

Behavioural Biases and Investment Decisions: Evidence from Equity and Mutual Fund Investors in India

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Abstract

Retail participation in Indian equity and mutual fund markets has expanded rapidly since 2020, drawing in investors whose financial sophistication has not kept pace with their market access. Drawing on the current (2020–2026) evidence base, this study examines how four Behavioural biases overconfidence, herd behaviour, loss aversion and risk perception shape investment decision-making among Indian retail investors, and whether their influence differs between equity and mutual fund investors. Primary data were collected from 720 retail investors across major Indian metropolitan centres using a structured, five-point Likert-scale questionnaire and a multistage random sampling design, with construct reliability assessed using Cronbach's alpha and hypothesised relationships tested using Pearson correlation, multiple regression and Structural Equation Modelling (SEM). All four biases showed a significant, positive path to investment decision-making, with overconfidence exerting the strongest influence, followed by herd behaviour, loss aversion and risk perception; the model met conventional fit thresholds (CFI = 0.94; RMSEA = 0.064) and explained approximately 70 per cent of the variance in decision-making, with equity investors showing higher overconfidence and herding while mutual fund investors were more loss-averse and risk-conscious. The paper synthesises current, Scopus- and Web of Science-indexed behavioural finance research into a single, comparative model spanning both equity and mutual fund investors, offering guidance for advisers, asset managers and SEBI in designing bias-sensitive investor education.

Keywords: Behavioural finance 1; Overconfidence bias 2; Herd behaviour 3; Risk perception 4; Financial literacy 5; Investment decision-making 6; Structural Equation Modelling 7.

1. Introduction

Financial systems perform one of the most consequential tasks an economy can ask of them: mobilising household savings and channelling them into productive investment. In India, equity markets and mutual funds have become the principal conduits for this, and the years since 2020 have brought a structural, arguably generational, shift. The number of demat accounts grew from around 4.1 crore in March 2020 to over 21.6 crore by December 2025. The mutual fund AUM crossed ₹81 lakh crore by mid-2026, driven by monthly SIP inflows, which now regularly exceed ₹30,000 crore (Association of Mutual Funds in India, 2026; National Securities Depository Limited, 2026). This growth, driven by financial-inclusion initiatives, smartphone-based trading apps and simplified digital onboarding, has drawn in a generation of

investors with limited prior market exposure, uneven financial literacy, and for many, their first sustained encounter with risk-bearing assets.

The core of the study is that quick participation is not equal to rational participation. Classical asset-pricing frameworks model the investor as a coherent, utility-maximising agent: Markowitz (1952) mean-variance portfolio theory, Sharpe (1964) Capital Asset Pricing Model, and Fama (1970) Efficient Market Hypothesis. The decisive counterargument came from Kahneman and Tversky (1979) with their Prospect Theory, and Thaler's (1985) mental accounting framework, according to which investors evaluate outcomes in terms of a reference point, that losses hurt about twice as much as equivalent gains, and that money is psychologically compartmentalised rather than 100% fungible. These insights, though decades old, are still being retested rather than replaced – recent systematic reviews confirm overconfidence, herding, loss aversion and related heuristics are still the dominant, most replicated biases in the post-pandemic literature (Karki, Bhatia, & Sharma, 2024; Sharma & Negi, 2025; Singh, Kumar, Goel, & Johri, 2023).

These include overconfidence, herding, loss aversion and risk perception, which are consistently the strongest, most replicable predictors of retail trading behaviour. Recent Indian evidence associates overconfidence with high trading frequency and poorer realised outcomes, a pattern as evident among first-time post-pandemic entrants as among experienced traders (Karki et al., 2024; Reddy et al., 2026). A newly validated 30-item scale now differentiates overprecision, overestimation and overplacement as separable manifestations of the bias (Costa, Soares, Moreira, & Tonelli, 2025). Social media and digital trading platforms have increased herding, which rose during COVID-19 and has continued in changing forms (Dhall & Singh, 2020; Dhuri & Patkar, 2024; Nain et al., 2025). Loss aversion is associated with unwillingness to terminate underperforming positions in equity, real-estate and crypto-related portfolios; a 2025–2026 bibliometric mapping characterizes it as a core organizing construct linking the emotional, cognitive and structural dimensions of investment decision-making (Islam, Abu, Binti, Sood, & Srivastava, 2024; Shah & Malik, 2021; Singh et al., 2023). Risk perception, a product of cognition, emotion and financial literacy, has been demonstrated to mediate the influence of other biases on eventual behaviour, rather than simply accompany it (Mohta & Shunmugasundaram, 2024). These biases are also increasingly implicated in individual and aggregate market outcomes, particularly in India where literacy remains uneven across geography, gender, and income, and where investment information is dominated by peer networks and social media (Kumar, Pillai, Kumar, & Tabash, 2023; Suresh, 2024).

One common limitation of recent Indian literature is the limited number of studies that focus on either equity or mutual fund investors independently, rarely both in one jointly estimated comparative framework (Bhatia, Arora, & Mehrotra, 2024; Makwana, 2024), which has been corroborated by recent bibliometric reviews (Karki et al., 2024; Sharma & Negi, 2025). This distinction matters in practice. Equity investors have direct, undiversified exposure and make their own decisions about security selection and timing, perhaps increasing exposure to overconfidence and herding; mutual fund investors delegate selection to professional managers and instead face decisions about fund choice, timing of redemptions and loss framing at the portfolio level. Understanding whether biases operate differently across these groups has direct implications for how advisers, asset managers and SEBI design investor-facing interventions.

The practical stakes are illustrated starkly by SEBI's own research. A study of individual F&O traders found that 91 per cent incurred net losses in FY24, with cumulative FY22–FY24 losses exceeding ₹1.8 trillion; a follow-up FY25 study found losses had widened further despite tighter contract-size and expiry-day risk controls (SEBI, 2023, 2025). More than three-quarters of loss-making traders continued trading

the same segment across consecutive loss-making years — a pattern hard to reconcile with rational decision-making and far more consistent with the overconfidence and loss-aversion mechanisms documented in the behavioural literature. This regulatory evidence directly motivates the present study. This study develops and empirically tests an integrated four-bias model — overconfidence, herd behaviour, loss aversion and risk perception — using survey data from 720 retail equity and mutual fund investors across major Indian cities, analysed via correlation, multiple regression and SEM, and situated within a current (2020–2026) evidence base spanning technology-mediated investing, ESG, cryptocurrency, gender and cross-market comparisons. Section 2 profiles Indian investor participation; Section 3 reviews the literature and develops five hypotheses; Section 4 details methodology; Section 5 presents results; Sections 6–7 discuss findings and implications; Section 8 concludes with limitations.

2. Investor Participation in the Indian Capital Market

Indian households have historically favoured physical savings — bank deposits, gold, real estate — over market-linked assets, reflecting risk aversion, limited access, and underdeveloped retail infrastructure. This composition has shifted markedly since 2020, consistent with rising digital and financial literacy (Kumar et al., 2023). Table 1 summarises the change.

Table 1. Key Indicators of Investor Participation in the Indian Capital Market

Indicator	March 2020	Latest available (2025–26)	Approx. growth
Total demat accounts (NSDL + CDSL)	4.1 crore	21.6 crore (Dec. 2025)	~5-fold
Mutual fund AUM	₹27 lakh crore	₹81.6 lakh crore (May 2026)	~3-fold
Mutual fund folios	9.0 crore	27.5 crore (Apr. 2026)	~3-fold
Monthly SIP contributions	₹8,641 crore	₹31,115 crore (Apr. 2026)	~3.6-fold

Sources: Association of Mutual Funds in India (2026); National Securities Depository Limited (2026); Central Depository Services Limited (2026).

The almost five times increase in demat accounts and three times increase in mutual fund AUM point to real broadening of retail participation, aided by SEBI’s investor-awareness initiatives and low-cost digital platforms — although several studies argue that many trading interfaces’ gamified, attention-optimised design exacerbates rather than mitigates behavioural biases (Bhatia, Chandani, & Chhateja, 2020). Retail investors now provide large amounts of liquidity and significantly influence short-term price dynamics around earnings announcements, index events and periods of high social-media attention (Nain et al., 2025). Much of this growth is driven by first time and relatively inexperienced investors, the very group that has featured in SEBI’s F&O loss statistics. It is important to understand their psychological drivers for market stability and investor protection. Growth has also not been demographically even: women continue to be significantly under-represented in new demat-account openings, making up about 30 per cent of SIP assets but a smaller share of direct-equity AUM – a difference that is directly relevant for the bias comparisons developed later.

3. Theoretical Background and Literature Review

3.1 Theoretical Foundations

The investor is rational in standard finance, through mean-variance optimization (Markowitz, 1952), risk-return equilibrium pricing (Sharpe, 1964) and the assumption that prices completely reflect information (Fama, 1970). The behavioural alternative is given by the Prospect Theory of Kahneman and Tversky (1979) and the mental accounting theory of Thaler (1985): decision-makers evaluate outcomes relative to a reference point, overweight losses compared to corresponding gains and treat money as non-fungible across mental accounts. These trace back to Tversky and Kahneman's (1974) early work on heuristics, which was the first to formalise the idea that much of human decision-making is characterised by systematic, predictable departures from rational choice (rather than random noise) (Costa et al., 2025). These papers are still the theoretical basis that current empirical work continues to test and to extend, although they are before the current literature window; recent reviews confirm that prospect-theory-consistent biases continue to dominate the published record (Karki et al., 2024; Sharma & Negi, 2025; Singh et al., 2023).

3.2 Overconfidence Bias

Overconfidence leads investors to overestimate the precision of their private information, the accuracy of their forecasts and their ability relative to other players. Building on Moore and Healy's (2008) tripartite distinction, the construct now consists of overprecision, overestimation and overplacement — three empirically separable dimensions with distinct behavioural signatures (Costa et al., 2025; Grežo, 2021). Overconfidence is confirmed as one of the most consistently documented predictors of excessive trading in Karki et al.'s (2024) systematic review, while Kumar and Prince (2023) connect it to demographic traits and earlier positive returns.

This is directly confirmed by Indian evidence. Makwana (2024) identified overconfidence as one of the strongest cognitive predictors of equity investment choice. Reddy et al. (2026) confirmed the dominant role of overconfidence even after controlling for literacy and experience. Ahmed, Rasool, Saleem, Khan, and Kanwal (2022) showed that the effect is partially mediated by risk perception, and Shunmugasundaram and Sinha (2025) showed it as a significant serial mediator among insurance-linked investors. A recent review finds that overconfidence works less as an isolated quirk than as a hub around which the disposition effect, self-attribution bias and confirmation bias cluster (Singh, Malik, & Jha, 2024). It is also involved in the outcomes at the market level, where overconfident investors sustain speculative price runs by discounting warning signs, while less-confident participants herd into the same trades, together amplifying mispricing beyond what either bias produces alone (Prabhakar & Varma, 2025). In line with this evidence:

H1: Overconfidence bias has a significant positive effect on investors' investment decision-making.

3.3 Herd Behaviour

Herd, which occurs when investors follow the crowd rather than conducting independent analysis, can arise in informational cascades, reputational externalities, or unreflective imitation motivated by fear or a perceived lack of skill (Altaf & Jan, 2023; Bharti, Soti, & Kumar, 2025). Indian specific evidence has reported persistent herding at the market and industry level, concentrated around structural breakpoints and high-volume periods and not constant (Gupta & Kohli, 2021; Dhuri & Patkar, 2024). Nain et al. (2025), using SEM, found herding materially reduced pricing efficiency, while Dhali and Singh (2020) documented sharp intensification during COVID-19, corroborated by neural-network evidence that pandemic-era trading was significantly shaped by behavioural biases rather than fundamentals (Talwar,

Talwar, Tarjanne, & Dhir, 2021). Goyal, Gupta, and Yadav (2021) found herding a dominant heuristic among Indian millennials; a 2025 thematic review confirms herding is generally event-contingent rather than a stable trait (Bharti et al., 2025).

Internationally, the 2021 GameStop episode showed social-media-coordinated herding driving extreme, fundamentals-detached price movements (Betzer & Harries, 2022; Malz, 2021; Mancini, Desiderio, Di Clemente, & Cimini, 2022). Herding is also intensifying in cryptocurrency markets, where continuous trading and socially mediated sentiment amplify imitation (Haryanto, Subroto, & Ulpah, 2020; Kyriazis, 2020; Youssef & Waked, 2022). Given herding's repeated intensification in India's post-2020 boom, it is expected to remain a robust predictor here:

H2: Herd behaviour has a significant positive effect on investors' investment decision-making.

3.4 Loss Aversion and the Disposition Effect

Loss aversion causes investors to weigh losses more heavily than equivalent gains, producing the disposition effect: selling winners too early while holding losers too long, hoping to break even (Shefrin & Statman, 1985). Shah and Malik (2021) found both regret aversion and loss aversion significantly increased trading frequency, with risk perception moderating the relationship; Banerji, Kundu, and Alam (2023) found loss aversion among the most robust predictors of financial choice in an Indian sample. Islam et al. (2024) confirmed the relationship using recent Indian data, and a 2023 systematic review found loss aversion and anchoring among the most extensively studied biases across stock, mutual fund and real-estate investment (Singh et al., 2023).

A 2025–2026 bibliometric analysis of 427 Scopus-indexed articles concludes loss aversion functions as a central organising construct connecting emotional, cognitive and structural dimensions of decision-making, with the disposition effect its most consistent manifestation. Recent evidence refines the mechanism further: portfolio-level framing moderates disposition-effect strength at the individual-stock level, and trading-activity transparency has been found to reduce disposition-effect magnitude by roughly a third. Social-media information exposure also reduces the effect, though asymmetrically, and the debiasing effect is weaker among less financially literate investors. Because Indian equity investors on self-directed mobile platforms show a pronounced disposition effect, loss aversion is expected to be a robust predictor across both investor groups:

H3: Loss aversion has a significant positive effect on investors' investment decisions.

3.5 Risk Perception, Financial Literacy and Anchoring

Risk perception reflects an investor's subjective assessment of uncertainty, shaped by cognition, emotion and literacy, and is increasingly treated as a mediating mechanism through which other biases translate into portfolio behaviour rather than merely an antecedent. Mohta and Shunmugasundaram (2024) found financial literacy significantly moderated the risk-tolerance-to-risky-behaviour relationship among Indian millennials; Kumar et al. (2023) showed digital literacy and decision autonomy jointly shaped financial well-being. Kumar, Islam, Pillai, and Tabash (2024), using PLS-SEM, found risk perception shaped both heuristic and prospect-theory-consistent biases, with gender moderating the risk-perception-to-performance pathway. Anchoring — over-reliance on an initial reference price or forecast — remains one of the two most heavily studied biases in current research, appearing in 37 of the studies reviewed by Singh et al. (2023). Suresh (2024) found framing-related biases, including mental accounting and regret aversion, jointly shaped literacy-linked outcomes. Because risk perception mediates how other biases translate into portfolio choices, it is treated here as a direct antecedent:

H4: Risk perception has a significant positive effect on investors' investment decision-making.**3.6 Personality, Emotion and Individual Differences**

A growing literature links bias intensity to personality, demographics and emotional traits rather than treating investors as homogeneous. Shanmugam, Chidambaram, and Parayitam (2023) found Big Five traits shape both financial literacy and risk propensity among Indian investors, suggesting personality is a distal antecedent of the proximate biases modelled here. Gambetti, Zucchelli, Nori, and Giusberti (2022) showed that default-heavy choice architectures influence decision style with respect to trait anxiety. Gender differences deserve special attention. Jain, Ashalatha, Nandan Prabhu and Ramaprasad (2025) have also found gender-conditioned patterns in the selection of mutual funds by Indian women. Recent survey evidence continues to find women reporting lower risk tolerance and heavier reliance on herding and anchoring than men. This is not India-specific; a large analysis of the US Survey of Consumer Finances found that gender differences in risk tolerance were largely explained in terms of underlying determinants, income uncertainty and net worth, rather than gender per se, and closing demographic gaps may close the bias gap more than generic gender-targeted education. The formal test of equity versus mutual fund divergence in H5 continues. Women's SIP share grows but remains under-represented in direct equity in India.

3.7 Technology-Mediated Investing: Robo-Advisory, Social Media and Digital Assets

Digitisation since 2020 has introduced new channels through which biases are transmitted and, sometimes, mitigated. Bhatia, Chandani, and Chhateja's (2020) early study found robo-advisory tools could moderate, though not eliminate, behavioural influence, extended by Bhatia, Chandani, Divekar, Mehta, and Vijay (2022) and Oehler, Horn, and Wendt (2021). International evidence reinforces this: a discount broker's algorithm-driven advisory rollout reduced the disposition effect and trend-chasing among adopters. More recent evidence suggests the relationship is more nuanced than uniform debiasing. AI-powered robo-advisors have been shown to reduce loss aversion and overconfidence through interactive, personalised feedback (Barile, Secundo, & Bussoli, 2024), though effectiveness depends on interactivity, personalisation, algorithmic interpretability and structural assurance — not all design choices debias equally. Many Indian investors nonetheless resist such systems for trust and control reasons, with algorithm aversion interacting with pre-existing overconfidence such that the most overconfident investors are also the most resistant to ceding control (Verma, Schulze, Goswami, & Upreti, 2025). A recent systematic review concludes robo-advisory's debiasing potential remains only partially realised, with adoption itself the binding constraint (Akhtar et al., 2025); NYSE evidence similarly finds investors' cognitive biases shape how they interpret robo-advisor recommendations, suggesting algorithmic advice is filtered through, not substituted for, pre-existing tendencies (Ahmad, Van Keulen, & Briassouli, 2025). Cryptocurrency markets — an increasingly important, high-volatility segment — show distinct, intensifying herding and disposition effects under continuous, socially mediated trading (Haryanto et al., 2020; Kyriazis, 2020). Technology platforms thus do not simply neutralise biases but reshape how, when and among whom they manifest — relevant for India, where fintech brokerages have begun marketing behavioural-nudge features (trading alerts, cooling-off periods, portfolio-level rather than stock-level displays) intended to curb exactly the biases modelled here.

3.8 ESG and Sustainable Investment Behaviour

An emerging strand examines how biases interact with India's rapidly growing ESG-investing segment. Bihari, Choudhary, Sharma, Kumar, and Upadhyay (2025) found ESG considerations and behavioural bias factors jointly shape sustainable investment decisions, using PLS-SEM combined with an artificial

neural network. As ESG-labelled products expand, framing and affect-driven biases — including “warm-glow” effects, whereby investors who previously held carbon-intensive assets report heightened preference for subsequent ESG investment as psychological compensation — are likely to interact with, rather than replace, the biases modelled here. Default-setting field experiments show that simply making a sustainable option the default can raise adoption from roughly 23 to 36 per cent — illustrating how behavioural design, not information alone, shapes ESG outcomes.

3.9 Crisis-Period and Cross-Market Evidence

Evidence from times of crisis puts the Indian findings in a larger pattern. Studies on COVID-19 in several markets observed sharp, transitory increases in herding, panic-selling and household decision distortion (Harjoto, Rossi, & Paglia, 2021; He, Sun, Zhang, & Li, 2020; Liu, Manzoor, Wang, Zhang, & Manzoor, 2020; Sha & Sharma, 2020; Yue, Korkmaz, & Zhou, 2020), which were reflected in India (Dhall & Singh, 2020; Talwar et al., 2021; Ritika, Himanshu, & Kishor, 2023). Similar dynamics are observed in more recent geopolitical shocks, although the direction (herding versus anti-herding) is sensitive to the asset class and the information environment.

Cross-country evidence shows that overconfidence and herding are robust predictors among Chinese investors (Xia & Madni, 2024), and that financial literacy moderates the bias-decision relationship among Pakistani investors (Mahmood, Arshad, Khan, & Ahmad, 2024) — reinforcing that these biases reflect a wider South Asian and emerging-market pattern and not an Indian idiosyncrasy, and are present and consequential during ordinary conditions and not just during acute crises.

SEBI has taken behaviourally informed measures in response to the post-2020 retail boom, including tightened F&O contract sizes and expiry-day risk controls, enhanced account-opening disclosures, and restrictions on unregistered financial influencers implicated in herding-driven trading. Data from the NSE and BSE show that retail investors now constitute an increasing share of cash-market turnover, which is a key driver of short-run market dynamics.

3.10 Equity versus Mutual Fund Investors

Equity investors bear direct, undiversified exposure and independently perform valuation, timing and exit decisions, plausibly heightening overconfidence and herding. Mutual fund investors, delegating selection to professional managers, are structurally insulated from some pressures but remain susceptible to loss aversion in redemption decisions and to familiarity- or recency-based heuristics in fund selection. Bhatia, Arora, and Mehrotra (2024) found financial literacy and firm characteristics conditionally mediated the bias-choice relationship across Indian segments, and Jain et al. (2025) found mutual fund investors' decisions shaped by a distinct combination of biases relative to direct equity investors. This motivates the study's final hypothesis:

H5: There is a significant difference in the behavioural bias profile of equity investors and mutual fund investors in India.

3.11 Synthesis of the Reviewed Evidence

Table A synthesises the core findings across Sections 3.2–3.10. A pattern recurs throughout: recent (2023–2026) evidence increasingly treats these constructs as interlocking components of a single behavioural system, with overconfidence often functioning as an entry point reinforced by herding, loss aversion and biased risk perception — consistent with the intercorrelations reported in Table 3, and motivating modelling all four jointly.

Table A. Synthesis of Reviewed Constructs and Representative Recent Evidence

Construct	Principal mechanism	Representative recent evidence
Overconfidence	Overprecision, overestimation and overplacement lead to excessive trading and underestimated risk	Karki et al. (2024); Costa et al. (2025); Grežo (2021); Reddy et al. (2026)
Herd behaviour	Informational cascades and social imitation substitute for independent analysis	Nain et al. (2025); Bharti et al. (2025); Dhuri & Patkar (2024)
Loss aversion	Asymmetric weighting of losses relative to gains produces the disposition effect	Shah & Malik (2021); Islam et al. (2024); Banerji et al. (2023)
Risk perception	Cognitive, affective and literacy-linked appraisal mediates bias in decision pathways	Mohta & Shunmugasundaram (2024); Kumar et al. (2024)
Technology mediation	Robo-advisory and fintech platforms both attenuate and reshape bias expression	Bhatia et al. (2020, 2022); Verma et al. (2025); Akhtar et al. (2025)
ESG and sustainability framing	Affect-driven and framing biases interact with cognitive biases in sustainable choice	Bihari et al. (2025)

This synthesis also highlights where the study's four-construct model leaves ground uncovered — anchoring, mental accounting and ESG-linked framing — each documented as influential but omitted here for parsimony, a limitation discussed in Section 8.

3.12 Research Gap

The current literature establishes overconfidence, herding, loss aversion and risk perception as robust correlates of investment behaviour, situated within a fast-growing Indian evidence base (Karki et al., 2024; Nain et al., 2025; Reddy et al., 2026). Recent bibliometric reviews confirm these four biases dominate the published record, while validated multi-bias structural models of the kind developed by Ritika and Kishor (2022) remain scarce, and technology-mediated investing, ESG-linked bias and vehicle-level comparisons remain under-studied (Agudelo Aguirre & Agudelo Aguirre, 2024; Hachicha, Argoubi, & Guesmi, 2024; Paul & Sundaram, 2023; Rumysa & Islam, 2025; Sharma & Negi, 2025; Singh et al., 2023). A 2025 PRISMA-based review of 63 Scopus-indexed studies corroborates this: overconfidence, herding and loss aversion remain over-represented relative to regret aversion and anchoring, and few studies test real-world debiasing interventions (Herathmenike, Dewasiri, Munasinghe, Kapoor, Jayawardena, Koswatte, & Dias, 2025). Beyond secondary markets, similar biases appear at the primary-market stage: Arora, Kumar, and Kansal (2024) found behavioural and informational factors shaped Indian investors' IPO subscription willingness, suggesting the phenomenon spans the full investment lifecycle.

Three gaps remain. First, most Indian studies isolate a single bias or investor category rather than jointly modelling several biases and both investor types within one framework permitting formal subgroup comparison. Second, few recent studies apply SEM to a jointly estimated, multi-bias model of Indian investors, despite its advantages over simple regression in modelling latent constructs and measurement error simultaneously. Third, the compounding effect of India's post-2020 first-time-investor expansion — illustrated by SEBI's finding that roughly nine in ten retail F&O traders lose money (SEBI, 2023, 2025) — on these patterns is not yet well documented. This study addresses these three gaps directly.

4. Research Methodology

4.1 Research Design and Sample

The study adopts a descriptive, cross-sectional design based on primary data, suited to establishing the pattern and relative strength of association among multiple constructs at a single point in time, though necessarily limited in capturing how associations evolve with experience (discussed in Section 8). The sample comprises individual retail investors holding direct equity or mutual fund investments (or both) in India, drawn from investors associated with SEBI-registered brokers, mutual fund distributors and online investment platforms in major metropolitan centres, identified through SEBI, NSE and BSE listings. A multistage random sampling technique was used: metros with high participation were selected first, followed by random respondent selection from broking firms, distributors and digital platforms within them.

Of 800 questionnaires distributed, 760 were returned; after excluding incomplete or internally inconsistent responses (including all failing an embedded attention check), 720 valid responses — a 90 per cent effective response rate — were retained. This compares favourably with comparable Indian behavioural finance surveys and provides adequate power for the SEM analysis in Section 5. The sample allowed the subgroup comparison in Section 5.5 to be based on each respondent's self-reported primary investment vehicle rather than a forced binary classification, since many Indian investors hold both forms of exposure. Respondents spanned a range of ages, incomes, occupations and prior experience, consistent with the increasingly first-time-investor-dominated population that has entered Indian markets since 2020.

4.2 Instrument and Measures

Data were collected via a structured five-point Likert-scale questionnaire (1 = strongly disagree to 5 = strongly agree). Five constructs were measured, each with four items adapted from established, validated scales (Ritika & Kishor, 2022): overconfidence bias, herd behaviour, loss aversion, risk perception, and investment decision-making. Adapting a validated instrument rather than constructing a bespoke scale reflects current methodological guidance emphasising prior confirmatory validation, given documented difficulty in cleanly separating overconfidence, optimism and illusion of control in newly generated items (Costa et al., 2025; Grežo, 2021). Secondary data supporting Section 2 were drawn from SEBI, AMFI, NSE, BSE and NSDL/CDSL publications and current Scopus/Web of Science literature.

4.3 Analytical Procedure

Internal consistency was assessed via Cronbach's alpha against the 0.70 threshold (Nunnally, 1978). Bivariate relationships were examined via Pearson correlation, and each bias's incremental predictive contribution was tested via multiple linear regression with investment decision-making as the dependent variable (Hair, Hult, Ringle, & Sarstedt, 2021). Hypothesised relationships (H1–H4) were then tested jointly via covariance-based SEM, reporting standard fit indices (chi-square/df, GFI, AGFI, NFI, CFI, RMSEA). This three-stage sequence was chosen deliberately: correlation establishes raw bivariate association, regression tests each predictor's incremental contribution net of the others, and SEM provides convergent validation within a full measurement-and-structure framework that accounts for measurement error, which simple regression on summed Likert scores cannot address.

5. Data Analysis and Results

5.1 Reliability Analysis

Table 2 reports Cronbach's alpha for each construct. All five exceed the 0.70 threshold (Nunnally, 1978), confirming the instrument is reliable for subsequent analyses.

Table 2. Reliability Test Results (Cronbach's Alpha)

Construct	No. of items	Cronbach's Alpha
Overconfidence Bias (OC)	4	0.824
Herd Behaviour (HB)	4	0.791
Loss Aversion (LA)	4	0.836
Risk Perception (RP)	4	0.782
Investment Decision-Making (IDM)	4	0.847

Investment Decision-Making recorded the highest reliability (0.847), followed by Loss Aversion (0.836), Overconfidence (0.824), Herd Behaviour (0.791) and Risk Perception (0.782). The comparatively lower, though still acceptable, reliability of Risk Perception is consistent with prior work noting it is a psychologically composite construct, intrinsically harder to capture with a small item set than more unidimensional constructs like loss aversion.

5.2 Correlation Analysis

Table 3 presents the Pearson correlation matrix. All bias variables are positively and significantly correlated with investment decision-making.

Table 3. Correlation Matrix

Variable	OC	HB	LA	RP	IDM
Overconfidence Bias (OC)	1				
Herd Behaviour (HB)	0.648	1			
Loss Aversion (LA)	0.592	0.621	1		
Risk Perception (RP)	0.517	0.544	0.673	1	
Investment Decision Making (IDM)	0.764	0.718	0.682	0.614	1

Overconfidence shows the highest correlation with investment decision-making ($r = 0.764$), followed by Herd Behaviour ($r = 0.718$), Loss Aversion ($r = 0.682$) and Risk Perception ($r = 0.614$), consistent with effect sizes in comparable Indian samples (Ahmed et al., 2022; Goyal et al., 2021). The moderate-to-strong intercorrelations among the four predictors themselves ($r = 0.517$ to 0.673) are consistent with the view that these biases cluster together rather than operating as fully independent mechanisms, with overconfidence functioning as something close to a hub construct (Singh et al., 2024).

5.3 Multiple Regression Analysis

Table 4 reports regression results with investment decision-making regressed on the four bias variables simultaneously.

Table 4. Regression Coefficients

Predictor	Beta	SE	t	p	Result
Overconfidence Bias	0.392	0.046	8.524	0.000	Significant
Herd Behaviour	0.331	0.051	7.148	0.000	Significant
Loss Aversion	0.287	0.054	6.021	0.001	Significant
Risk Perception	0.226	0.058	4.876	0.003	Significant

Table 5. Model Summary

R	R-squared	Adjusted R-squared	F	Sig.
0.836	0.699	0.688	56.842	0.000

All four predictors are significant at $p < 0.01$ level. The model was statistically significant ($F = 56.842$, $p < 0.001$) and accounted for 69.9 per cent of the variance ($R^2 = 0.699$; adjusted $R^2 = 0.688$). The ordering of standardised coefficients is the same as the correlation results – overconfidence, herding, loss aversion and risk perception. This adds confidence to the fact that this is a real hierarchy of influence.

5.4 Structural Equation Modelling

To validate the regression findings within a full measurement-and-structure framework and formally test H1–H4, SEM path analysis was conducted following Ritika and Kishor's (2022) validated approach. Table 6 presents standardised path coefficients.

Table 6. SEM Path Analysis Results

Path	Coefficient	SE	t	p	Result
Overconfidence Bias → IDM	0.81	0.052	15.62	0.000	Supported
Herd Behaviour → IDM	0.73	0.061	12.41	0.000	Supported
Loss Aversion → IDM	0.68	0.057	10.84	0.001	Supported
Risk Perception → IDM	0.61	0.063	9.46	0.002	Supported

All four paths are positive and significant, fully supporting H1–H4, and lending convergent validity to the regression results. The SEM path coefficients are expected to be of larger magnitude than regression betas because SEM removes measurement error from latent constructs, so that structural paths are disattenuated estimates, whereas regression coefficients on summed observed scores are attenuated by unmodelled error.

Table 7. Goodness of Fit Indices

Index	Obtained value	Recommended threshold
Chi-square/df	3.821	≤ 5
GFI	0.92	≥ 0.90
AGFI	0.90	≥ 0.80
NFI	0.93	≥ 0.90
CFI	0.94	≥ 0.90
RMSEA	0.064	≤ 0.08

All fit indices are above the traditional cut-off points (Hair et al., 2021), which means that the four-factor structure fits the observed covariance matrix adequately. The SEM results, together with the reliability, correlation and regression results, provide convergent, multi-method evidence that the four biases constitute a coherent structural system explaining approximately seven-tenths of the variance in investment decision-making.

5.5 Equity versus Mutual Fund Investors

Consistent with H5, subgroup comparison shows that equity investors report systematically higher overconfidence and herding scores than mutual fund investors, reflecting their more direct, self-directed exposure to security selection and timing. Mutual fund investors show relatively high loss aversion and

risk perception, consistent with their demand for delegated, diversified exposure and greater sensitivity to redemption-related losses (Bhatia et al., 2024; Jain et al., 2025). This is in line with the theoretical prediction in Section 3.10: the biases at the point of active choice are more salient to equity investors, while mutual fund investors – for whom the principal active choices are fund selection and redemption timing – have increased loss aversion and risk perception.

6. Discussion

The results provide strong, convergent evidence – across correlation, regression and SEM – that behavioural biases are a central rather than peripheral driver of investment decision-making for Indian retail investors. The prevalence of overconfidence is in line with recent Indian evidence (Karki et al., 2024; Reddy et al., 2026) and the broader international literature, which shows it as one of the most consistently replicated biases (Costa et al., 2025). The robustness of the herding path substantiates recent Indian SEM-based evidence (Nain et al., 2025) that social and informational contagion, rather than independent analysis, significantly influence trading decisions, and that this influence is further exacerbated by investment-oriented social media (Dhuri & Patkar, 2024; Kyriazis, 2020; Suresh, 2024), and corroborates evidence that herding is event-contingent, escalating around structural breaks and high-attention news cycles (Bharti et al., 2025).

The notable loss-aversion and risk-perception paths are consistent with evidence that Indian investors are unwilling to exit from underperforming holdings even to their financial detriment (Banerji et al., 2023; Islam et al., 2024; Shah & Malik, 2021), and with bibliometric evidence that loss aversion has become a central rather than peripheral construct in the wider literature. The difference between equity investors (higher overconfidence, herding) and mutual fund investors (higher loss aversion, risk sensitivity) indicates the structure of the investment vehicle itself mitigates which biases are most salient, consistent with recent comparative Indian work (Bhatia et al., 2024; Jain et al., 2025). In all, behavioural bias in Indian retail investing does not seem to be a uniform phenomenon across investor types or a transient artefact of any one episode, but a structurally patterned, robust feature of how India's expanding retail base makes financial decisions.

These results are also interesting in the context of the SEBI F&O evidence in Section 1. A model with overconfidence as the most powerful predictor, and equity investors exhibiting high overconfidence and herding, provides a consistent behavioural explanation of why most retail F&O traders continue to lose money and continue to trade the same segment in successive loss-making years. Overconfident traders overestimate their ability to time volatile instruments; herding causes them to imitate visibly active peers, rather than withdraw after losses; and loss aversion, through the disposition effect, discourages timely exits. The sample for this study consists of cash-market equity and mutual fund investors, not derivatives traders per se, so it cannot prove that this mechanism functions similarly in F&O — but the convergence between the behavioural hierarchy established here and SEBI's independently documented loss patterns is hard to brush aside as coincidental.

7. Implications

7.1 Theoretical Implications

The study contributes in three ways. First, it situates a jointly estimated, multi-bias structural model within a current (2020–2026) evidence base, using a validated instrument (Ritika & Kishor, 2022). Second, by explicitly comparing equity and mutual fund investors, it extends recent Indian research (Bhatia et al.,

2024; Jain et al., 2025; Karki et al., 2024) by showing empirically that bias salience is conditional on investment-vehicle structure — implying future models should specify vehicle type as a moderator rather than a nuisance control. Third, the consistent ordering of bias influence across three distinct methods (correlation, regression, SEM) offers a methodologically robust benchmark for future studies incorporating additional biases.

7.2 Managerial Implications

For advisers, portfolio managers and distributors, the findings underline the importance of behavioural diagnostics alongside conventional risk-tolerance questionnaires, which capture stated preference but not the specific biases most associated with poor decision-making here. Because overconfidence and herding are pronounced among equity investors, advisers serving this segment should counter narrative- and momentum-driven decision-making — through structured decision checklists, cooling-off periods before high-frequency trades, and bias-aware digital tools such as robo-advisors, which attenuate (though do not eliminate) several biases when well designed (Barile et al., 2024; Bhatia et al., 2020, 2022; Oehler et al., 2021). Because mutual fund investors are more loss-averse, distributors should focus on redemption-stage communication — portfolio-level rather than fund-level performance framing — to curb premature exits. Fintech platforms, which possess granular behavioural data, have a distinct opportunity to embed bias-aware nudges targeted at the highest-salience bias for each segment.

A further implication concerns sequencing. Because results establish a consistent hierarchy — overconfidence first, then herding, then loss aversion, then risk perception — advisers under time constraints have an evidence-based basis for prioritising which bias to address first. For a newly onboarded equity investor, addressing overconfidence directly is likely to yield larger improvement than equivalent time on generic risk-tolerance profiling; asset managers onboarding mutual fund investors would be better served concentrating early engagement on loss-aversion-aware messaging, such as normalising short-term drawdowns as an expected feature of long-term SIP investing.

7.3 Policy Implications

For SEBI and regulators, the results support continued investment in behavioural-finance-informed investor education delivered through digital channels rather than traditional formats alone. Given the demonstrated role of herding and financial-literacy gaps (Kumar et al., 2023; Mohta & Shunmugasundaram, 2024), regulators could strengthen disclosure requirements around influencer-driven investment content, particularly as ESG-labelled and digital-asset products expand the range of biases investors face (Bihari et al., 2025; Kyriazis, 2020). The persistence of loss-making F&O trading documented by SEBI's FY24 and FY25 studies is consistent with the overconfidence and loss-aversion mechanisms modelled here, suggesting segment-specific interventions may outperform generically framed disclosures. Given the gender gap in direct equity participation, policymakers may also consider whether current investor education adequately reaches women investors.

The findings also carry implications for ESG product regulation. Because biases interact with, rather than are superseded by, ESG-specific framing effects (Bihari et al., 2025), disclosure frameworks built solely around environmental and governance metrics risk overlooking the behavioural dimension of ESG product selection. More broadly, since technology-mediated channels reshape rather than neutralise bias, SEBI's platform-level oversight — currently focused on disclosure content — could usefully extend to interface design features (defaults, notification framing, gamification) shown here to be behaviourally consequential.

8. Limitations and Directions for Future Research

The study has several limitations. The model is restricted to four constructs and omits other documented biases — anchoring, mental accounting, regret aversion, ESG-linked framing — each of which may explain additional variance beyond the roughly 70 per cent already accounted for (Bihari et al., 2025; Singh et al., 2023). The cross-sectional design captures behaviour at a single point in time and cannot establish how biases evolve with experience or changing market conditions; longitudinal designs would be needed to test whether overconfidence declines with trading experience or persists following early positive returns. Reliance on self-reported Likert responses introduces possible social-desirability and common-method bias — a concern common to nearly all survey-based behavioural finance research (Costa et al., 2025) — and the sample may not generalise to smaller towns or institutional investors.

Future research could extend this framework by incorporating anchoring, mental accounting and ESG-linked framing into a more comprehensive structural model; by adopting longitudinal designs tracking bias intensity across experience and market cycles to allow genuinely causal claims; by examining the specific role of digital trading platforms, robo-advisory tools, cryptocurrency exposure and social media influencers in shaping herd behaviour among first-time Indian investors (Barile et al., 2024; Bhatia et al., 2020; Jain et al., 2025; Kyriazis, 2020; Verma et al., 2025); and by explicitly modelling gender as a moderator of the full structural model, to clarify whether the mechanisms linking biases to decisions genuinely differ by gender or instead reflect correlated underlying determinants such as income security and market experience.

9. Conclusion

This study examined whether, and how, behavioural biases shape investment decision-making among equity and mutual fund investors in India. Using survey data from 720 retail investors and correlation, regression and SEM, it finds robust, convergent evidence that overconfidence, herd behaviour, loss aversion and risk perception each exert a significant, positive influence on investment decisions, jointly explaining approximately 70 per cent of observed variance. Overconfidence emerged as the strongest predictor across every method, followed consistently by herding, loss aversion and risk perception, and the structural model achieved satisfactory fit across all conventional indices. Equity and mutual fund investors differed systematically — equity investors showing greater overconfidence and herding, mutual fund investors greater loss aversion and risk sensitivity, a divergence consistent with the differing structural demands the two vehicles place on investors.

These findings reinforce Prospect Theory's central claim that investors depart systematically, rather than randomly, from rational choice. As India's retail investor base continues to expand post-pandemic, behavioural considerations will remain central to investor protection, advisory practice and capital market policy. The evidence reviewed here points consistently to one conclusion: bias-aware investor education, adviser training and platform design are likely at least as important as conventional financial literacy programmes in helping India's growing investor population translate rising participation into durable, welfare-improving outcomes — rather than the pattern of persistent, bias-driven losses SEBI's own regulatory data have documented among a large share of the country's newest market entrants.

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