

Behavioral Biases and Stock Market Investment Behavior: An Empirical Investigation

A Quantitative Empirical Study with Statistical Evidence

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Abstract

This paper presents an empirical investigation of the influence of seven behavioral biases — overconfidence, loss aversion, herding, anchoring, availability heuristic, representativeness, and framing — on individual investor decision-making in stock markets. Using a quantitative research design with data collected from 414 individual investors, the study employs multiple linear regression (MLR) and structural equation modelling (SEM) via SmartPLS 4.0. Findings confirm that all seven biases exert statistically significant positive effects on investment decision-making ($R^2 = 0.561$, Adj. $R^2 = 0.549$; $F(7, 406) = 74.23$, $p < .001$). Loss aversion ($\beta = 0.301$, $p < .001$) and overconfidence ($\beta = 0.296$, $p < .001$) emerge as the most influential predictors. The SEM model demonstrates excellent fit (CFI = 0.961; RMSEA = 0.047). These findings contribute to the behavioral finance literature by providing comprehensive multivariate evidence of simultaneous bias effects on stock investment behavior. Policy and practitioner implications for investor education and financial advisory are discussed.

Keywords: *behavioral finance, behavioral biases, overconfidence, loss aversion, herding, anchoring, stock market, investment decision, prospect theory, structural equation modelling.*

1. Introduction

Conventional financial theory, rooted in the Efficient Market Hypothesis (EMH) proposed by Fama (1970), assumes that investors are rational actors who process all available information optimally and make decisions that maximise expected utility. Under this paradigm, asset prices should reflect their true fundamental values at all times, and systematic patterns of investor irrationality should be arbitrated away. Yet decades of empirical evidence have accumulated to challenge these assumptions, documenting consistent and predictable departures from rationality that the rational expectations framework cannot explain.

Behavioral finance, which formally emerged through the seminal contributions of Kahneman and Tversky (1979) and Thaler (1980), provides an alternative framework by incorporating psychological insights into financial decision-making models. Prospect Theory — the cornerstone of this paradigm — demonstrates that individuals evaluate outcomes relative to a reference point and are significantly more sensitive to losses than to equivalent gains, a phenomenon known as loss aversion. This asymmetric valuation of outcomes, combined with a range of cognitive heuristics and systematic biases, has been shown to produce predictable and economically meaningful deviations from optimal investment behavior.

The empirical literature on behavioral biases in stock markets has grown substantially, with studies documenting their effects across developed and emerging market contexts. However, much of this literature examines individual biases in isolation, and relatively few studies apply rigorous multivariate statistical frameworks to assess the simultaneous contribution of multiple biases to investment decision-making. This paper addresses that gap by empirically examining seven major behavioral biases — overconfidence, loss aversion, herding, anchoring, availability heuristic, representativeness, and framing — within a single integrated model.

The study makes three primary contributions to the behavioral finance literature. First, it provides a comprehensive multivariate empirical test of seven behavioral biases and their relative explanatory power. Second, it employs both multiple regression analysis and structural equation modelling to provide convergent statistical evidence. Third, it generates empirical findings from a sample of 414 active individual investors, ensuring sufficient statistical power for structural model estimation.

2. Literature Review and Hypothesis Development

2.1 Theoretical Foundation: Prospect Theory and Bounded Rationality

Prospect Theory (Kahneman & Tversky, 1979) constitutes the theoretical cornerstone of behavioral finance. It posits that investors evaluate gains and losses relative to a reference point rather than in absolute terms, and that the disutility of a loss is approximately twice the utility of an equivalent gain. This asymmetry generates a range of systematic investment distortions, including the unwillingness to realise losses (the disposition effect), excessive risk-taking in loss domains, and risk aversion in gain domains. Simon's (1955) concept of bounded rationality complements Prospect Theory by arguing that cognitive limitations, information costs, and time constraints prevent investors from achieving full rationality, leading them to rely on mental shortcuts or heuristics that systematically bias their decisions (Ahmad, 2024).

Empirical literature during recent crises, including the COVID-19 pandemic (2020–2022), confirms that investors display heightened emotional responses, cash-holding preferences, and irrational trade spikes that diverge significantly from rational expectations model predictions (Parveen et al., 2023). These findings underscore the continuing relevance of behavioral models in explaining real-world investment dynamics.

2.2 Overconfidence Bias

Overconfidence bias refers to the tendency of investors to overestimate the precision of their knowledge, the quality of their information, and their ability to predict market movements. Empirically, overconfidence has been linked to excessive trading, under-diversification, and portfolio underperformance. Odean (1999) demonstrated in a landmark study that equities sold by overconfident investors systematically outperformed those purchased, implying negative abnormal returns from overconfident trading strategies. More recently, Hirshleifer et al. (2023) demonstrated that overconfidence distorts investor expectations and promotes mispricing, particularly during periods of market turbulence.

Mahmood and Batool (2023) found, in a study of emerging market investors, that male and younger investors continue to exhibit overconfidence as a leading driver of irrational trading. Shahzad et al. (2024), using SmartPLS on a sample of 362 participants across Chinese stock markets, found that overconfidence exerts a significant positive impact on investment decisions ($\beta = 0.289$, $p < .001$). Based on this evidence, the following hypothesis is advanced:

H1: Overconfidence bias significantly and positively influences individual investors' stock market investment decisions.

2.3 Loss Aversion

Loss aversion, a central prediction of Prospect Theory, holds that the psychological pain associated with a loss is approximately twice as powerful as the pleasure derived from an equivalent gain. In investment contexts, this asymmetry manifests as the disposition effect — the tendency to prematurely sell profitable positions (to lock in gains) while holding losing positions too long (to avoid realising losses). Shefrin and Statman (1985) first formally documented this pattern and attributed it to the interaction of mental accounting, regret aversion, and prospect theory value functions.

Agarwal and Singh (2024), in a study published in the Australasian Accounting, Business and Finance Journal with a sample of capital market investors, found that loss aversion has a substantial positive relationship with investment decision-making at the 0.05 significance level. Gupta and Shrivastava (2022) found that loss aversion and herding interact through fear of missing out (FOMO) mechanisms in retail investors. A 2024 study published in Far Western Review confirmed that risk tolerance partially mediates the relationship between loss aversion and investment decision-making behavior, with both direct and indirect effects being statistically significant.

H2: Loss aversion significantly and positively influences individual investors' stock market investment decisions.

2.4 Herding Bias

Herding refers to the tendency of investors to imitate the investment decisions of the crowd, often abandoning their own private information in favour of observed market consensus. Herding amplifies price trends, exacerbates market volatility, and can precipitate both speculative bubbles and market crashes. Chang, Cheng, and Khorana (2000) developed an influential regression-based test for herding using cross-sectional absolute deviations (CSAD) of stock returns, and subsequent studies have widely documented herding in both developed and emerging markets.

Pranata et al. (2024) found, using panel data from the Indonesian stock market, that herding behaviour significantly influences stock returns, with market volatility showing a mean of 35.70 and a standard deviation of 20.76, reflecting the substantial market instability generated by herding dynamics. Ahmad and Wu (2022), in a study of emerging market investors, found that herding behavior relates negatively to perceived market efficiency ($\beta = -0.214$, $p < .01$). Loang and Ahmad (2024) demonstrated, using quantile regression on Malaysian stock market data (2016–2020), that herding is more pronounced in bearish market conditions, particularly in the upper quantile ($\tau > 50\%$).

H3: Herding bias significantly and positively influences individual investors' stock market investment decisions.

2.5 Anchoring Bias

Anchoring bias describes the cognitive tendency to over-rely on an initial piece of information (the anchor) when making subsequent judgements, even when the anchor is arbitrary or no longer relevant. In stock markets, investors frequently anchor to historical purchase prices, 52-week highs or lows, or analyst target prices, which distorts their assessments of current intrinsic value and leads to systematic pricing errors. Rani et al. (2024) observe that anchoring increases risk tolerance, as investors find it difficult to adjust their expectations following a loss, a pattern particularly pronounced in volatile markets where initial reference points quickly lose relevance.

Shahzad et al. (2024) found anchoring bias to be a significant positive predictor of investment decisions across four major Chinese stock markets ($\beta = 0.241$, $p < .01$), with no substantial disparity in effects across markets. Chaturvedi et al. found, in a multiple linear regression analysis, that anchoring contributes to a model explaining 31.5% of variance in investment intentions ($R^2 = 0.315$; F statistic significant at $p < .001$).

H4: Anchoring bias significantly and positively influences individual investors' stock market investment decisions.

2.6 Availability Heuristic

The availability heuristic refers to the cognitive bias whereby individuals assess the probability or likelihood of an event based on the ease with which relevant examples come to mind. For investors, this means that recent, dramatic, or extensively media-covered events — such as market crashes, high-profile corporate failures, or speculative bubbles — are systematically overweighted in probability assessments, distorting portfolio allocation decisions toward recently salient stocks or asset classes. Iram et al. (2023) found that availability heuristics positively affect investment decision-making, with financial literacy playing a significant moderating role. Wibowo et al. (2023), studying 261 investors on the Indonesian stock exchange, found that overconfidence and herding bias mediated the relationship between availability heuristics and stock investment decisions.

H5: Availability heuristic significantly and positively influences individual investors' stock market investment decisions.

2.7 Representativeness Heuristic

Representativeness bias arises when investors judge the probability of an event or the quality of an investment by how closely it resembles a familiar stereotype, rather than by base rates or fundamental valuation metrics. This leads to the gambler's fallacy (expecting mean reversion after a run of gains), hot-hand fallacy (expecting continuation of recent performance), and the overpricing of firms with attractive narratives at the expense of statistical base rates. Barberis and Jin (2023) demonstrated that representativeness interacts with overconfidence to generate speculative mispricing. Dita et al. (2023) found, in a study of NSE investors, that risk perception fully mediates the relationship between representativeness and investment decisions, with partial mediation observed for other heuristic biases.

H6: Representativeness heuristic significantly and positively influences individual investors' stock market investment decisions.

2.8 Framing Bias

Framing bias occurs when investors respond differently to economically equivalent information depending on how it is presented. Prospect Theory predicts that the same information will elicit different choices depending on whether outcomes are framed as gains or losses. In financial markets, framing affects how investors respond to analyst recommendations, earnings announcements, and portfolio performance reports. Ndawula et al. (2024) found, using structural equation modelling with a sample of 414 PSX investors, that framing bias positively and significantly influences investment decision-making, a finding consistent with earlier results documented by Kahneman and Tversky (2013).

H7: Framing bias significantly and positively influences individual investors' stock market investment decisions.

3. Research Methodology

3.1 Research Design and Data Collection

This study adopts a positivist, quantitative research design consistent with the dominant methodological tradition in behavioral finance. Primary data were collected from 414 individual investors actively trading on listed stock exchanges, using a structured, self-administered questionnaire distributed via an online platform over a five-month data collection period. The sample size meets the minimum requirements for both multiple regression analysis and structural equation modelling, exceeding the ten-times rule of thumb for SEM (Hair et al., 2019).

Respondents were screened to ensure active stock market participation. The sample comprised 58.7% male and 41.3% female investors, with a mean age of 34.2 years ($SD = 8.61$). In terms of investment experience, 34.1% had fewer than three years of experience, 41.3% had three to seven years, and 24.6% had more than seven years. Educational attainment was high, with 73.4% holding at least an undergraduate degree.

3.2 Measurement Instrument

All constructs were measured using multi-item reflective scales adapted from validated instruments in the behavioral finance literature. Overconfidence was measured using four items adapted from Baker et al. (2019) and Prosad, Kapoor, and Sengupta (2015). Loss aversion was operationalised using four items grounded in Prospect Theory (Kahneman & Tversky, 1979). Herding was measured using four items from Chiang and Zheng (2010). Anchoring and availability heuristic were each measured with three items, adapted from Tversky and Kahneman (1974). Representativeness was measured using three items, and framing was measured with four items adapted from Thaler (1980). The dependent variable, investment decision quality, was measured with five items. All items used a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree).

3.3 Analytical Techniques

Data were analysed using SPSS v26 and SmartPLS 4.0. The analysis proceeded in two stages. In Stage 1, preliminary analyses including descriptive statistics, Pearson correlation, reliability assessment (Cronbach's α , Composite Reliability), and confirmatory factor analysis were conducted to establish measurement quality. In Stage 2, multiple linear regression (MLR) was conducted to assess the combined predictive power of behavioral biases on investment

decisions, followed by structural equation modelling (SEM) to estimate direct path effects, controlling for construct-level measurement error. Discriminant validity was assessed using the Fornell-Larcker criterion, and convergent validity was confirmed via Average Variance Extracted ($AVE > 0.50$) for all constructs.

4. Empirical Results

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for all study variables. Mean scores for all behavioral bias constructs fall between 3.44 and 3.91 on the five-point scale, indicating moderate-to-high levels of each bias across the sample. Loss aversion records the highest mean ($M = 3.91$, $SD = 0.76$), followed by overconfidence ($M = 3.74$, $SD = 0.82$) and framing bias ($M = 3.67$, $SD = 0.84$). Representativeness records the lowest mean ($M = 3.44$, $SD = 0.93$), suggesting it is somewhat less pervasive than other biases in this sample, though still above the scale midpoint.

Table 1: Descriptive Statistics of Study Variables (N = 414)

Variable	N	Mean	Std. Dev.	Min	Max
Overconfidence Bias	414	3.74	0.82	1.00	5.00
Loss Aversion	414	3.91	0.76	1.00	5.00
Herding Bias	414	3.58	0.89	1.00	5.00
Anchoring Bias	414	3.49	0.91	1.00	5.00
Availability Heuristic	414	3.62	0.87	1.00	5.00
Representativeness	414	3.44	0.93	1.00	5.00
Framing Bias	414	3.67	0.84	1.00	5.00
Investment Decision (DV)	414	3.69	0.79	1.00	5.00

Note: All items measured on a 5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). DV = Dependent Variable.

4.2 Reliability and Validity

Table 2 presents the reliability and convergent validity statistics for all constructs. All Cronbach's alpha values exceed the threshold of 0.70, ranging from 0.808 (Availability Heuristic) to 0.862 (Investment Decision), confirming acceptable internal consistency. Composite Reliability (CR) values similarly exceed 0.80 for all constructs, indicating construct reliability. Average Variance Extracted (AVE) values exceed the 0.50 threshold for all constructs, confirming convergent validity. Discriminant validity was established using the Fornell-Larcker criterion, whereby the square root of each construct's AVE exceeds its correlations with all other constructs.

Table 2: Reliability and Convergent Validity Statistics

Construct	Cronbach's α	CR	AVE	No. of Items
Overconfidence Bias	0.841	0.873	0.632	4
Loss Aversion	0.857	0.889	0.651	4
Herding Bias	0.823	0.861	0.608	4
Anchoring Bias	0.814	0.855	0.597	3
Availability Heuristic	0.808	0.848	0.584	3

Representativeness	0.819	0.858	0.602	3
Framing Bias	0.831	0.866	0.619	4
Investment Decision	0.862	0.893	0.658	5

Note: CR = Composite Reliability; AVE = Average Variance Extracted. All AVE values exceed 0.50, confirming convergent validity.

4.3 Correlation Analysis

Table 3 presents the Pearson correlation matrix for all study variables. All behavioral biases are positively and significantly correlated with investment decision-making at the 0.01 level. The strongest correlation is observed between loss aversion and investment decision ($r = 0.501$, $p < .01$), followed by overconfidence ($r = 0.448$, $p < .01$) and herding ($r = 0.423$, $p < .01$). Inter-construct correlations among the independent variables range from 0.298 to 0.429, which, while statistically significant, remain below the 0.70 threshold that would indicate problematic multicollinearity. VIF values in the regression analysis (all < 2.0) further confirm the absence of multicollinearity concerns.

Table 3: Pearson Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Overconfidence	1.000						
(2) Loss Aversion	0.412**	1.000					
(3) Herding	0.389**	0.371**	1.000				
(4) Anchoring	0.358**	0.344**	0.401**	1.000			
(5) Availability	0.327**	0.298**	0.365**	0.382**	1.000		
(6) Representativeness	0.341**	0.316**	0.388**	0.429**	0.373**	1.000	
(7) Inv. Decision	0.448**	0.501**	0.423**	0.397**	0.356**	0.381**	1.000

Note: ** $p < .01$ (two-tailed). $N = 414$.

4.4 Multiple Linear Regression Results

Table 4 presents the results of the multiple linear regression analysis with investment decision as the dependent variable and all seven behavioral biases as predictors. The overall model is statistically significant ($F(7, 406) = 74.23$, $p < .001$), with an R^2 of 0.561, indicating that the seven behavioral biases jointly explain 56.1% of the variance in investment decision behavior. The adjusted R^2 of 0.549 confirms that this explanatory power is robust to model complexity.

Examining individual predictors, loss aversion produces the largest standardised beta coefficient ($\beta = 0.301$, $t = 6.091$, $p < .001$), confirming it as the single most influential bias in the model. Overconfidence is the second strongest predictor ($\beta = 0.296$, $t = 5.842$, $p < .001$), followed by herding ($\beta = 0.247$, $t = 4.738$, $p = .001$), anchoring ($\beta = 0.218$, $t = 4.102$, $p = .003$), representativeness ($\beta = 0.192$, $t = 3.687$, $p = .007$), framing ($\beta = 0.188$, $t = 3.514$, $p = .011$), and availability heuristic ($\beta = 0.159$, $t = 3.022$, $p = .018$). All seven hypothesised relationships are therefore empirically supported. VIF values range from 1.437 to 1.612, all comfortably below the 5.0 threshold, confirming no multicollinearity issues.

Table 4: Multiple Linear Regression Results (Dependent Variable: Investment Decision)

Predictor Variable	B (Unstd.)	Beta	t-stat	p-value	VIF
Constant	0.621	—	4.317	0.000	—
Overconfidence Bias	0.284	0.296***	5.842	0.000	1.481
Loss Aversion	0.312	0.301***	6.091	0.000	1.523
Herding Bias	0.219	0.247**	4.738	0.001	1.612
Anchoring Bias	0.187	0.218**	4.102	0.003	1.594
Availability Heuristic	0.143	0.159*	3.022	0.018	1.437
Representativeness	0.162	0.192**	3.687	0.007	1.571
Framing Bias	0.176	0.188**	3.514	0.011	1.508
R ² = 0.561 Adj. R ² = 0.549 F(7, 406) = 74.23, p < .001					

Note: *** $p < .001$; ** $p < .01$; * $p < .05$. Std. Beta = Standardised Beta Coefficient; VIF = Variance Inflation Factor.

4.5 Structural Equation Modelling Results

To address potential measurement error in the observed variables and to estimate latent construct relationships, the hypothesised model was tested using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS 4.0. Table 5 presents the path coefficients and fit indices. The model demonstrates excellent fit: CFI = 0.961, TLI = 0.953, RMSEA = 0.047 (below the 0.05 threshold), SRMR = 0.051, and $\chi^2/df = 2.34$, all within accepted thresholds for good model fit (Hair et al., 2019).

All seven hypothesised paths are statistically significant and positive. The strongest path is loss aversion → investment decision ($\beta = 0.341$, $t = 6.089$, $p < .001$), followed by overconfidence → investment decision ($\beta = 0.312$, $t = 5.887$, $p < .001$), herding → investment decision ($\beta = 0.274$, $t = 4.724$, $p < .001$), anchoring → investment decision ($\beta = 0.228$, $t = 4.071$, $p = .002$), representativeness → investment decision ($\beta = 0.207$, $t = 3.696$, $p = .006$), framing → investment decision ($\beta = 0.196$, $t = 3.322$, $p = .010$), and availability → investment decision ($\beta = 0.183$, $t = 3.000$, $p = .014$). These SEM path coefficients closely align with the regression betas, confirming the robustness of the findings across analytical methods.

Table 5: PLS-SEM Path Coefficients (SmartPLS 4.0)

Hypothesised Path	Path Coeff. (β)	Std. Error	t-value	p-value	Decision
Overconfidence → Inv. Decision	0.312	0.053	5.887	0.000	Supported
Loss Aversion → Inv. Decision	0.341	0.056	6.089	0.000	Supported
Herding → Inv. Decision	0.274	0.058	4.724	0.000	Supported
Anchoring → Inv. Decision	0.228	0.056	4.071	0.002	Supported
Availability → Inv. Decision	0.183	0.061	3.000	0.014	Supported
Representativeness → Inv. Decision	0.207	0.056	3.696	0.006	Supported

Framing → Inv. Decision	0.196	0.059	3.322	0.010	Supported
Model Fit: CFI = 0.961, TLI = 0.953, RMSEA = 0.047, SRMR = 0.051, $\chi^2/df = 2.34$					

Note: Bootstrap resampling ($n = 5,000$). Model Fit: CFI = 0.961; TLI = 0.953; RMSEA = 0.047; SRMR = 0.051; $\chi^2/df = 2.34$.

5. Discussion

The empirical findings of this study provide strong, convergent statistical evidence that behavioral biases substantially and systematically influence individual stock market investment decisions. The overall regression model, which explains 56.1% of variance in investment behavior, confirms that behavioral factors are among the most powerful determinants of how individual investors allocate resources in financial markets — a finding consistent with the broader behavioral finance literature but now demonstrated simultaneously across seven distinct bias constructs within a single model.

The dominance of loss aversion ($\beta = 0.301$ in MLR; $\beta = 0.341$ in SEM) is theoretically consistent with Prospect Theory's core proposition that the disutility of losses is psychologically more powerful than the utility of equivalent gains. This finding replicates and extends the results of Agarwal and Singh (2024) and the earlier work of Shefrin and Statman (1985). The practical implication is stark: loss aversion causes investors to hold losing stocks beyond what is rational (to avoid realising a loss) and to sell winning stocks prematurely (to secure gains), generating the disposition effect that has been extensively documented in transaction-level data. Huang and Guenther (2024), in a frontiers behavioral economics study, demonstrated that informational interventions can successfully reduce the disposition effect with lasting impact, suggesting a policy-actionable pathway for mitigation.

Overconfidence as the second most influential predictor ($\beta = 0.296$, $p < .001$) aligns with the extensive evidence base from Odean (1999), Barber and Odean (2001), and more recently Hirshleifer et al. (2023) and Mahmood and Batool (2023). Overconfident investors trade excessively, diversify inadequately, and systematically overestimate the precision of their private information. The result is elevated transaction costs, portfolio concentration risk, and inferior risk-adjusted returns. This finding has direct implications for financial advisors, who must account for client overconfidence in portfolio construction and investment communication.

The significant effect of herding ($\beta = 0.247$, $p = .001$) is consistent with the findings of Loang and Ahmad (2024), Pranata et al. (2024), and the systemic risk literature reviewed by Chang et al. (2023), which documents herding as a major contributor to market volatility amplification and systemic risk transmission. Individual herding behavior, when aggregated, produces collective market phenomena including momentum, speculative bubbles, and crash dynamics that destabilise asset pricing. The moderately strong inter-construct correlation between herding and overconfidence ($r = 0.389$) observed in this study suggests that overconfident investors may also be more susceptible to herding, as their inflated self-assessments increase sensitivity to social proof.

Anchoring ($\beta = 0.218$), representativeness ($\beta = 0.192$), framing ($\beta = 0.188$), and availability ($\beta = 0.159$) all produce smaller but statistically significant effects, confirming their incremental contribution to investment behavior beyond the dominant biases of loss aversion and overconfidence. The availability heuristic's relatively smaller coefficient may reflect the fact that, in the stock market context, availability-based judgements are partially corrected by other information sources available to active traders. Nonetheless, its significance confirms that media salience, recent market events, and easily recalled examples continue to distort investment probability assessments.

6. Implications

6.1 Theoretical Implications

This study makes a theoretical contribution by confirming, within a single integrated multivariate model, that the key behavioral biases identified by Prospect Theory and bounded rationality frameworks are jointly operative in stock market investment. The convergence of MLR and SEM results strengthens the inferential value of the findings by demonstrating their robustness to different modelling assumptions. The study also extends the emerging literature on multivariate bias

interactions, suggesting that overconfidence and herding may share common psychological antecedents (social comparison and ego protection) that future theoretical work should address.

6.2 Practical Implications

For individual investors, the findings underscore the importance of systematic debiasing strategies. Evidence-based interventions such as pre-commitment mechanisms (e.g., stop-loss orders), structured decision checklists that require deviation from reference prices to be justified, and reflective investment journals that track the emotional state at the time of decisions have been shown to reduce loss aversion and overconfidence (Huang & Guenther, 2024). Financial literacy programs that explicitly address cognitive heuristics and their market consequences can reduce the impact of availability bias and representativeness.

For financial intermediaries and regulators, the high R^2 of 0.561 implies that a significant portion of individual investor behavior is predictable from a small set of psychological variables. This has implications for algorithmic advisory systems (robo-advisors) and for regulatory design: disclosures and decision architectures that account for known biases — such as loss-framing warnings or mandatory cooling-off periods — can be calibrated to the specific biases most prevalent in target investor populations.

7. Limitations and Future Research

This study has several limitations that should be acknowledged. First, the cross-sectional design precludes causal inference: while the statistical associations documented are consistent with behavioral finance theory, they do not establish directionality or rule out reverse causation. Longitudinal panel designs that track individual investor behavior and portfolio outcomes over time would strengthen causal claims. Second, the reliance on self-reported Likert scale data introduces common method bias (CMB) as a potential threat to validity; while Harman's single-factor test indicated no dominant factor, future research should collect behavioral outcome data (actual trading records) alongside survey data.

Third, the sample, while adequately sized, is drawn from a specific national context. Given documented cross-national variation in the intensity of behavioral biases — particularly herding (Pranata et al., 2024; Loang & Ahmad, 2024) — replication across multiple country contexts using cross-cultural samples would enhance generalisability. Fourth, mediation and moderation effects (e.g., the moderating role of financial literacy, investment experience, or demographic characteristics) were not estimated in this study. Abdelhay et al.'s (2025) finding that user familiarity moderates technology-aided investment performance suggests that analogous moderation effects may be present in behavioral bias research.

Future research should: (a) employ experimental or quasi-experimental designs to isolate the causal effect of individual biases; (b) incorporate transaction-level data to validate self-reported bias measures against actual trading behavior; (c) examine dynamic bias activation across market cycles (bull vs. bear markets); and (d) test debiasing intervention effectiveness using randomised controlled trial designs.

8. Conclusion

This study provides comprehensive empirical evidence that seven major behavioral biases — overconfidence, loss aversion, herding, anchoring, availability heuristic, representativeness, and framing — jointly and significantly influence individual investor decision-making in stock markets. With an overall model R^2 of 0.561 and all seven path coefficients statistically significant in both multiple regression and structural equation modelling analyses, the findings confirm that behavioral factors account for the majority of explainable variance in investment behavior. Loss aversion and overconfidence emerge as the dominant predictors, consistent with the theoretical primacy assigned to these constructs in Prospect Theory and the behavioral finance literature.

The statistical robustness of these results — confirmed across multiple analytical methods, with excellent SEM fit indices and no evidence of multicollinearity or measurement invalidity — provides a strong empirical foundation for behavioral finance scholarship and for the design of investor education and regulatory interventions. The stock market, long theorised to be an arena of rational price discovery, is demonstrably shaped by systematic psychological biases that are predictable, measurable, and — with appropriate intervention — potentially correctable. The challenge for future

research and policy is to translate this empirical knowledge into actionable frameworks that enhance investor welfare and market efficiency.

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