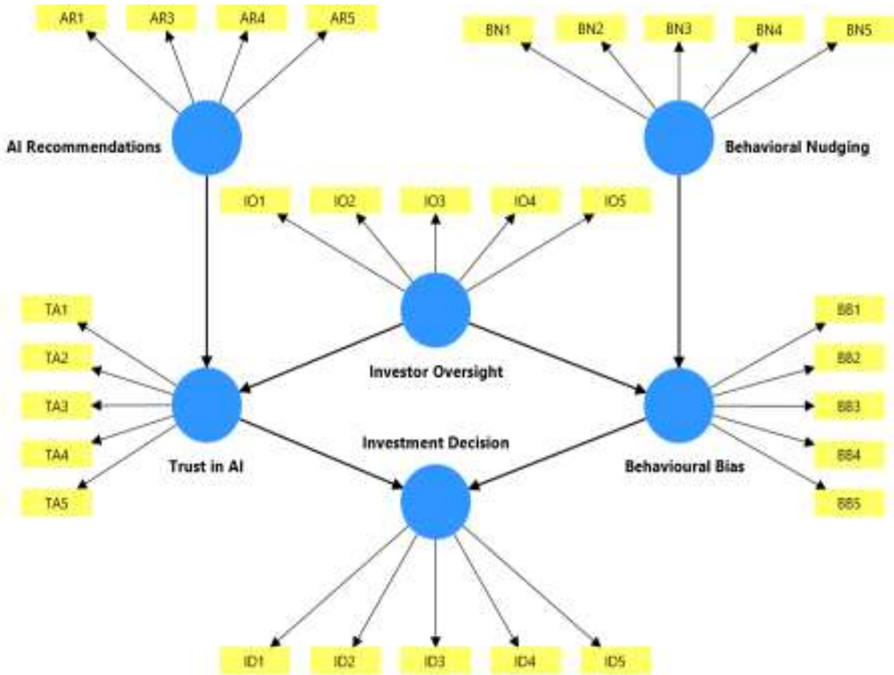

Image 5.4 PLS-SEM Model after Bootstrapping.

6. DISCUSSION

Five of six direct hypotheses were supported. The only unsupported hypothesis was predicting a negative relationship between perceived oversight and behavioural bias. This emerged as one of the most meaningful findings of the study. The discussion below follows the sequence of relationships tested in the structural model.

6.1 AI Recommendation Quality and Trust in AI (H1)

The positive and significant effect of AI recommendation quality on trust in AI systems ($\beta = 0.260$, $p < 0.001$) shows that investors who find AI-generated advice objective and useful develop stronger confidence in the investment platform. This is consistent with the Trust-in-Automation literature, according to which trust as an active judgment based on perceived system competence rather than a passive response to technology use (Trinh et al., 2025; Logg et al., 2019). In the Indian context where most young investors have limited experience and few alternatives to platform-based advice the quality of AI recommendations is becoming the primary basis on which trust is built.

This trust however is likely fragile. Dietvorst, Simmons and Massey (2014) showed that people abandon algorithmic advice quickly after a single visible error, and Gupta, Sehgal and Sharma (2024) found that opacity and perceived loss of control were significant barriers to AI acceptance among Indian investors.

Platforms need to manage investor expectations carefully particularly around recommendation errors, to prevent wear away of trust quickly.

6.2 Behavioural Nudging and Bias Activation (H2)

The strongest relationship in the model is between behavioural nudging and bias tendencies ($\beta = 0.492$, $p < 0.001$, $f^2 = 0.324$). This is a medium effect size in the study which is notable in behavioural finance research where many competing factors are involved. The result confirms that platform design features like notifications, default settings, peer activity cues, gamification systematically activate heuristic processing and amplify herding, loss aversion, and anchoring tendencies among investors.

This supports the predictions of Nudge Theory and Prospect Theory operating together, and aligns with empirical evidence on how Indian retail platforms function in practice (Gupta, 2025; Rakovic and Inal, 2023; Pancholi and Shukla, 2024). The finding also challenges the more optimistic view in the design literature that nudges improve investor outcomes but, in the platforms, used by this sample, nudges appear to be amplifying bias rather than correcting it.

6.3 Perceived Oversight and Trust in AI (H3)

Perceived investor oversight had a positive and significant effect on trust in AI systems ($\beta = 0.180$, $p = 0.002$). Investors who feel that regulatory safeguards, risk disclosures, and platform transparency mechanisms are in place in the platforms they use are more willing to trust AI-driven tools while making decisions. This aligns with the Trust-in-Automation framework and with regulatory literature which argues that institutional credibility is a precondition for appropriate trust in automated systems (Baker and Dellaert, 2018; Kofman, 2025; Brüggen et al., 2024). The finding suggests how SEBI's evolving disclosure and governance requirements have been providing a meaningful effect on individual investor confidence beyond their formal compliance function.

6.4 Perceived Oversight and Behavioural Bias (H4 — Not Supported)

The predicted negative relationship between perceived oversight and bias tendencies was not supported ($\beta = 0.103$, $p = 0.096$). This is the study's most significant finding. The expectation here that did not hold was that investors who feel regulated and protected would think more carefully and be less susceptible to heuristic-driven decision-making.

The result is consistent with Mei et al. (2025), who found that even vigilant users do not necessarily rely less on AI and with the broader behavioural finance literature showing that cognitive biases are persistent psychological tendencies that do not easily respond to informational interventions (Kahneman and Tversky, 1979). Oversight appears to build confidence which H3 confirms but it does not change how investors cognitively process information. This finding suggests that oversight may function more as a confidence-building mechanism than as a debiasing mechanism The two effects operate independently. In other words, investors may feel more secure using AI-supported platforms when oversight is visible but they are not necessarily less vulnerable to herding, anchoring, or loss-aversion driven decisions

This has direct implications for regulation. If perceived oversight increases trust but does not reduce bias, then disclosure-based regulatory frameworks may be increasing investor reliance on AI without improving the quality of the decisions being made. Oversight is building confidence and not better thinking. Regulators have to balance disclosure requirements with investor education tools and platform design standards that actively work against bias, instead of assuming that transparency alone is sufficient.

6.5 Trust in AI and Investment Decision Behaviour (H5)

Trust in AI systems had a positive and significant effect on investment decision behaviour ($\beta = 0.157$, $p = 0.012$). Investors who trust AI platforms are more likely to actively engage with recommendations follow portfolio suggestions and use platform tools when making investment decisions. This confirms the central proposition of both TAM and the Trust-in-Automation framework which is that trust is the mechanism through which perceived system quality translates into actual behaviour (Fatima and Chakraborty, 2024; Trinh et al., 2025). Trust is not just an attitude but it is what converts platform confidence into action.

6.6 Behavioural Bias and Investment Decision Behaviour (H6)

Behavioural bias tendencies had a positive and significant effect on investment decision behaviour ($\beta = 0.143$, $p = 0.025$). Investors with stronger herding, anchoring, and loss aversion tendencies make more reactive decisions even when AI-generated advice is available. This confirms the core prediction of Prospect Theory and is consistent with evidence that cognitive biases persist in algorithmically assisted investment environments (Sayeed and Kapoor, 2025; Kulkarni, Patil and Pramod, 2025).

When this read alongside H2 this creates a clear and concerning chain: platform nudges activate cognitive biases and those biases then shape investment decisions. The platform is not a neutral tool; rather, it may create an environment where design choices are associated with lower-quality investor decisions.

6.7 Mediation Through Trust (H7)

The indirect effect of AI recommendation quality on investment decision behaviour through trust was significant (indirect $\beta = 0.041$, $p = 0.036$, 95% CI [0.003, 0.079]), which confirms partial mediation. AI recommendations do not directly drive investment decisions they do so by first building platform trust which then motivates AI-assisted decision behaviour. For platform operators this is important as it points recommendation quality as the most important trust-building lever than interface design or personalisation features.

6.8 Mediation Through Bias (H8)

The indirect effect of behavioural nudging on investment decision behaviour through bias tendencies was also significant (indirect $\beta = 0.070$, $p = 0.034$, 95% CI [0.006, 0.135]), confirming partial mediation. Platform nudges do not directly determine investment decisions they work by activating cognitive biases first, which then shape behaviour. This confirms the theoretical pathway proposed by Nudge Theory and Prospect Theory and provides empirical evidence that the route from interface design to investor behaviour runs through bias activation rather than direct persuasion.

7. IMPLICATIONS

7.1 Theoretical Implications

This paper has a contribution to the literature on the behavioural finance and AI-assisted decision-making in a few aspects.

To begin with, the results indicate that the trust in AI-assisted investing works on several levels. Investors seem to make a distinction between trust in individual recommendations, and more general trust in the platform. The mediation findings (H7) show that trust in the recommendation level leads to system level trust, which in turn, affects investment behaviour. This multi-layered perspective of trust has been addressed in the trust-in-automation literature but has yet to be validated empirically in an investment setting. The current results thus suggest the need to treat these dimensions as two separate measures in future studies as opposed to putting them into one measure of trust.

Second, the perceived investor oversight is a personal level construct introduced in this study. Past studies have generally viewed oversight through the institutional or regulatory lens. With the emphasis on the perception of oversight by investors, this paper shows that oversight affects trust without a significant decrease in behavioural bias. This difference indicates that control systems can be more of a legitimacy indicator than a system that transforms thinking. The result adds to the current discussion on the behavioural implications of disclosure and regulatory transparency.

Third, the paper combines various theoretical models, such as Technological Acceptance Model (TAM), Nudge Theory, Prospect Theory, and Trust-in-Automation into one behavioural channel. Both of these frameworks describe a different step of making investment decisions with the help of AI. TAM helps to understand the formation of trust, Nudge Theory helps explain the use of biases by platform design, Prospect Theory helps explain how biases affect decision-making, and Trust-in-Automation helps understand how perceived reliability affects behavioural adoption. This combined solution provides a more detailed account of AI-impacted investor behaviour than individual-framework research.

Fourth, the medium effect size of behavioural nudging on bias activation ($f^2 = 0.324$) is significant. In behavioural finance studies, the effect sizes tend to be quite small, especially when researching psychological factors that affect investment choices. The size of this effect implies that platform design can be a significant factor in behavioural influences in digital investment contexts.

7.2 FinTech Platforms implications.

As established in Section 6.4 he positive correlation between behavioural nudging and bias activation (β = 0.492) shows the significance of platform design in the determination of investor behaviour. Interfaces features must not just be assessed based on the engagement with the interface but also based on behaviour. Social proof messages, trending stock labels, and framing of scarcity can be all be used as elements of design which inadvertently promote herding, anchoring, and loss aversion. These results indicate that the decision-making process of platform design may affect the quality of decisions beyond the informational content.

The transparency to decision-making (H5) pathway also is implying that transparency is significantly important to enhance AI-assisted decision-making. Transparency in the logic of the recommendations, confidence levels, and the availability of documentation can potentially enable investors to analyse AI based advice in a more efficient manner. On the other hand, more personalisation or an interface might not always enhance trust or the quality of decisions when the processes of making recommendations are not transparent.

The results pertaining to perceived oversight (H4) are another design consideration. We see that increased oversight does not decrease bias and only increases trust, platforms that focus on regulatory compliance but have highly persuasive interfaces can cause behavioural risks unintentionally. To resolve this platforms can think about adding functions that are intended to facilitate more deliberate decision-making. Few examples can be market volatility reminders, context of trending investments, or the ability to take a cooling off period before making significant changes to the portfolio.

7.3 Implications to Regulators and Policymakers.

As established in section 6.4 tcohe perceived oversight and trust (H3) are positively correlated, which implies that regulatory visibility is significant in determining investor confidence. Investors seem to be more ready to follow the recommendations of the platform when they feel that AI-driven tools can be controlled. The result justifies the further focus on transparency, disclosure, and accountability in regulatory policies of AI-assisted investing.

Yet the lack of the association between oversight and behavioural bias (H4) indicates that disclosure alone might not be effective in enhancing the quality of investor decisions. In case regulation by disclosure can make people more confident and less biased, regulation strategies that emphasize disclosure can have the unintended effect of making people more reliant on AI systems without reducing performance. This difference emphasizes the fact that regulatory frameworks should be in place to deal with behavioural risks besides informational transparency.

The direct path discovered in this paper nudging influencing bias, which subsequently influences investment choices also indicates that one should take into account digital choice architecture when discussing regulation. The interface design and behavioural cues in the investment platforms are increasingly influencing investors behaviour. These types of influences are not similar to the traditional financial advice and they could be subject to different regulatory requirements. It can be beneficial to develop guidelines regarding the behavioural design, default settings, and decision-support mechanisms to make sure that AI-assisted investment environments will promote informed and balanced decision-making.

8. LIMITATIONS AND FUTURE RESEARCH

This research has a number of limitations which also present new research opportunities. First, it has the limitation of cross-sectional design which does not allow the study of changes in perceptions of investors with time. Trust, behavioural bias, and interaction with the digital platforms are bound to change depending on the market conditions, experience of the investors and changes in design of the platform. Consequently, the results present perceptions at one instance as opposed to the vibrancy of investor behaviour. Studies in future might adopt a longitudinal design, where they can follow the same investors through the various cycles of the market, particularly when conditions are volatile or when recommendations are unsuccessful to improve understanding insight into behavioural changes.

Second, the research is based on self-reported data, which can cause a disparity between reported behaviour and real investment choices. The possibility of the response bias cannot be excluded even though the single-factor test, conducted by Harman, did not show the presence of the severe common method bias. Future research can support validity through the integration of survey data with real trading histories or behavioural data so that the patterns of decision making of investors can be more accurately predicted.

Third the sample is restricted majorly to investors in Karnataka a region with comparatively good digital infrastructure and increased platform adoption. This geographic concentration influences the applicability of the results to areas with varying technological access, financial literacy, or demographic profiles. This model can be repeated in various states among various income groups and age groups in future to enhance external validity.

The other weakness is associated with the fact that the investment decision behaviour model has a rather low explanatory power ($R^2 = 5.0\%$). This indicates that there are other factors that affect investments decisions but are not reflected in the current study which include factors like financial literacy, risk tolerance, income levels, and previous investment experience. Although the model has shown a better explanation of behavioural bias ($R^2 = 25.2\%$), future studies ought to be conducted with a wider range of variables to explain better the results of investment decisions.

Lastly, perceived oversight in this research is based on investor perception and not objective governance of the platform or regulatory adherence. This limitation can be overcome by combining investor surveys with platform-level evaluations. A research with closer look at the design characteristics, nudging, and disclosure techniques of trading platforms may shed more light on how regulatory intent is converted to investor protection and behavioural results.

9. CONCLUSION

This paper investigated the effect of AI-based investment recommendations, behavioural nudges, and perceived investor oversight on trust, cognitive biases, and investment decision behaviour of young retail investors in India. These results support five out of six direct hypotheses and both mediation relationships to offer a systematic perspective of the effects of AI-assisted platforms on investor behaviour.

The findings suggest that the trust in AI recommendations is not limited to the individual recommendations but tapers off to the overall platform confidence that in turn affects the investment choices. This highlights the role of trust as a behavioural tool of AI assisted investing. Simultaneously behavioural nudges incorporated into platform design turned out to be the most powerful predictor of cognitive bias activation. The results indicate that the properties of interfaces, including notifications, default settings, and social cues, have a significant influence on investor psychology. These biases can also generate a prolonged effect since once activated they determine the decision even in the presence of AI-generated recommendations.

One of the most interesting results is that there is no significant correlation between perceived oversight and behavioural bias. Although perceived oversight was linked with an increased degree of trust in AI systems, it failed to diminish the tendencies to bias. This implies that the checks and balances can increase investor confidence without necessarily raising the quality of decisions. The implications of such a gap on platform design and regulatory frameworks, especially those based largely on disclosure and transparency measures, are significant.

The results suggest that disclosure-oriented solutions might not be adequate to mitigate behavioural risks in AI-assisted investing. To enhance investor performance, complementary controls, like behavioural design controls, and decision-support applications, might be required. Likewise, the platform design decision cannot be regarded as either technical or engagement-oriented decisions. The fact that in this paper the pathway has been identified, where nudging is related to bias activation, which in turn is related to investment decisions, indicates that design characteristics can be used to affect investor behaviour on a large scale.

In India, AI-based platforms are now emerging as the main platform by which young investors can access financial information and make investment decisions. With increasing adoption, the behavioural aspects of these systems become increasingly important. The ability to design AI-supported platforms and facilitate informed decision-making, as opposed to enhancing engagement, is a key concern to researchers, platform developers, and regulators alike. This paper is a contribution to that debate in the backdrop of India where the retail investor base is increasingly becoming a large part of the population, as well as a demand to conduct further studies in this developing field.

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