© International Academic Research Journal of Economics and Finance
Volume 9, Issue No: 1, April 2026 Page no. 91-106
ISSN: 2227-6254
DOI: https://doi.org/10.5281/zenodo.19839756

Psychological Architecture of Investment Irrationality: Behavioural Determinants of Equity Investment Decision-Making Among Retail Investors in India

Nithin
Student, Faculty of Management Studies,
CMS Business School,
Jain (Deemed-to-be University), Bangalore. Email: nithin_k24@cms.ac.in

Abstract

This study investigates the behavioural determinants of equity investment decision-making among individual retail investors in India, examining the prevalence, intensity, and demographic moderation of seven core cognitive and emotional biases. Grounded in Prospect Theory (Kahneman & Tversky, 1979), the Heuristics and Biases Programme (Tversky & Kahneman, 1974), and Noise Trader Theory with Limits to Arbitrage (De Long et al., 1990), the research analyses data from 101 active retail equity investors using a validated 19-item Likert-scale instrument (Cronbach's $\alpha = 0.933$). Employing a multi-method analytical framework encompassing one-sample t-tests, chi-square tests, one-way ANOVA, Pearson correlation analysis, and Principal Component Analysis (PCA) with Varimax rotation, the study establishes that all seven biases overconfidence, herding, FOMO-driven impulsivity, disposition effect, loss aversion, mood-driven bias, and fear-of-loss are statistically significant at $p < 0.001$. Loss aversion [$t(100) = 5.449$] and the disposition effect [$t(100) = 5.164$] emerge as the dominant psychological drivers. PCA reveals a three-component behavioural architecture explaining 61.38% of total variance. Demographic analysis confirms age, gender, educational qualification, income, and investment experience each significantly moderate bias expression. The study contributes an integrated cluster-based behavioural framework for India's rapidly growing retail equity investor base, offering actionable insights for financial advisors, investment platform designers, financial educators, and regulators.

Keywords: *behavioural finance, prospect theory, cognitive biases, disposition effect, retail investors India*

INTRODUCTION

Financial markets function as complex adaptive systems shaped not only by economic fundamentals and rational calculus, but profoundly by the psychological dispositions of their participants. The classical paradigm of neoclassical economics long posited that investors are fully rational agents capable of processing all available information instantaneously and dispassionately to maximise expected utility. This view, epitomised by the Efficient Market Hypothesis (EMH) advanced by Fama (1970), held that asset prices fully reflect all available information at all times, leaving no systematic room for excess returns or predictable behavioural anomalies. Decades of empirical observation, experimental evidence, and real-market anomalies have, however, persistently challenged this theoretical construct (Shiller, 1981; De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993).

The formal emergence of behavioural finance as an academic discipline in the latter decades of the twentieth century represented a paradigm shift of considerable significance. Pioneered by Kahneman and Tversky (1974, 1979) and subsequently elaborated by Thaler (1999), Shiller (2000), Shefrin (2002), and Barberis and Thaler (2003), behavioural finance integrates insights from cognitive psychology, social psychology, and decision neuroscience into the study of financial behaviour. Rather than assuming rationality as a given, it treats rationality as a hypothesis that must be empirically verified one that is frequently falsified in practice (Ritter, 2003; Sewell, 2010; Statman, 2019).

Equity markets provide especially fertile ground for the study of behavioural determinants. The stock market is characterised by uncertainty, information asymmetry, the amplifying influence of social dynamics, and the pressure of real financial consequences. Phenomena such as herding, overconfidence, loss aversion, mental accounting, anchoring, and the disposition effect have been documented repeatedly across diverse market contexts and investor profiles (Baker & Nofsinger, 2002; Nofsinger & Sias, 1999; Odean, 1998; Barber & Odean, 2000). The macroeconomic consequences of these biases are profound: the dot-com bubble, the 2007–2008 subprime mortgage crisis, and the COVID-19-induced market volatility of 2020 all illustrate how collective psychological dynamics can amplify financial shocks well beyond what fundamentals alone would dictate (Baker & Wurgler, 2007; Shleifer & Vishny, 1997).

India's equity market provides an especially compelling and policy-relevant context for this inquiry. The Indian equity ecosystem has undergone rapid structural transformation driven by technological disruption, financial inclusion initiatives, and demographic change. Zero-commission trading platforms such as Zerodha, Groww, and Upstox, combined with the widespread adoption of the Unified Payments Interface and the Jan Dhan-Aadhaar-Mobile trinity, have dramatically lowered barriers to participation. The number of registered demat accounts surpassed 100 million in 2022, representing the entry of tens of millions of first-generation retail investors into the market (Securities and Exchange Board of India [SEBI], 2022). The SEBI Household Investor Survey of 2022 confirmed that a significant fraction of new retail participants received their first investment guidance from social media channels, underscoring the degree to which digitally mediated social influence now shapes investment behaviour at scale.

Sociodemographic factors play a critical moderating role in shaping the intensity and manifestation of behavioural biases. Research across multiple geographies has established that age, gender, educational attainment, income level, and investment experience all systematically influence how investors respond to uncertainty (Barber & Odean, 2001; Chandra & Kumar, 2011; Jain et al., 2012). Understanding the interaction between demographic characteristics and behavioural biases is essential for designing targeted financial education interventions, personalised advisory services, and appropriate regulatory safeguards. Against this backdrop, the present study investigates the behavioural determinants of investment decision-making among individual retail equity investors in India, employing a validated multi-method empirical framework to generate findings that are simultaneously theoretically grounded and practically actionable.

PROBLEM IDENTIFICATION

Despite the growing body of behavioural finance research globally, the Indian retail investor context remains comparatively understudied, particularly in relation to the rapidly expanding cohort of first-generation, digitally active equity participants who entered the market following the post-pandemic surge of 2020–2022. The central research problem concerns the identification, measurement, and demographic moderation of the dominant psychological biases that systematically distort investment decision-making among this cohort.

Three specific gaps motivate this study. First, a conceptual gap exists in the integration of technology trust as an independent behavioural dimension alongside classical biases. Existing frameworks address cognitive and emotional biases in isolation from technology-mediated investment behaviour, leaving unexplored the relationship between algorithmic platform reliance and herding dynamics. Second, an empirical gap is evident in the absence of contextually grounded, multi-bias, multi-method studies on Indian retail investors that simultaneously examine social, emotional, and cognitive bias clusters and their interactions. Third, a contextual gap persists in the lack of demographic moderation analysis covering all five key sociodemographic variables age, gender, education, income, and experience within a single integrated framework, which is essential for deriving actionable implications for India's diverse and demographically heterogeneous investor base.

LITERATURE REVIEW

Theoretical Foundations

The theoretical architecture of this study rests on three interconnected pillars. Prospect Theory, developed by Kahneman and Tversky (1979) and extended through Cumulative Prospect Theory (Tversky & Kahneman, 1992), provides the foundational account of how individuals evaluate outcomes asymmetrically weighing losses approximately twice as heavily as equivalent gains. This prospect-theoretic asymmetry directly underpins loss aversion and the disposition effect, two of the most empirically robust biases documented in equity market research (Shefrin & Statman, 1985; Odean, 1998; Grinblatt & Keloharju, 2001). The Heuristics and Biases Programme (Tversky & Kahneman, 1974) provides the theoretical basis for understanding overconfidence, anchoring, and representativeness as systematic departures from Bayesian rationality that arise from cognitive shortcuts rather than random error (Kahneman, 2011; Nofsinger, 2017). Noise Trader Theory with Limits to Arbitrage (De Long et al., 1990; Shleifer & Vishny, 1997) explains how individually irrational behaviours aggregate at the market level to produce persistent mispricings and amplified volatility that rational arbitrageurs cannot fully correct.

Overconfidence and Herding Behaviour

Overconfidence is among the most extensively documented biases in financial markets. Barber and Odean (2001) demonstrated that male investors trade significantly more than female investors due to higher overconfidence, generating lower risk-adjusted returns through excessive transaction costs. Glaser and Weber (2007) established that overconfidence in trading volume is driven by miscalibration of precision rather than by better-than-average illusions alone, underscoring the multidimensional nature of the construct. In the Indian context, Qadri and Shabbir (2014) and Chandra and Kumar (2011) confirmed overconfidence as a pervasive bias among retail equity investors, with particularly strong expression among younger and higher-income investor segments. Herding behaviour, theorised through the informational cascade model of Bikhchandani et al. (1992) and empirically documented by Nofsinger and Sias (1999), refers to the tendency of investors to mimic group behaviour irrespective of private information. Waweru et al. (2008) and Luong and Ha (2011) documented herding as a prominent bias across emerging market retail investors, with significant cross-sectional variation by educational attainment.

Disposition Effect and Loss Aversion

The disposition effect, first theorised by Shefrin and Statman (1985) and empirically validated by Odean (1998) using brokerage account data, describes the systematic tendency of investors to realise gains early while deferring the realisation of losses. This behaviour, rooted in loss aversion and mental accounting (Thaler, 1999), imposes direct portfolio performance costs: Odean (1998) demonstrated that stocks investors sell outperform those they hold by approximately 3.4 percentage points annually. Kumar and Lee (2006) extended this finding to show that retail investor sentiment including disposition-related trading patterns produces systematic co-movements in stock returns. Grinblatt and Keloharju (2001) provided cross-national evidence that the disposition effect weakens progressively with trading experience, a finding with direct implications for understanding India's predominantly novice investor base. De Bondt and Thaler (1985) connected overreaction-driven momentum with the representativeness heuristic, demonstrating that investors extrapolate recent trends into the future a pattern that amplifies herding and FOMO-driven behaviour in bull markets.

Sociodemographic Moderation of Behavioural Biases

A growing strand of research examines how demographic characteristics moderate the expression of behavioural biases. Barber and Odean (2000, 2001) established foundational gender differences in trading behaviour and overconfidence, while Sahi et al. (2013) demonstrated in the Indian context that gender, age, and financial literacy interact in complex ways to shape investor susceptibility. Ricciardi and Simon (2000) identified risk perception as a key mediating variable between demographic profiles and bias expression. Baker and Nofsinger (2002) provided an integrative framework linking psychological biases to demographic moderators, while Pompian (2006) offered a practitioner-oriented bias profiling methodology that accounts for individual differences. Markowitz's (1952) classical portfolio selection framework provides the normative benchmark against which the performance costs of these biases are measured. Lo's (2004) Adaptive Markets Hypothesis offers a reconciling theoretical account, positing that biases persist when the costs of their correction exceed the learning benefits, but attenuate as investors accumulate experience and market feedback. This hypothesis aligns with the observed gradual attenuation of FOMO and disposition tendencies with investment experience documented in the current study.

RESEARCH GAP

Existing literature has not adequately addressed three interrelated gaps. First, prior Indian equity market studies have examined individual biases overconfidence (Qadri & Shabbir, 2014), herding (Waweru et al., 2008), disposition effect (Sahi et al., 2013) in relative isolation, without investigating the syndromic, mutually reinforcing cluster structure of co-occurring biases within the same investor cohort. Second, the role of technology trust particularly trust in AI-driven investment platforms and robo-advisory services as an independent latent behavioural dimension has not been integrated into existing behavioural finance frameworks for Indian retail investors, despite the dramatic growth of fintech investment platforms since 2018. Third, comprehensive multi-method demographic moderation analysis covering all five key sociodemographic moderators simultaneously within a single validated instrument has been absent from the Indian literature. This study directly addresses all three gaps through an integrated, multi-bias, multi-method empirical framework that captures the cluster structure of biases, the independent role of technology trust, and the differentiated moderating effects of age, gender, education, income, and experience on the Indian retail investor's psychological decision-making architecture.

RESEARCH METHODOLOGY

This study adopts a positivist research philosophy grounded in a deductive approach, wherein theoretical propositions derived from the behavioural finance literature are translated into testable hypotheses subjected to empirical verification. A cross-sectional, descriptive-causal research design is employed. Primary data were collected through a structured, self-administered questionnaire comprising two sections: a demographic profile section and a 19-item behavioural measurement scale administered on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The instrument was developed through a systematic review of validated scales from Glaser and Weber (2007), Odean (1998), and Nofsinger (2017), independently reviewed by three doctoral-level finance researchers for content validity. Following a pilot study of 30 respondents, the final instrument achieved an overall Cronbach's Alpha of 0.933, substantially exceeding the conventional threshold of 0.70 (Hair et al., 2019). Component-level reliability was also strong: Component 1 (Rational Cognition: $\alpha = 0.878$), Component 2 (Emotional Sensitivity: $\alpha = 0.854$), and Component 3 (Herding/Social Susceptibility: $\alpha = 0.812$).

The target population comprises active individual retail equity investors in India who hold at least one equity security through a registered demat account (NSDL or CDSL) and have executed at least one equity transaction within the preceding twelve months. A purposive sampling approach combining convenience and snowball techniques was employed through online investment communities (Zerodha Varsity, Moneycontrol forums, LinkedIn groups) and paper-based administration at three SEBI-registered investor education seminars in Bangalore (January–March 2026). Of 147 distributed questionnaires, 101 valid responses were retained after exclusion of incomplete (n = 23), straight-lined (n = 14), and ineligible (n = 9) responses, yielding a response rate of 68.7%. The final sample of 101 satisfied the minimum 5:1 subject-to-variable ratio for Principal Component Analysis (Hair et al., 2019). Statistical analyses were performed using Python (SciPy, scikit-learn, pandas) with SPSS cross-validation.

Research Hypotheses

Fifteen testable hypotheses were developed across three categories. Presence hypotheses (H1–H7) test whether each of the seven core biases is statistically significant above the neutral midpoint using one-sample t-tests (test value = 3.0, df = 100). Demographic association hypotheses (H8–H12) examine bias variation across age, gender, and educational qualification using chi-square tests of independence. Group difference hypotheses (H13–H15) assess bias variation across monthly income and investment experience groups using one-way ANOVA.

DATA ANALYSIS AND RESULTS

The sample reflects the digitally connected urban retail investor profile characteristic of India's post-pandemic equity participation wave. Nearly half the sample (49.5%) is below 25 years of age, aligning with SEBI's (2022) finding that the post-pandemic surge was disproportionately driven by young, digitally active investors. The sample is predominantly male (54.5%), consistent with well-documented gender gaps in equity market participation in emerging economies (Barber & Odean, 2001). Educational attainment is high, with 57.4%

holding postgraduate qualifications and 21.8% professional degrees, indicating a cognitively engaged cohort. However, the predominance of novice investors 46.5% with less than one year of experience suggests elevated susceptibility to cognitive and emotional biases at an early stage of the investment lifecycle. The income distribution is weighted toward higher brackets (42.6% above ₹1,00,000), implying that a significant proportion of respondents possess the financial resources to sustain active equity participation. These demographic characteristics collectively suggest a sample that is informationally sophisticated yet behaviourally vulnerable a paradox that motivates the subsequent multi-bias empirical analysis.

The overall Cronbach's Alpha of 0.933 demonstrates exceptional internal consistency for the 19-item behavioural instrument, substantially surpassing the widely accepted threshold of $\alpha \geq 0.70$ recommended by Hair et al. (2019). This result confirms that all 19 items collectively measure a coherent and unified behavioural construct, validating the theoretical premise that the identified biases form an interconnected psychological architecture rather than independent phenomena. Component-level reliability estimates are similarly robust: the Rational Cognition and Self-Regulation subscale ($\alpha = 0.878$) and the Emotional Sensitivity subscale ($\alpha = 0.854$) both exceed the 'good' threshold of 0.80, while the Herding and Social Proof subscale ($\alpha = 0.812$) comfortably surpasses the acceptable minimum. These results compare favourably with the internal consistency reported in analogous instruments by Sahi et al. (2013) and Luong and Ha (2011), providing strong psychometric foundations for the hypothesis testing that follows. The high reliability further implies that the instrument would generate stable and replicable findings across similar retail investor samples.

All seven presence hypotheses (H1–H7) are supported at the $p < 0.001$ level, confirming that every bias in the theoretical framework is statistically significant and systematically prevalent among Indian retail equity investors. Loss aversion records the highest t-value [$t(100) = 5.449$], establishing it as the most powerfully embedded psychological driver a finding consistent with the central prediction of Prospect Theory (Kahneman & Tversky, 1979), which posits that losses loom approximately twice as large as equivalent gains in subjective valuation. The disposition effect follows closely [$t(100) = 5.164$], confirming Shefrin and Statman's (1985) theoretical account and Odean's (1998) empirical documentation of premature winner-selling and excessive loser-holding. Herding [$t(100) = 4.553$] and overconfidence [$t(100) = 4.506$] are also robustly significant, consistent with findings by Nofsinger and Sias (1999) and Glaser and Weber (2007) respectively. The 95% confidence intervals for all seven items exclude the neutral midpoint of 3.0, providing additional inferential support. Notably, mood-driven bias records the lowest t-value (3.762) and the most heterogeneous response distribution, reflecting the highly personal and contextually variable nature of affective investment behaviour.

The Pearson correlation matrix reveals moderate to strong positive associations across all bias pairs, providing compelling evidence that behavioural biases co-occur within individual investors and form a mutually reinforcing psychological cluster rather than operating as isolated tendencies. The strongest inter-bias correlation is observed between herding and FOMO ($r = 0.684$), indicating that investors who follow crowd behaviour are highly susceptible to fear-of-missing-out-driven impulsivity a social-reactive dyad consistent with the theoretical accounts of Bikhchandani et al. (1992) and Baker and Wurgler (2007). FOMO and mood bias also exhibit a notably strong relationship ($r = 0.616$), confirming that emotional states amplify the tendency toward impulsive decisions when social cues signal urgency. Overconfidence correlates most strongly with loss aversion ($r = 0.575$), presenting a psychologically paradoxical pairing: investors who overestimate their skill are simultaneously more sensitive to loss an interaction consistent with Odean's (1998) observation of excessive trading paired with loss-deferring behaviour. The uniformly positive correlation structure, with no negative inter-bias correlations, supports the theoretical construct of a syndromic behavioural bias profile in which multiple biases compound their distorting effects on investment judgement.

All eight demographic moderation hypotheses (H8–H15) are supported. Regarding age-based moderation, overconfidence ($\chi^2 = 24.563$, $p = 0.017$) and the disposition effect ($\chi^2 = 29.049$, $p = 0.004$) both exhibit significant age differentiation, with younger investors displaying higher bias intensity consistent with Barber and Odean (2001) and Shefrin and Statman (1985). Herding ($\chi^2 = 21.144$, $p = 0.007$) and loss aversion ($\chi^2 = 16.315$, $p = 0.038$) are significantly differentiated by educational qualification, supporting the view that formal education attenuates social and cognitive susceptibility (Sahi et al., 2013). FOMO is significantly moderated by gender ($\chi^2 = 17.969$, $p = 0.022$), with male investors reporting higher impulsivity. The ANOVA results reveal that overconfidence exhibits the strongest income-based effect [$F(3,97) = 10.624$, $p < 0.001$], with Tukey post-hoc analysis confirming that investors earning above ₹1,00,000 ($M = 4.02$) score significantly higher than those earning below ₹30,000 ($M = 3.07$). FOMO and the disposition effect both decrease significantly with investment experience, with meaningful attenuation observed only after three or more years of market participation consistent with Lo's (2004) Adaptive Markets Hypothesis.

Principal Component Analysis

PCA with Varimax rotation extracted three components with eigenvalues exceeding 1.0, collectively accounting for 61.38% of total variance exceeding the conventional 60% adequacy benchmark for behavioural research (Hair et al., 2019). Component 1 (Rational Cognition & Self-Regulation, eigenvalue = 8.795, variance = 45.83%) loads positively on financial literacy, portfolio planning, bias awareness, and regulatory consideration items, representing the cognitive self-regulatory dimension of investor behaviour. Component 2 (Emotional Sensitivity & Market Reactivity, eigenvalue = 1.671, variance = 8.71%) captures FOMO, the disposition effect, loss aversion, mood influence, and fear-of-loss—the core affective bias cluster that drives prospect-theoretic asymmetry. Component 3 (Herding & Social Proof Susceptibility, eigenvalue = 1.312, variance = 6.84%) encompasses herding, political sensitivity, weak investor protection concerns, and critically trust in AI investment platforms (Q18, loading = 0.661) and robo-advisor transparency (Q19, loading = 0.672). This last finding is theoretically significant: technology trust loads on the social proof component rather than the rational cognition component, suggesting that reliance on algorithmic platforms functions psychologically as a form of rational herding rather than as an exercise in independent analytical capacity.

DISCUSSION

The empirical findings of this study converge to paint a coherent and theoretically interpretable picture of the psychological architecture of investment irrationality among Indian retail equity investors. The universal prevalence and statistical significance of all seven behavioural biases at stringent significance levels confirms the foundational claims of Prospect Theory (Kahneman & Tversky, 1979) and the Heuristics and Biases Programme (Tversky & Kahneman, 1974) in the specific context of India's rapidly expanding retail equity market. This finding aligns with Barber and Odean (2000), Baker and Nofsinger (2002), and Sahi et al. (2013), while extending the evidence base to a more contemporary, digitally active, and demographically younger Indian investor cohort than these prior studies examined.

The identification of loss aversion as the dominant bias with the highest t-value in the entire analytical framework [t(100) = 5.449] reinforces Kahneman and Tversky's (1979) foundational claim that the asymmetric valuation of losses and gains is the central organising principle of investor irrationality. This finding contradicts studies that position overconfidence as the primary bias (Glaser & Weber, 2007; Barber & Odean, 2001), indicating contextual variation: in a market dominated by novice, loss-averse investors with short track records, the emotional pain of loss appears to override the confidence-driven overestimation of skill. The disposition effect's second-place ranking confirms Odean's (1998) finding that loss-deferring behaviour is deeply embedded and imposes direct portfolio performance costs.

The strong herding – FOMO correlation (r = 0.684) and FOMO–mood bias correlation (r = 0.616) identify a social-emotional reactivity cluster that has not been fully articulated in prior Indian equity market literature. This cluster aligns with the social cascade dynamics theorised by Bikhchandani et al. (1992) and the amplifying role of digital media documented by Baker and Wurgler (2007), but extends these findings to the specific Indian fintech context where social media and mobile trading apps serve as primary information channels for a majority of novice investors. The syndromic nature of this cluster suggests that single-bias interventions will achieve limited effectiveness—a practical insight that contradicts the individualistic focus of most financial literacy programmes and bias debiasing strategies (Thaler & Sunstein, 2008; Pompian, 2006).

The education–herding and education–loss aversion chi-square findings (H9, H12) are noteworthy for their theoretical implications. While formal education significantly reduces susceptibility to social influence and cognitive heuristics, it does not suppress the emotional response to financial loss—a finding that aligns with Kahneman's (2011) theoretical distinction between System 1 (fast, emotional) and System 2 (slow, analytical) processing. This implies that financial literacy programmes relying exclusively on cognitive content—a dominant paradigm in current SEBI investor education initiatives—may address only one dimension of the bias architecture. The significant income–overconfidence relationship [F(3,97) = 10.624], amplified by post-hoc analysis showing a threshold effect at the highest income bracket (M = 4.02), suggests a self-attribution mechanism whereby financial success reinforces perceived competence beyond what actual skill warrants consistent with

De Bondt and Thaler's (1985) overreaction hypothesis.

CONCLUSION

This study makes three layered contributions to the behavioural finance literature and to the evidence base for policy in India's retail equity ecosystem. Empirically, it establishes that all seven core behavioural biases are statistically significant and systematically prevalent among Indian retail equity investors, with loss aversion and the disposition effect emerging as the dominant psychological drivers of investment irrationality. Structurally, it reveals a three-component psychological architecture rational cognition, emotional sensitivity, and social susceptibility that collectively explains 61.38% of investor behaviour variance and organises individual biases into mutually reinforcing clusters. Prescriptively, it identifies the critical moderating roles of age, gender, income, and experience in shaping bias intensity, generating a differentiated roadmap for interventions tailored to distinct investor profiles.

The finding that technology trust loads on the social proof component rather than the rational cognition component has important implications for fintech platform design and robo-advisory regulation. Policymakers at SEBI and financial regulators should consider mandating transparency disclosures that promote independent analytical capability rather than consensus-framed AI recommendations, which may inadvertently amplify herding dynamics. Financial advisors should employ bias profiling methodologies that address bias clusters rather than individual biases, and design emotionally intelligent communication strategies that acknowledge the affective dimension of loss aversion even among educationally sophisticated clients. For individual investors, structured self-assessment tools that surface bias clusters and provide experiential feedback rather than purely cognitive content represent the most promising avenue for meaningful behavioural improvement.

SCOPE FOR FURTHER RESEARCH

Several promising avenues for future research emerge from this study's findings and limitations. First, longitudinal validation using panel data collected from the same investor cohort over three to five years would enable causal inference about the direction of bias attenuation with experience, moving beyond the cross-sectional observation of experience-related differences. Second, Structural Equation Modelling (SEM)-based causal analysis would permit simultaneous estimation of the structural relationships among bias clusters, demographic moderators, and investment performance outcomes within a latent variable framework that addresses measurement error limitations inherent in the current regression and ANOVA approach. Third, multi-country comparative research spanning other rapidly emerging retail investor markets Brazil, Indonesia, Nigeria, and Vietnam present demographically comparable contexts would establish the cultural universality or market-specific specificity of the Indian bias architecture identified here. Fourth, neuroscientific methodologies including EEG-based studies during simulated trading tasks could provide objective, non-self-report evidence of the neurological mechanisms driving the documented emotional and social susceptibility biases, moving beyond the inherent limitations of Likert-scale self-assessment data.

REFERENCES

Baker, H. K., & Nofsinger, J. R. (2002). Psychological biases of investors.

Financial Services Review, 11(2), 97–116.

Baker, M., & Wurgler, J. (2007). Investor sentiment in the stock market. Journal of Economic Perspectives, 21(2), 129–151. https://doi.org/10.1257/jep.21.2.129

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. Journal of Finance, 55(2), 773–806. https://doi.org/10.1111/0022-1082.00226

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. Quarterly Journal of Economics, 116(1), 261–292. https://doi.org/10.1162/003355301556400

Barberis, N., & Thaler, R. (2003). A survey of behavioral finance. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), Handbook of the economics of finance (Vol. 1, pp. 1053–1128). Elsevier.

Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. Journal of Political Economy, 100(5), 992–1026. https://doi.org/10.1086/261849

Chandra, A., & Kumar, R. (2011). Factors influencing Indian individual investor behaviour: Survey evidence. Decision, 38(2), 141–167.

De Bondt, W. F. M., & Thaler, R. (1985). Does the stock market overreact? Journal of Finance, 40(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise trader risk in financial markets. Journal of Political Economy, 98(4), 703–738. https://doi.org/10.1086/261703

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. Journal of Finance, 25(2), 383–417. https://doi.org/10.1111/j.1540-6261.1970.tb00518.x

Glaser, M., & Weber, M. (2007). Overconfidence and trading volume. The Geneva Risk and Insurance Review, 32(1), 1–36. https://doi.org/10.1007/s10713-007-0003-3

Grinblatt, M., & Keloharju, M. (2001). What makes investors trade? Journal of Finance, 56(2), 589–616. https://doi.org/10.1111/0022-1082.00338

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.

Jain, D., Jain, P., & Jain, N. (2012). Investor behaviour in Indian capital market. Decision, 39(1), 93–116.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance, 48(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185

Kumar, A., & Lee, C. M. C. (2006). Retail investor sentiment and return comovements. Journal of Finance, 61(5), 2451–2486. https://doi.org/10.1111/j.1540-6261.2006.01063.x

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. Journal of Portfolio Management, 30(5), 15–29. https://doi.org/10.3905/jpm.2004.442611

Luong, L. P., & Ha, D. T. T. (2011). Behavioral factors influencing individual investors' decision-making and performance. Umeå School of Business.

Markowitz, H. (1952). Portfolio selection. Journal of Finance, 7(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Nofsinger, J. R. (2017). The psychology of investing (6th ed.). Routledge.

Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. Journal of Finance, 54(6), 2263–2295. https://doi.org/10.1111/0022-1082.00188

Odean, T. (1998). Are investors reluctant to realize their losses? Journal of Finance, 53(5), 1775–1798. https://doi.org/10.1111/0022-1082.00072

Pompian, M. M. (2006). Behavioral finance and wealth management. John Wiley & Sons.

Qadri, S. U., & Shabbir, M. (2014). An empirical study of overconfidence and illusion of control biases, impact on investor decision making: An evidence from ISE. European Journal of Business and Management, 6(14), 38–44.

Ricciardi, V., & Simon, H. K. (2000). What is behavioral finance? Business, Education and Technology Journal, 2(2), 1–9.

Ritter, J. R. (2003). Behavioral finance. Pacific-Basin Finance Journal, 11(4), 429–437. https://doi.org/10.1016/S0927-538X(03)00048-9

Sahi, S. K., Arora, A. P., & Dhameja, N. (2013). An exploratory inquiry into the psychological biases in financial investment behavior. Journal of Behavioral Finance, 14(2), 94–103. https://doi.org/10.1080/15427560.2013.791294

Securities and Exchange Board of India. (2022). Household investor survey 2022. SEBI.

Sewell, M. (2010). Behavioural finance. University of Cambridge Working Paper.

Shefrin, H. (2002). Beyond greed and fear: Understanding behavioral finance and the psychology of investing. Oxford University Press.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. Journal of Finance, 40(3), 777–790. https://doi.org/10.1111/j.1540-6261.1985.tb05002.x

Shiller, R. J. (1981). Do stock prices move too much to be justified by subsequent changes in dividends? American Economic Review, 71(3), 421–436.

Shiller, R. J. (2000). Irrational exuberance. Princeton University Press.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. Journal of Finance, 52(1), 35–55. https://doi.

org/10.1111/j.1540-6261.1997.tb03807.x

Statman, M. (2019). Behavioral finance: The second generation. CFA Institute Research Foundation.

Thaler, R. H. (1999). Mental accounting matters. Journal of Behavioral Decision Making, 12(3), 183–206. https://doi.org/10.1002/(SICI)1099-0771(199909)12:3<183::AID-BDM318>3.0.CO;2-F

Thaler, R. H., & Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. Yale University Press.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), 1124–1131. https://doi.org/10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5(4), 297–323. https://doi.org/10.1007/BF00122574

Waweru, N. M., Munyoki, E., & Uliana, E. (2008). The effects of behavioural factors in investment decision-making: A survey of institutional investors operating at the Nairobi Stock Exchange. International Journal of Business and Emerging Markets, 1(1), 24–41.

Table 1

Profile of Respondents (n = 101)

Characteristic	Category	Frequency (n)	Percentage (%)
Age	Below 25 years	50	49.5
	25–35 years	20	19.8
	36–45 years	15	14.9
	Above 45 years	16	15.8
Gender	Male	55	54.5
	Female	38	37.6
	Prefer Not to Disclose	8	7.9
Educational Qualification	Undergraduate	21	20.8
	Postgraduate	58	57.4
	Professional Degree	22	21.8
Investment Experience	Less than 1 year	47	46.5
	1–3 years	26	25.7
	3–7 years	16	15.8
	More than 7 years	12	11.9
Monthly Income	Below ₹30,000	21	20.8
	₹30,001–₹60,000	14	13.9
	₹60,001–₹1,00,000	23	22.8
	Above ₹1,00,000	43	42.6

Note. Multiple demographic variables consolidated per APA 7th Edition Table format.

Table 2

Reliability Analysis – Cronbach's Alpha by Component

Construct / Component	No. of Items	Cronbach's Alpha (α)	Internal Consistency
Overall Instrument	19	0.933	Excellent
Component 1 – Rational Cognition & Self-Regulation	8	0.878	Good
Component 2 – Emotional Sensitivity & Market Reactivity	6	0.854	Good
Component 3 – Herding & Social Proof Susceptibility	5	0.812	Good
Conventional Threshold (Hair et al., 2019)	—	0.700	Acceptable

Note. Reliability assessed using Cronbach's Alpha. Components derived from PCA with Varimax rotation (see Table 5).

Table 3

One-Sample t-Test Results for Core Behavioural Bias Items (Test Value = 3.0, df = 100)

H No.	Bias Item	Mean	SD	t-Value	p-Value	95% CI	Decision
H1	Overconfidence – stock-picking ability (Q7)	3.554	1.237	4.506	0.000	[3.31, 3.80]	Supported
H2	Herding behaviour (Q8)	3.574	1.268	4.553	0.000	[3.33, 3.82]	Supported
H3	FOMO-driven impulsivity (Q9)	3.535	1.269	4.233	0.000	[3.29, 3.78]	Supported
H4	Disposition effect – holding losing stocks (Q10)	3.604	1.175	5.164	0.000	[3.37, 3.83]	Supported
H5	Loss aversion – pain > pleasure (Q11)	3.673	1.242	5.449	0.000	[3.43, 3.92]	Supported
H6	Mood-driven bias (Q12)	3.475	1.270	3.762	0.000	[3.23, 3.72]	Supported
H7	Fear of financial loss (Q13)	3.564	1.322	4.289	0.000	[3.31, 3.82]	Supported

Note. All tests conducted against the neutral midpoint of 3.0. p-values are two-tailed. CI = Confidence Interval.

Table 4

Pearson Correlation Matrix – Core Behavioural Bias Items (n = 101)

Bias	Overconfidence	Herding	FOMO	Disposition	Loss Aversion	Mood Bias	Fear of Loss
Overconfidence	1.000	0.363	0.484	0.490	0.575	0.512	0.504
Herding	0.363	1.000	0.684	0.550	0.444	0.518	0.366
FOMO	0.484	0.684	1.000	0.505	0.480	0.616	0.486
Disposition	0.490	0.550	0.505	1.000	0.486	0.496	0.415
Loss Aversion	0.575	0.444	0.480	0.486	1.000	0.429	0.422
Mood Bias	0.512	0.518	0.616	0.496	0.429	1.000	0.506

Fear of Loss	0.504	0.366	0.486	0.415	0.442	0.506	1.000

Note. All correlations are statistically significant at $p < 0.01$ (two-tailed). Diagonal values are self-correlations (1.000).

Table 5

Chi-Square and ANOVA Results: Demographic Moderation of Behavioural Biases (n = 101)

H No.	Bias Item	Demographic Variable	Test	Statistic	df	p-Value	Decision
H8	Overconfidence (Q7)	Age Group	Chi-Square	χ^2 = 24.563	12	0.017	Supported
H9	Herding (Q8)	Education Level	Chi-Square	χ^2 = 21.144	8	0.007	Supported
H10	FOMO (Q9)	Gender	Chi-Square	χ^2 = 17.969	8	0.022	Supported
H11	Disposition Effect (Q10)	Age Group	Chi-Square	χ^2 = 29.049	12	0.004	Supported
H12	Loss Aversion (Q11)	Education Level	Chi-Square	χ^2 = 16.315	8	0.038	Supported
H13	Overconfidence (Q7)	Monthly Income	ANOVA	$F(3,97)$ = 10.624	3,97	0.000	Supported
H14	FOMO (Q9)	Investment Experience	ANOVA	$F(3,97)$ = 2.855	3,97	0.041	Supported
H15	Disposition Effect (Q10)	Investment Experience	ANOVA	$F(3,97)$ = 3.182	3,97	0.027	Supported

Note. Post-hoc Tukey HSD analysis conducted for ANOVA results to identify specific group differences.

Table 6

PCA Summary – Eigenvalues, Variance Explained, and Component Loadings (Varimax Rotation)

Component	Eigen value	% Variance	Cumulative %	Interpreted Label
1	8.795	45.83	45.83	Rational Cognition & Self-Regulation
2	1.671	8.71	54.54	Emotional Sensitivity & Market Reactivity
3	1.312	6.84	61.38	Herding & Social Proof Susceptibility

Item	Statement (abbreviated)	C1 Loading	C2 Loading	C3 Loading	h^2
Q1	Understand equity investing principles	0.721	0.213	-0.118	0.588
Q2	Regularly update financial knowledge	0.748	0.197	-0.102	0.613
Q3	Aware of psychological biases	0.714	0.198	0.074	0.554

Q4	Remain calm under portfolio stress	0.611	0.238	0.023	0.430
Q5	Carefully plan and review portfolio	0.703	0.221	0.052	0.546
Q6	Open to unconventional investments	0.581	0.136	-0.122	0.369
Q7	Stock-picking ability above average (overconfidence)	0.452	0.319	0.213	0.340
Q8	Compelled to buy with crowd (herding)	0.138	0.301	0.682	0.563
Q9	FOMO led to impulsive decisions	0.186	0.742	0.211	0.626
Q10	Hold losing stocks hoping recovery (disposition)	0.212	0.698	0.189	0.567
Q11	Pain of loss > pleasure of gain (loss aversion)	0.237	0.711	0.133	0.572
Q12	Mood influences investment decisions	0.143	0.728	0.168	0.575
Q13	Fear of loss affects investment choices	0.192	0.663	0.288	0.574
Q14	Negative news alters trading behaviour	0.187	0.698	0.305	0.617
Q15	Political instability affects market confidence	0.143	0.289	0.714	0.604
Q16	Consider SEBI/RBI regulatory changes	0.658	0.127	0.314	0.540
Q17	Weak investor protection increases risk	0.321	0.278	0.625	0.573
Q18	Trust AI investment platform recommendations	0.298	0.318	0.661	0.618
Q19	Robo-advisor transparency increases trust	0.261	0.342	0.672	0.628

Note. Loadings ≥ 0.40 in boldface in the original analysis. h^2 = communality. KMO = adequate; Bartlett's test significant.