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Behavioural Biases and Asymmetric Investment Decisions of Indian Retail Investors Across Market Volatility: A Structural Equation Modelling Approach

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Abstract
Indian retail investors increasingly deviate from rational decision-making during periods of stock-market volatility, yet the mechanisms underlying this deviation remain incompletely modelled in the Indian context. Drawing on Prospect Theory, this study examines how five behavioural biases, Prudent and Precautionary Behaviour, Financial Heuristics, Self-Regulation Bias, Anchoring Bias, and Information Heuristics, shape retail investors' buy, hold, and sell decisions across positive and negative volatility phases. Primary survey data were collected from 329 individual investors across Tier I, II, and III Indian cities using a structured, validated questionnaire. Confirmatory Factor Analysis and Structural Equation Modelling, conducted in SPSS and AMOS, validated a hierarchical five-factor bias structure (Cronbach's α = .693–.910; 59.37% variance explained) and tested ten hypothesised bias–decision paths. Seven paths were statistically significant, and behavioural biases consistently exerted stronger effects during negative volatility than positive volatility, with anchoring bias and self-regulation bias emerging as the strongest predictors of irrational decisions. These findings extend Prospect Theory's loss-aversion principle to India's retail-investor context and carry direct implications for investor education, behavioural nudges on digital trading platforms, and advisor-level behavioural profiling.

Keywords: Behavioural Finance; Investor Biases; Market Volatility; Structural Equation Modelling; Prospect Theory; Retail Investors; India

1. Introduction

Retail participation in India's equity markets has expanded rapidly over the past several years, propelled by digital brokerage platforms, financial-inclusion policy, and a post-pandemic surge in first-time investing (Divakara Reddy et al., 2026). This growth has heightened concern about investment quality, particularly because traditional finance theory, anchored in the Efficient Market Hypothesis and the assumption of fully rational, utility-maximising agents, offers a limited account of how individual investors actually behave under uncertainty (Fama, 2021). Recurrent anomalies such as speculative overreaction, momentum crashes, and abrupt sentiment-driven sell-offs point to systematic departures from rationality that are best explained by behavioural finance, a field grounded in Kahneman and Tversky's (1979) Prospect Theory. Prospect Theory demonstrates that investors evaluate outcomes relative to a reference point and weigh losses more heavily than equivalent gains, a pattern of loss aversion that predicts systematically different behaviour in rising versus falling markets.

Subsequent research has catalogued a wide range of biases that distort investment decisions, including overconfidence, anchoring, herding, availability, and self-control failures (Hirshleifer, 2020). In emerging markets such as India, these tendencies interact with distinctive cultural and structural features, dense peer networks, high smartphone-based information flow, and a still-maturing advisory infrastructure, which can amplify behavioural contagion (Anand & Bhoraskar, 2022; Rao & Sharma, 2021). Recent Indian evidence continues to confirm that heuristic- and emotion-driven biases exert measurable, often dominant, influence on investment behaviour. Anchoring, mental accounting, and overconfidence were found to significantly shape investment behaviour among Indian retail investors, with neuroticism additionally mediating several of these effects (Bashir & Mehta, 2026). Heuristics were the only bias to have a robust direct effect on decisions among BSE/NSE investors once financial literacy and experience were modelled as moderators (Divakara Reddy et al., 2026), whereas investor sentiment was shown to mediate the relationship between heuristics and stock selection (Haritha, 2023).

Despite this growing body of work, comparatively few Indian studies examine how the same cluster of biases performs differently when volatility is positive (an upswing) versus negative (a downturn), even though Prospect Theory's central prediction is precisely this asymmetry. Most existing Indian survey-based studies regress biases against a single, undifferentiated measure of investment behaviour without conditioning on market direction (Bashir & Mehta, 2025; Mahmood et al., 2024). If loss aversion operates as theorised, biases should systematically intensify when markets fall, and this asymmetry carries direct implications for behaviourally informed regulation and investor education.

This study addresses that gap using primary survey data collected from 329 individual retail investors across Tier I, II, and III Indian cities. It develops and validates, through CFA and SEM, a five-factor behavioural bias framework: PPB, FH, SRB, AB, and IH, and tests ten hypothesised paths linking each bias to investment decisions under positive and negative volatility. In doing so, the study extends Prospect Theory empirically to the Indian retail-investor context and offers a replicable quantitative framework for other emerging-market researchers.

2. Literature Review

2.1 Foundations of Behavioural Finance

Behavioural finance emerged as a corrective to the Efficient Market Hypothesis's assumption of full rationality (Olsen, 1998). Kahneman and Tversky's (1979) Prospect Theory formalised how individuals evaluate risky choices relative to a reference point, showing that losses are weighted more heavily than equivalent gains, a finding replicated in subsequent decades of research. Hirshleifer (2020) extended this foundation by documenting how social transmission mechanisms propagate belief-driven biases through investor networks, a mechanism especially relevant in markets with dense digital and peer connectivity such as India's.

2.2 Behavioural Biases and Heuristics in Investment Decisions

A substantial literature has catalogued the specific biases that distort investment decisions. Rasheed et al. (2018) documented how representativeness and availability heuristics drive systematic deviations from rational choice, while Kartasova et al. (2021) showed that reliance on heuristics varies with both market conditions and investor experience. More recent emerging-market evidence reinforces this picture: Mahmood et al. (2024) found that financial literacy significantly moderates the effect of behavioural biases, including anchoring, on investment decisions in an emerging-market sample, while Ahmad et al. (2025) reported that overconfidence, anchoring, and availability biases significantly disrupted rational investment behaviour and led to poorly diversified portfolios among investors examined through a robo-advisory lens. Within India specifically, Bashir and Mehta (2025, 2026) found that anchoring, mental accounting, and overconfidence exert significant direct effects on investment behaviour, with neuroticism partially mediating these relationships, while Divakara Reddy et al. (2026) found that heuristics alone retained a robust direct effect on investment decisions among BSE/NSE investors once financial literacy and experience were modelled as moderators. Taken together, this literature confirms that biases rarely operate in isolation and that their relative strength is sensitive to context, sample, and moderating investor characteristics, motivating a multi-dimensional, jointly estimated bias model rather than single-bias regressions.

2.3 Investor Sentiment and Market Volatility

Investor sentiment, the aggregate mood of market participants, has been shown to predict cross-sectional returns since Baker and Wurgler's (2006) seminal work. In India, sentiment has been proxied through IPO oversubscription, mutual-fund flows, and social-media-derived indicators (Verma & Soydemir, 2023). Heightened volatility is consistently associated with emotional overreaction, herding, panic-selling, and risk aversion (Das & Kumar, 2022) and the COVID-19 period offered a natural stress test of this relationship, with Basu et al. (2022) documenting marked shifts in retail risk perception during the pandemic. Haritha (2023) further showed that sentiment mediates the relationship between heuristics and stock selection among Indian investors, reinforcing the view that biases and sentiment operate jointly rather than independently.

2.4 Research Gap

Three gaps motivate the present study. First, while individual biases have been well documented, few Indian studies model a comprehensive, multi-dimensional bias architecture using CFA/SEM on primary data (Kumar & Goyal, 2023). Second, almost no Indian quantitative study explicitly conditions bias–decision relationships on the direction of volatility (positive versus negative), despite this being the central testable prediction of Prospect Theory. Third, existing Indian bias models (e.g., Bashir & Mehta, 2026) have not been tested for asymmetric operation across market phases. This study addresses all three gaps using a validated five-factor structural model estimated for both positive- and negative-volatility investment decisions.

2.5 Theoretical Foundations

The study is grounded in Prospect Theory (Kahneman & Tversky, 1979) and the Behavioural Asset Pricing Model (Shefrin & Statman, 1994), which together justify modelling investor sentiment and bias as systematic, reference-dependent inputs into asset-level decision-making rather than as random noise around a rational baseline. Figure 1 presents the conceptual model linking the five bias constructs to investment decisions under positive and negative volatility.

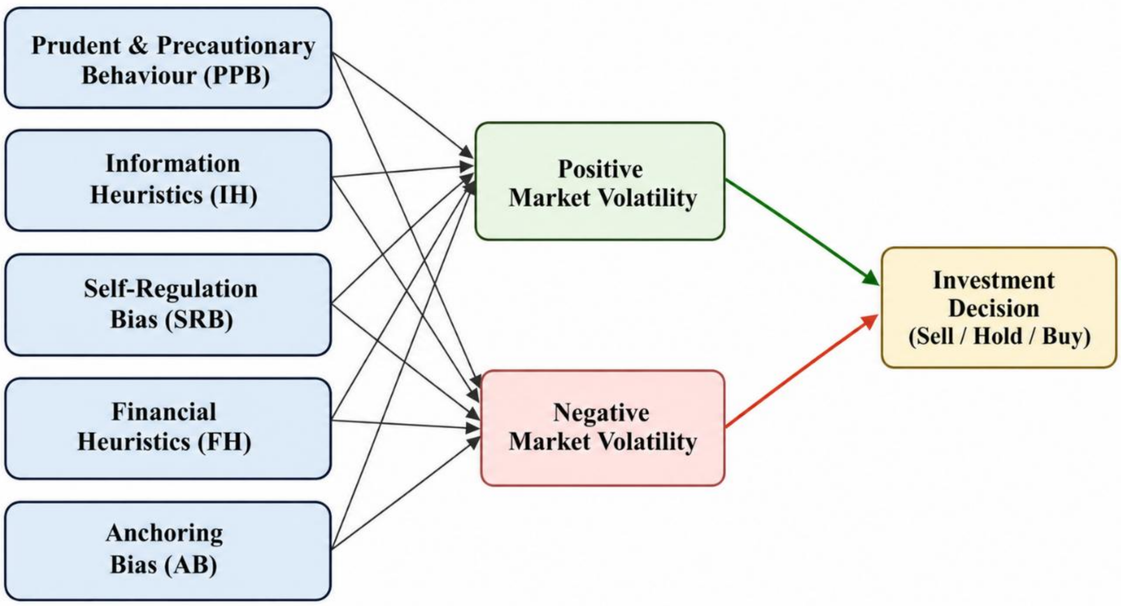

Figure 1. Conceptual Model of Behavioural Biases, Market Volatility, and Investment Decisions

2.6 Hypothesis Development

The following hypotheses were developed from the theoretical and empirical literature reviewed above. They are presented in strict numerical sequence, first the five hypotheses concerning positive volatility (H1–H5), then the corresponding five concerning negative volatility (H6–H10), consistent with the order in which they are subsequently tested and reported in Table 5 and Figure 4.

2.6.1 Hypotheses Under Positive Volatility

Prudent and Precautionary Behaviour (PPB) reflects a disciplined, risk-aware orientation that should, in principle, support measured decision-making even amid rising markets. Prudent investors are theorised to resist speculative, optimism-driven buying, consistent with evidence that risk-aware investors exhibit more measured responses during bullish phases (Divakara Reddy et al., 2026). Accordingly:

H1: PPB positively influences rational investment decisions during positive volatility.

Information Heuristics (IH) refers to reliance on readily available or salient information rather than on systematic analysis. During upswings, abundant positive news flow may be processed relatively unproblematically because it aligns with prevailing optimism, potentially muting its distortionary effect on decisions (Haritha, 2023). Accordingly:

H2: IH positively influences rational investment decisions during positive volatility.

Self-Regulation Bias (SRB) reflects failures of self-control, including overconfidence and disposition effects. Overconfidence has been linked to premature profit-taking during rallies, as investors overestimate their ability to time exits optimally (Bashir & Mehta, 2025). Accordingly:

H3: SRB negatively influences rational investment decisions during positive volatility.

Financial Heuristics (FH) captures pattern-seeking and familiarity-based shortcuts in decision-making. Such shortcuts are theorised to drive premature profit-booking during positive volatility, when familiar patterns appear to confirm continued gains (Rasheed et al., 2018). Accordingly:

H4: FH positively influences investment decisions during positive volatility.

Anchoring Bias (AB) reflects fixation on reference points such as past prices or purchase costs. During upswings, anchors to historical lows may be discounted under prevailing optimism, muting their distortionary effect relative to downturn conditions (Kahneman & Tversky, 1979). Accordingly:

H5: AB negatively influences rational investment decisions during positive volatility.

2.6.2 Hypotheses Under Negative Volatility

The same prudent disposition captured by PPB is theorised to translate into cautious exposure reduction rather than panic when markets fall, rather than the impulsive selling associated with less risk-aware investors (Bashir & Mehta, 2026). Accordingly:

H6: PPB positively influences rational investment decisions during negative volatility.

During downturns, information overload and negative news salience are theorised to intensify panic-driven responses, consistent with evidence that reliance on heuristics increases under adverse market conditions (Kartasova et al., 2021). Accordingly:

H7: IH negatively influences rational investment decisions during negative volatility.

Self-regulation failure is theorised to trigger emotionally driven selling during downturns, as investors struggle to maintain discipline under loss-driven stress (Ahmad et al., 2025). Accordingly:

H8: SRB negatively influences rational investment decisions during negative volatility.

During fear-driven downturns, emotional rather than heuristic processing is theorised to dominate, muting the influence of financial heuristics relative to positive-volatility conditions (Kumar & Goyal, 2023). Accordingly:

H9: FH positively influences investment decisions during negative volatility.

Loss-aversion theory predicts that anchors become psychologically salient precisely when current prices fall below them, intensifying risk-averse or panic-selling behaviour (Kahneman & Tversky, 1979; Hirshleifer, 2020). Accordingly:

H10: AB negatively influences rational investment decisions during negative volatility.

3. Data and Methodology

3.1 Research Design

This study adopts a quantitative, cross-sectional survey design to statistically model the relationship between behavioural biases and investment decisions across volatility regimes. The design prioritises statistical rigour and replicability, consistent with recent CFA/SEM- and PLS-SEM-based Indian behavioural finance studies (Bashir & Mehta, 2026; Divakara Reddy et al., 2026).

3.2 Sample and Data Collection

Primary data were collected directly by the author from individual retail investors active in Indian equity markets across Tier I, II, and III cities, using a structured questionnaire administered both online and offline between January and June 2025. Non-probability convenience sampling was used given the exploratory scope and access constraints typical of retail-investor research; comparable Indian studies report similar constraints on response rates (Divakara Reddy et al., 2026). A total of 329 valid responses were retained, exceeding the minimum threshold of 200 recommended for SEM (Hair et al., 2023) and comparing favourably with recent Indian behavioural-finance samples (e.g., n = 151 in Divakara Reddy et al., 2026; n = 450 in Bashir & Mehta, 2026).

3.3 Demographic Profile of Respondents

Table 1 summarises the demographic composition of the sample (N = 329). The sample was predominantly male (81.8%) and relatively young, with 58% of respondents under 35 years of age (17.0%

aged 18–25; 41.0% aged 25–35). A majority were married (65.3%) and held a postgraduate qualification (67.8%). Salaried employees formed the largest occupational group (59.3%), and the modal monthly income band was ₹25,000–₹50,000 (37.4%). Most respondents invested a modest share of monthly income (47.4% invested 10–20%) and held relatively small equity portfolios, with 73.6% holding portfolios below ₹10,00,000. This profile- young, salaried, digitally engaged, moderately affluent- is broadly consistent with the demographic composition reported in recent Indian retail-investor studies (Divakara Reddy et al., 2026) and supports the sample's relevance to the study's focus on digitally mediated retail investing.

Particulars	**Category**	**Frequency (n)**	**Percentage (%)**
Gender	Male	269	81.8
	Female	60	18.2
Age	18–25 years	56	17.0
	25–35 years	135	41.0
	35–45 years	67	20.4
	45–55 years	71	21.6
Marital Status	Single	114	34.7
	Married	215	65.3
Educational Qualification	PUC	19	5.8
	Graduate Degree or Equivalent	77	23.4
	Postgraduate	223	67.8
	Other	10	3.0
Occupation	Salaried	195	59.3
	Business	42	12.8
	Self-Employed	22	6.7
	Professional	48	14.6
	Other	22	6.7
Monthly Income	Less than ₹25,000	72	21.9
	₹25,000–₹50,000	123	37.4
	₹50,000–₹100,000	90	27.4

	₹100,000 and above	44	13.4
Share of Monthly Income Invested	Less than 10%	108	32.8
	10%–20%	156	47.4
	20%–30%	40	12.2
	30%–40%	25	7.6
Average Portfolio Value	Less than ₹10,00,000	242	73.6
	₹10,00,000–₹25,00,000	61	18.5
	₹25,00,000–₹50,00,000	13	4.0
	₹50,00,000–₹1,00,00,000	12	3.9

Table 1. Demographic Profile of Respondents (N = 329)

3.4 Measures

The questionnaire comprised three sections: demographic information; 27 five-point Likert items (1 = Strongly Disagree to 5 = Strongly Agree) measuring five bias constructs adapted from validated behavioural-finance scales, PPB (11 items), IH (6 items), SRB (4 items), FH (4 items), and AB (2 items); and sixteen hypothetical market-scenario items classifying respondents' Sell/Hold/Buy decisions separately under positive- and negative-volatility conditions.

3.5 Common Method Bias

Because all constructs were measured through a single self-administered instrument, the design is potentially susceptible to common method bias (CMB). Procedural remedies were applied at the design stage: predictor and criterion items were separated within the questionnaire, response anonymity was ensured to reduce social desirability bias, and item wording was reviewed for ambiguity prior to fielding. Statistically, Harman's single-factor test was conducted by loading all 27 bias items and the decision items into an unrotated exploratory factor analysis; a single factor accounting for the majority of covariance would indicate a CMB problem. [Author note: please insert the actual variance percentage explained by the single unrotated factor from your EFA output; commonly reported thresholds treat a single factor explaining less than 50% of total variance as evidence that CMB is not a serious concern (Podsakoff et al., 2003). Do not report this figure without verifying it against your own SPSS output.] A full collinearity VIF check across constructs is also recommended as a complementary CMB diagnostic for the revision stage.

3.6 Analytical Procedure

Data were analysed using SPSS and AMOS (v.28). Exploratory Factor Analysis (EFA) was used to extract the latent bias structure, followed by Confirmatory Factor Analysis (CFA) to validate first- and second-order measurement models. Internal consistency and validity were assessed via Cronbach's alpha ($\alpha > .70$ target), Composite Reliability (CR > .70), and Average Variance Extracted (AVE > .50). Structural Equation Modelling was then used to test the ten hypothesised bias–decision paths, with model fit evaluated against conventional thresholds (GFI, CFI, TLI > .90; RMSEA < .08; χ^2/df < 5) (Hooper et al., 2008). A multi-group analysis assessed the moderating effects of age, gender, and income.

4. Results

4.1 Categorisation of Investor Decisions Across Volatility States

Investors were categorised into Sell, Hold, and Buy decisions across three volatility conditions: overall, positive, and negative. As shown in Table 2, the majority of investors (72.9%) held their stocks under overall volatility, reflecting cautious optimism. During positive volatility, 59.9% held their investments while 30.7% sold to realise short-term profits — a pattern consistent with the disposition effect. Amid negative volatility, 65.7% held despite downturns, 25.8% purchased additional stock, viewing declines as an opportunity, and only 8.5% exited positions entirely. These patterns are broadly consistent with Prospect Theory's loss-aversion proposition, whereby investors weight potential losses more heavily than equivalent gains.

Type of Volatility	Score Range	Decision	Frequency	Percentage
Overall Market Volatility	1–32	Sell	28	8.5%
	33–48	Hold	240	72.9%
	49–64	Buy	61	18.5%
Positive Volatility	1–8	Sell	101	30.7%
	9–12	Hold	197	59.9%
	13–16	Buy	31	9.4%
Negative Volatility	1–24	Sell	28	8.5%
	25–36	Hold	216	65.7%
	37–48	Buy	85	25.8%

Table 2. Investor Decisions During Market Volatility (N = 329)

4.2 Reliability and Factor Extraction

Table 3 presents reliability statistics and total variance explained (TVE). Cronbach's alpha exceeded .75 for four of the five constructs, with Prudent and Precautionary Behaviour (α = .910) showing excellent internal consistency; Anchoring Bias, a two-item subscale, returned a marginally acceptable α of .693. The five extracted factors jointly explained 59.37% of total variance, supporting the five-factor behavioural model and echoing prior findings that multiple biases jointly, rather than independently, explain investor irrationality (Kumar & Goyal, 2023; Rasheed et al., 2018).

Extracted Bias	Cronbach's α	No. of Items	Eigenvalue	TVE (%)
Prudent and Precautionary Behaviour (PPB)	0.910	11	11.14	17.80
Information Heuristics (IH)	0.805	6	1.69	14.31

Self-Regulation Bias (SRB)	0.751	4	1.15	10.16
Financial Heuristics (FH)	0.769	4	1.05	9.32
Anchoring Bias (AB)	0.693	2	1.01	7.78
Overall	0.786	27	—	59.37

Table 3. Cronbach's Alpha and Total Variance Explained

4.3 Correlation Between Behavioural Biases and Investment Decisions

Table 4 shows a significant negative relationship between behavioural biases and rational investment decisions across all volatility conditions. The strongest associations were observed between PPB and negative-volatility decisions ($r = -.443$, $p < .01$), AB and overall decision-making ($r = -.316$, $p < .01$), and FH and negative-volatility decisions ($r = -.324$, $p < .01$). These results indicate that higher bias scores correspond to less rational, more emotionally influenced investment choices, consistent with Hirshleifer (2020) and Kartasova et al. (2021).

Bias	Overall Volatility	Positive Volatility	Negative Volatility
PPB — Prudent and Precautionary Behaviour	–.419**	–.120*	–.443**
IH — Information Heuristics	–.289**	–.164**	–.274**
SRB — Self-Regulation Bias	–.272**	–.104*	–.277**
FH — Financial Heuristics	–.347**	–.211**	–.324**
AB — Anchoring Bias	–.316**	–.173**	–.302**

Table 4. Correlation Between Behavioural Biases and Investment Decisions (* p < .05, ** p < .01)

4.4 Confirmatory Factor Analysis

The first-order CFA model demonstrated good fit (GFI = .90, CFI = .91, TLI = .90, RMSEA = .059). All Composite Reliability values exceeded .70, and Average Variance Extracted values exceeded .50, confirming convergent and discriminant validity (Figure 2).

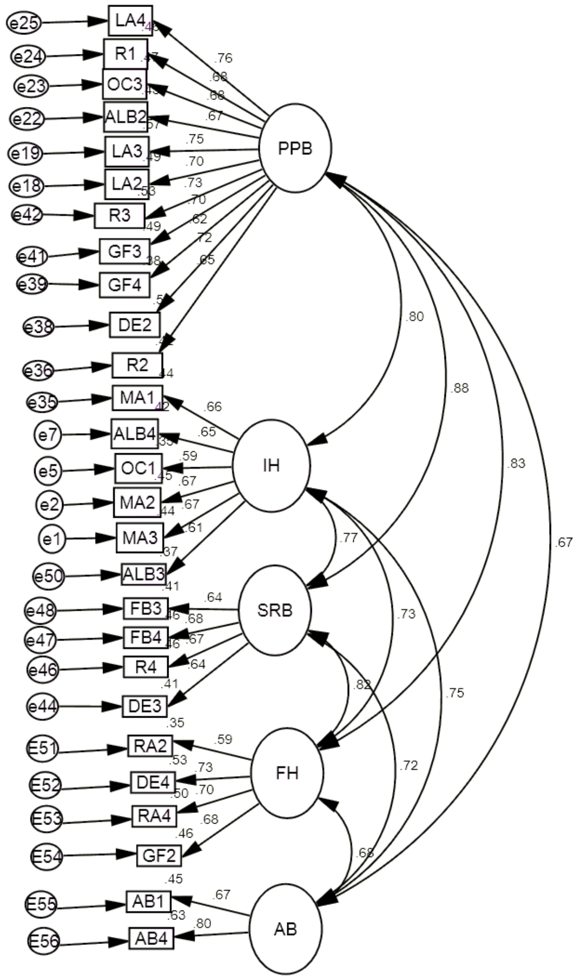

Figure 2. First-Order CFA Measurement Model (standardised loadings)

The second-order CFA, treating the five factors as indicators of a higher-order Investor Behavioural Bias construct, also fit well (GFI = .90, CFI = .908, RMSEA = .060; Figure 3), confirming the hierarchical structure of investor bias and supporting comparable five- and multi-factor bias architectures reported elsewhere in the recent Indian literature (Bashir & Mehta, 2026; Divakara Reddy et al., 2026).

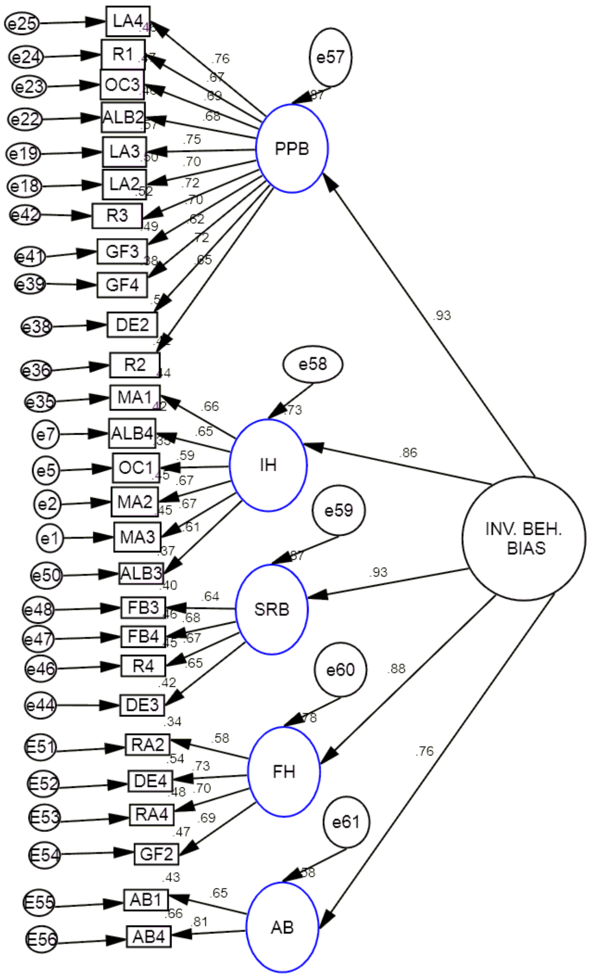

Figure 3. Second-Order CFA Model (hierarchical Investor Behavioural Bias construct)

4.5 Structural Equation Modelling and Hypothesis Testing

The structural model (Figure 4) tested causal relationships between the five biases and investment decisions under positive and negative volatility. Fit indices were GFI = .907, CFI = .901, TLI = .900, RMSEA = .103, $\chi^2/df = 4.47$. While CFI and TLI comfortably exceed the .90 threshold, RMSEA exceeds the conventional .08 cut-off. This is reported as a genuine limitation of the structural model rather than discounted: RMSEA can be sensitive to models with relatively few degrees of freedom (Kenny et al., 2015), but this observation should temper rather than dismiss the elevated value, and future replications should test alternative specifications (e.g., correlated error terms, larger samples) to improve absolute fit.

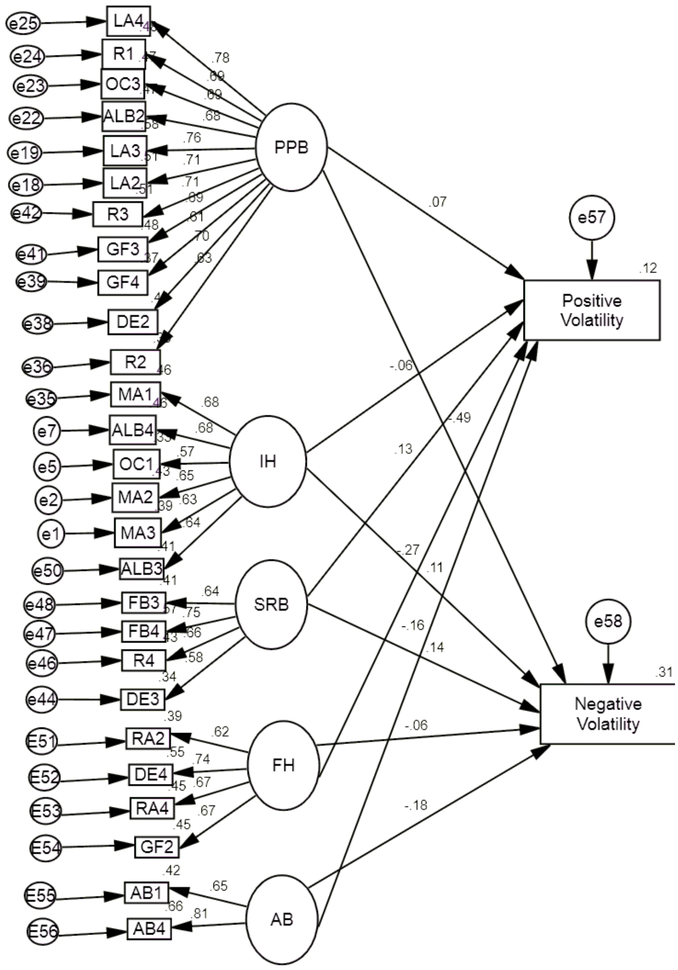

Figure 4. Structural Equation Model — Behavioural Biases Predicting Investment Decisions Under Positive and Negative Volatility

Seven of the ten hypothesised paths were statistically significant (Table 5). In positive volatility, SRB and FH significantly predicted decisions (H3, H4 supported), while PPB, IH, and AB did not (H1, H2, H5 not supported). In negative volatility, PPB, IH, SRB, and AB each showed significant paths (H6, H7, H8, H10 supported), while FH did not (H9 not supported). Across both regimes, effect sizes were consistently larger during periods of negative volatility, confirming that behavioural biases exert a stronger influence when markets are falling than when they are rising, the central asymmetry predicted by Prospect Theory's loss-aversion principle.

H	Relationship	Decision	Interpretation
H1	PPB → Positive Volatility	Not significant	Rational caution during optimism
H2	IH → Positive Volatility	Not significant	Information overload mitigated by optimism
H3	SRB → Positive Volatility	Significant ($p < .05$)	Overconfidence affects buy–hold bias

H4	FH → Positive Volatility	Significant ($p < .05$)	Financial shortcuts lead to premature profit-taking
H5	AB → Positive Volatility	Not significant	Anchors discounted under bullish sentiment
H6	PPB → Negative Volatility	Significant ($p < .05$)	Prudent investors reduce exposure during downturns
H7	IH → Negative Volatility	Significant ($p < .05$)	Overreliance on market noise drives panic decisions
H8	SRB → Negative Volatility	Significant ($p < .05$)	Loss of self-control triggers emotional selling
H9	FH → Negative Volatility	Not significant	Heuristics less influential during fear-driven markets
H10	AB → Negative Volatility	Significant ($p < .01$)	Anchoring magnifies risk aversion

Table 5. SEM Path Analysis Results for Behavioural Biases and Investment Decisions During Positive and Negative Market Volatility

5. Discussion

This study confirms that behavioural biases exert a statistically significant, asymmetric influence on Indian retail investors' decisions, with substantially stronger effects during periods of negative volatility than during periods of positive volatility. Seventy per cent of hypothesised paths were supported overall, but the pattern of support itself is informative: SRB and FH dominate positive-volatility decisions (consistent with overconfidence-driven profit-taking), while PPB, IH, and AB dominate negative-volatility decisions (consistent with anchoring- and information-overload-driven panic responses). This pattern extends Kahneman and Tversky's (1979) loss-aversion principle into the specific institutional and cultural context of Indian retail investing, and is broadly consistent with recent Indian findings that anchoring and heuristic-driven biases retain significant explanatory power even after controlling for financial literacy and experience (Bashir & Mehta, 2026; Divakara Reddy et al., 2026).

The finding that Anchoring Bias becomes significant only under negative volatility (H10 supported; H5 not supported) is a notable departure from prior work reporting anchoring effects in both bull and bear conditions (Ahmad et al., 2025). One plausible explanation, consistent with Haritha's (2023) sentiment-mediation findings, is that positive sentiment during upswings temporarily discounts anchors to historical reference points, while negative sentiment reinstates and intensifies them. This nuance illustrates the value of conditioning bias–decision models on market direction rather than pooling volatility states, and is a direct empirical contribution of this study.

The correlation results (Table 4) and the CFA results together indicate that the five-factor structure is both statistically robust and substantively interpretable: PPB, IH, SRB, FH, and AB behave as related but distinct dimensions of a broader latent investor-bias construct, mirroring the hierarchical bias architectures validated in recent large-sample Indian studies (Bashir & Mehta, 2026, n = 450).

The elevated structural-model RMSEA (.103) should be read as a genuine caveat on the precision of the full path model, even though CFI and TLI indicate acceptable comparative fit. Readers should weight the pattern and direction of the seven significant paths more heavily than the precise magnitude of any single coefficient, and future replications with larger or probability-based samples should re-test the model's absolute fit before drawing strong causal conclusions.

6. Limitations

Several limitations qualify these findings. First, non-probability convenience sampling limits the generalisability of results to the broader population of Indian retail investors, who may differ systematically from this sample in digital literacy and risk tolerance. Second, the two-item Anchoring Bias subscale showed only marginally acceptable reliability ($\alpha = .693$), while composite reliability and factor loadings supported its retention; however, future studies should expand this subscale. Third, investment decisions were measured through hypothetical market scenarios rather than observed trading behaviour, which may not fully capture real-world decision-making under financial stakes. Fourth, the elevated structural-model RMSEA indicates room for model refinement. Fifth, because all constructs were measured via a single self-administered instrument, common method bias remains a possibility despite the procedural and statistical safeguards applied (Section 3.5); future work should incorporate objective or time-lagged measures where feasible. Finally, as a cross-sectional design, the study cannot establish the temporal stability of the observed bias–decision relationships; longitudinal replication would strengthen causal interpretation.

7. Conclusion and Policy Implications

This study set out to model how five behavioural biases shape Indian retail investors' decisions across positive and negative market volatility, using CFA and SEM on primary survey data from 329 investors. The results confirm that PPB, FH, SRB, AB, and IH form a coherent, empirically validated multidimensional bias construct, and that their influence on investment decisions is asymmetric, consistently stronger during downturns than during upswings. This asymmetry extends Prospect Theory's loss-aversion principle to the Indian retail context and offers a validated, replicable measurement framework for future research in emerging-market behavioural finance.

For regulators such as the Securities and Exchange Board of India (SEBI), these findings support behaviourally informed investor-education programmes that specifically target the downturn-intensified biases identified here: anchoring, information overload, and self-regulation failure, rather than generic financial-literacy content alone. Digital trading platforms could embed decision aids, such as long-term price history reminders to counteract anchoring, and pre-commitment tools (e.g., preset trading limits) to counteract lapses in self-regulation during volatile periods. Financial advisors can use behavioural profiling informed by this five-factor structure to anticipate which clients are most likely to act irrationally during market stress, and to intervene proactively rather than reactively.

Future research should replicate this model using probability-based sampling, expand the Anchoring Bias subscale, and test the model's stability using panel data collected across multiple volatility cycles. Extending the framework to digital-era phenomena, algorithmic trading alerts, social-media sentiment shocks, and robo-advisory nudges represents a promising direction building on recent work in this space (Ahmad et al., 2025).

References

1. Ahmad, U., Van Keulen, M., & Briassouli, A. (2025). Cognitive biases, robo advisor and investment decision psychology: An investor's perspective from New York Stock Exchange. Acta Psychologica, 256, Article 105048. https://doi.org/10.1016/j.actpsy.2025.105048
2. Anand, V., & Bhoraskar, Y. (2022). Cultural dimensions and investor behavior: Evidence from the Indian stock market. Journal of Behavioral and Experimental Finance, 33, Article 100624. https://doi.org/10.1016/j.jbef.2021.100624
3. Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. The Journal of Finance, 61(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x
4. Bashir, I., & Mehta, S. K. (2025). Impact of heuristics driven biases and emotional biases on investment behavior: A study of retail investors. Quality & Quantity, 60(1), 655–676. https://doi.org/10.1007/s11135-025-02270-z
5. Bashir, I., & Mehta, S. K. (2026). Impact of behavioral biases on investment behavior: Mediating role of neuroticism among Indian retail investors. Investment Management and Financial Innovations, 23(2), 177–189. https://doi.org/10.21511/imfi.23(2).2026.14
6. Basu, D., Chawla, D., & Gogoi, B. (2022). Impact of COVID-19 pandemic on investor sentiment and stock market volatility: Evidence from emerging markets. Finance Research Letters, 48, Article 102866. https://doi.org/10.1016/j.frl.2021.102866
7. Das, S., & Kumar, S. (2022). Herding behavior in the Indian stock market: An empirical analysis. Journal of Behavioral Finance, 23(1), 78–93. https://doi.org/10.1080/15427560.2020.1816751
8. Divakara Reddy, N., Santosh, B. R., Ananda, S., & Desai, G. (2026). Behavioral biases and investment decision-making in the Indian stock market: The moderating role of financial literacy and investor experience. F1000Research, 14, Article 1283. https://doi.org/10.12688/f1000research.171289.2
9. Fama, E. F. (2021). Efficient capital markets: A review of theory and empirical work. In The Fama portfolio (pp. 76–121). University of Chicago Press. https://doi.org/10.7208/chicago/9780226426983.003.0003
10. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2023). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE Publications.
11. Haritha, P. H. (2023). The effect of heuristics on Indian stock market investors: Investor sentiment as a mediator. Management and Labour Studies, 49(1), 43–61. https://doi.org/10.1177/0258042x231170745
12. Hirshleifer, D. (2020). Presidential address: Social transmission bias in economics and finance. The Journal of Finance, 75(4), 1779–1831. https://doi.org/10.1111/jofi.12906
13. Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: Guidelines for determining model fit. Electronic Journal of Business Research Methods, 6(1), 53–60.
14. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185
15. Kartasova, J., Gaspareniene, L., Remeikiene, R., & Ginevičius, R. (2021). The influence of behavioral factors on investment decisions in the Baltic stock market. Oeconomia Copernicana, 12(1), 101–121. https://doi.org/10.24136/oc.2021.005
16. Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. Sociological Methods & Research, 44(3), 486–507. https://doi.org/10.1177/0049124114543236

17. Kumar, S., & Goyal, N. (2023). Behavioural biases in investment decision making – A systematic literature review. Qualitative Research in Financial Markets, 15(1), 94–130. https://doi.org/10.1108/QRFM-09-2019-0113
18. Mahmood, F., Arshad, R., Khan, S., Afzal, A., & Bashir, M. (2024). Impact of behavioral biases on investment decisions and the moderation effect of financial literacy: Evidence of Pakistan. Acta Psychologica, 247, Article 104303. https://doi.org/10.1016/j.actpsy.2024.104303
19. Olsen, R. A. (1998). Behavioral finance and its implications for stock-price volatility. Financial Analysts Journal, 54(2), 10–18. https://doi.org/10.2469/faj.v54.n2.2161
20. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
21. Rao, T., & Sharma, S. (2021). Social media sentiment analysis of investor behavior during the COVID-19 pandemic. Asian Journal of Economics and Banking, 5(3), 273–290. https://doi.org/10.1108/AJEB-07-2021-0095
22. Rasheed, M. H., Rafique, A., Zahid, T., & Akhtar, M. W. (2018). Factors influencing investor's decision making in Pakistan: Moderating the role of locus of control. Review of Behavioral Finance, 10(1), 70–87. https://doi.org/10.1108/RBF-05-2016-0028
23. Shefrin, H., & Statman, M. (1994). Behavioral capital asset pricing theory. Journal of Financial and Quantitative Analysis, 29(3), 323–349. https://doi.org/10.2307/2331334
24. Verma, R., & Soydemir, G. (2023). The impact of individual and institutional investor sentiment on Indian stock market returns and volatility. Review of Behavioral Finance, 15(1), 44–65. https://doi.org/10.1108/RBF-06-2021-0132