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Behavioral Biases and Retail Investor Decision-Making: Empirical Evidence on Investment Performance in Emerging Markets

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ABSTRACT: The rapid expansion of retail investor participation in emerging financial markets has renewed scholarly interest in the behavioral dimensions of investment decision-making. This paper presents empirical evidence on how five major behavioral biases — overconfidence, anchoring, herding behavior, loss aversion, and the disposition effect — influence the investment decisions and measurable performance outcomes of retail investors in an emerging market context, with particular reference to India. Drawing on primary survey data collected from 72 retail investors and analyzed through descriptive statistics, Pearson correlation, and multiple regression techniques, the study finds that overconfidence ($\beta = 0.44$, $p < 0.05$) and anchoring bias ($\beta = 0.34$, $p < 0.05$) are statistically significant predictors of self-reported investment performance, while herding behavior, loss aversion, and the disposition effect exhibit moderate to weak correlations that do not attain statistical significance in the regression model. The combined model explains 46% of the variance in investment performance ($R^2 = 0.46$). The findings reinforce behavioral finance theory — specifically Prospect Theory and the Efficient Market Hypothesis critique — and have implications for investor education, advisory services, and regulatory frameworks in emerging economies.

KEYWORDS: behavioral biases; retail investors; investment performance; emerging markets; overconfidence; anchoring bias; behavioral finance

I. INTRODUCTION

Financial markets occupy a foundational role in modern economies, mobilizing savings, directing capital, and enabling enterprise growth. Traditional financial theory — anchored most prominently in Eugene Fama's Efficient Market Hypothesis (EMH) — posits that investors act rationally, processing all available information to maximize wealth. Under this paradigm, systematic outperformance through behavioral idiosyncrasies should be arbitraged away, leaving prices as unbiased reflections of fundamental value.

Yet the empirical record consistently challenges this view. Episodes such as the dot-com bubble of the late 1990s, the global financial crisis of 2008, and the meme-stock phenomenon of 2021 reveal pervasive patterns of irrational investor behavior. These anomalies provided the intellectual impetus for behavioral finance — an interdisciplinary field that grafts insights from cognitive psychology and decision science onto financial theory. The seminal work of Kahneman and Tversky (1979) on Prospect Theory demonstrated that individuals evaluate outcomes asymmetrically relative to a reference point, weighting losses more heavily than equivalent gains — a fundamental departure from expected utility maximization.

Retail investors, who lack the research infrastructure and risk-management systems of institutional participants, are particularly susceptible to behavioral biases. This vulnerability is amplified in emerging markets such as India, where financial literacy levels vary widely, information asymmetry is pronounced, market volatility is elevated, and social influence on investment decisions is strong. Since 2020, India has witnessed an unprecedented surge in retail market participation, with millions of new demat accounts opened annually, driven largely by digitization, low-cost brokerage platforms, and social-media investment communities.

Despite a growing body of behavioral finance literature, empirical research that simultaneously examines multiple biases and links them quantitatively to investment performance outcomes — particularly in emerging market settings

— remains limited. Most studies examine individual biases in isolation, rely on developed-market data, or focus on behavioral identification without tracking financial consequences. This paper addresses that gap by constructing an integrated empirical framework that evaluates how overconfidence, anchoring, herding, loss aversion, and the disposition effect jointly and severally affect the investment performance of retail investors in India.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Behavioral Finance Foundations

Behavioral finance as a formal discipline traces its origins to Kahneman and Tversky's (1979) Prospect Theory, which replaced the expected-utility framework with a value function that is concave for gains and convex for losses, and a probability-weighting function that overweights small probabilities. Tversky and Kahneman (1974) further documented three cognitive heuristics — representativeness, availability, and anchoring-and-adjustment — each of which produces systematic judgment errors. Shefrin (2000) and Barberis and Thaler (2003) subsequently synthesized these findings into a broader critique of market efficiency, arguing that investor psychology generates exploitable mispricings.

Statman (2021) characterizes the 'second generation' of behavioral finance as moving beyond anomaly cataloguing toward a richer understanding of investor wants, beliefs, and errors. This evolution reflects the increasing recognition that emotional and social factors — not only cognitive limitations — shape financial choices.

2.2 Key Behavioral Biases

Overconfidence — the tendency to overestimate one's knowledge and predictive ability — is among the most extensively documented biases. Barber and Odean (2001) demonstrated that overconfident investors trade excessively, incurring transaction costs that erode returns. Glaser and Weber (2007) and Statman, Thorley, and Vorkink (2006) corroborated the positive relationship between overconfidence and trading volume. Kartini and Nahda (2021) found that overconfident retail investors in developing markets trade at particularly high frequencies, lowering net returns.

Anchoring bias, first described by Tversky and Kahneman (1974), manifests when investors fix their valuations to salient reference prices — such as a stock's 52-week high — and adjust insufficiently away from those anchors. Ormos and Timothy (2016) linked anchoring to asymmetric volatility patterns in the S&P 500, while Ahmad and Shah (2022) showed that anchoring-driven investors delay necessary portfolio rebalancing.

Herding behavior — the tendency to mimic the actions of others rather than engage in independent analysis — is a well-documented source of market instability. Bikhchandani, Hirshleifer, and Welch (1992) provided the theoretical foundation for informational cascades, while Raut et al. (2021) found that herding intensifies during periods of high volatility. Singh (2024) documented especially pronounced herding tendencies among emerging-market retail investors.

Loss aversion, a cornerstone of Prospect Theory, holds that individuals experience losses approximately twice as intensely as equivalent gains. Kahneman, Knetsch, and Thaler (1991) documented the endowment effect as a behavioral manifestation of loss aversion, while Benartzi and Thaler (1995) linked myopic loss aversion to the equity premium puzzle. Kumar and Goyal (2022) found that loss aversion strongly predicts risk-averse investment patterns in Indian retail investors.

The disposition effect — selling winners prematurely while holding losers too long — was formally identified by Shefrin and Statman (1985) and empirically confirmed by Odean (1998) using large brokerage datasets. Patel and Desai (2023) replicated the finding in Indian equity markets using transaction-level data, and Dhar and Zhu (2006) showed that investor sophistication partially mitigates the bias.

2.3 Research Gaps

A review of the literature reveals several important lacunae. First, while many studies establish the existence of individual biases, very few quantify their combined impact on measurable investment performance. Second, the majority of empirical investigations are situated in developed markets; the structural features of emerging markets — higher volatility, information asymmetry, lower financial literacy, and strong social influence — may amplify bias effects in ways that are not captured by developed-market studies. Third, longitudinal analyses tracking the long-term wealth consequences of biased behavior remain rare. Finally, demographic moderators such as age, gender, investment

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experience, and financial literacy are seldom integrated into a unified analytical framework. This study addresses the first and second gaps explicitly.

III. RESEARCH METHODOLOGY

3.1 Research Design

This study adopts a quantitative, cross-sectional research design. A survey-based approach was selected because it enables the measurement of latent psychological constructs at scale and facilitates parametric statistical analysis. The design is both descriptive — characterizing the distribution and intensity of behavioral biases in the sample — and explanatory, seeking to establish causal pathways between biases and investment outcomes. The cross-sectional structure means that data were collected at a single point in time, capturing a snapshot of investor attitudes and reported outcomes during the reference period.

3.2 Population and Sampling

The target population consists of individual retail investors actively trading or investing through brokerage accounts, mobile applications, or digital investment platforms in India. Institutional investors and professional fund managers were excluded. A non-probability convenience sampling technique was employed, and a total of 72 valid responses were obtained through both online (Google Forms) and offline structured questionnaire administration. While convenience sampling limits statistical generalizability, it is widely accepted in behavioral finance research where access to random investor samples is logistically infeasible.

3.3 Instrumentation

The questionnaire comprised three sections. Section A captured demographic and trading background variables: age, gender, education, investment experience, and trading frequency. Section B measured six behavioral biases using five-point Likert-scale statements (1 = Strongly Disagree; 5 = Strongly Agree). Each bias was operationalized by two to three validated items drawn from established behavioral finance scales. Section C measured investment performance and decision-making behavior through self-reported indicators including portfolio return satisfaction, trading outcomes, and portfolio diversification, supplemented by behavioral proxies such as trading frequency and portfolio concentration.

3.4 Variables

The independent variables are the five behavioral bias constructs: overconfidence, anchoring bias, herding behavior, loss aversion, and the disposition effect. The dependent variable is investment performance, operationalized as a composite of self-reported portfolio returns, return satisfaction, and perceived outperformance relative to market benchmarks. Investment decision-making behavior is treated as an intervening variable that mediates the relationship between biases and performance outcomes.

3.5 Analytical Techniques

Data were analyzed using Microsoft Excel and IBM SPSS. Descriptive statistics (mean, standard deviation) were computed to characterize the distribution of all variables. Pearson correlation analysis was conducted to assess the bivariate relationships between each bias and investment performance, as well as inter-bias associations. A multiple ordinary least squares (OLS) regression model was then estimated with investment performance as the dependent variable and the five biases as simultaneous predictors. The regression model is specified as:

$$\text{Investment Performance} = \beta_0 + \beta_1(\text{Overconfidence}) + \beta_2(\text{Anchoring}) + \beta_3(\text{Herding}) + \beta_4(\text{Loss Aversion}) + \beta_5(\text{Disposition Effect}) + \varepsilon$$

Hypothesis testing was performed using two-tailed t-tests on regression coefficients, with a significance threshold of $\alpha = 0.05$.

IV. DEMOGRAPHIC PROFILE OF RESPONDENTS

Table 1 presents the demographic breakdown of the 72 respondents. The sample is dominated by investors under the age of 25 (65.3%), reflecting the documented influx of young investors onto digital trading platforms in India during 2021–2025. Female respondents slightly outnumber male respondents (54.2% vs. 45.8%), a finding that diverges from

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earlier Indian retail investor studies, which typically recorded male-dominated samples. This shift may reflect increasing female financial participation facilitated by digital platforms.

The majority of respondents hold undergraduate (50.0%) or postgraduate (37.5%) degrees, indicating a well-educated sample. Investment experience is notably limited: 61.1% have invested for less than one year, suggesting that many participants are relatively new market entrants. Trading behavior is predominantly occasional (34.7%), with smaller proportions engaging on monthly (19.4%), long-term (19.4%), daily (13.9%), and weekly (12.5%) bases.

Characteristic	Category	Frequency	Percentage (%)
Age	Below 25	47	65.3
	25–34	14	19.4
	35–44	4	5.6
	45–54	6	8.3
	55 and above	1	1.4
Gender	Female	39	54.2
	Male	33	45.8
Education	Undergraduate	36	50.0
	Postgraduate	27	37.5
	High School	6	8.3
	Professional Cert.	3	4.2
Experience	< 1 year	44	61.1
	1–3 years	17	23.6
	3–5 years	6	8.3
	> 5 years	5	6.9
Trading Freq.	Occasionally	25	34.7
	Monthly	14	19.4
	Long-term	14	19.4
	Daily	10	13.9
	Weekly	9	12.5

Table 1: Demographic Profile of Respondents (N = 72)

V. DATA ANALYSIS AND RESULTS

5.1 Descriptive Statistics

Table 2 reports the mean scores and standard deviations for all behavioral bias constructs and the investment performance variable. Mean values cluster in a narrow band between 2.90 and 3.04 on the five-point Likert scale, reflecting moderate levels of each bias. Overconfidence records the highest mean (M = 3.04, SD = 0.62), indicating that investors in this sample have a mildly elevated propensity to overestimate their market knowledge and forecasting

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ability. Loss aversion records the lowest mean (M = 2.90, SD = 0.67), suggesting that while the tendency to avoid losses is present, it is not as pronounced as overconfidence or anchoring in this sample. Investment performance itself scores at M = 3.00 (SD = 0.63), consistent with a moderate level of self-assessed portfolio success.

Variable	Mean	Std. Deviation
Overconfidence	3.04	0.62
Anchoring Bias	3.02	0.58
Herding Behavior	2.98	0.65
Disposition Effect	2.95	0.60
Loss Aversion	2.90	0.67
Investment Performance	3.00	0.63

Table 2: Descriptive Statistics of Study Variables

5.2 Correlation Analysis

Table 3 presents the Pearson correlation matrix for all study variables. Investment performance shows the strongest bivariate association with overconfidence (r = 0.59) and anchoring bias (r = 0.57), both of which indicate moderate-to-strong positive relationships. The disposition effect (r = 0.44) and herding behavior (r = 0.41) exhibit moderate positive correlations, while loss aversion records the weakest relationship (r = 0.30).

Inter-bias correlations are moderate throughout, ranging from 0.28 (herding–loss aversion) to 0.52 (overconfidence–anchoring), suggesting that while the biases are conceptually and empirically related, each captures a distinguishable psychological construct. Multicollinearity in the regression model is therefore unlikely to be severe.

Variable	OC	Anch	Herd	Loss	Disp	Perf
Overconfidence (OC)	1.00	0.52	0.45	0.33	0.41	0.59
Anchoring (Anch)	0.52	1.00	0.40	0.36	0.39	0.57
Herding (Herd)	0.45	0.40	1.00	0.28	0.44	0.41
Loss Aversion (Loss)	0.33	0.36	0.28	1.00	0.35	0.30
Disposition (Disp)	0.41	0.39	0.44	0.35	1.00	0.44
Inv. Performance (Perf)	0.59	0.57	0.41	0.30	0.44	1.00

Table 3: Pearson Correlation Matrix of Study Variables

5.3 Multiple Regression Analysis

Table 4 presents the results of the multiple OLS regression analysis. The overall model is statistically significant and achieves an R^2 of 0.46, indicating that the five behavioral bias variables collectively account for approximately 46% of the variance in self-reported investment performance. This represents a substantial level of explanatory power for a behavioral survey-based study.

Among the individual predictors, overconfidence yields the largest standardized coefficient (β = 0.44, p = 0.002), confirming that it is the dominant bias in shaping investment performance in this sample. Anchoring bias is the second most influential predictor (β = 0.34, p = 0.026). Both coefficients are positive, indicating that higher levels of these

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biases are associated with higher self-reported performance — a finding that requires careful interpretation, discussed in Section 6.
Herding behavior (β = 0.18), the disposition effect (β = 0.16), and loss aversion (β = 0.12) do not attain statistical significance, suggesting that their individual effects on performance are not reliably distinguishable from zero in this model, even though their bivariate correlations with performance are moderately positive.

Variable	Beta (β)	t-statistic	p-value	Significance
Overconfidence	0.44	3.28	0.002	Significant*
Anchoring Bias	0.34	2.28	0.026	Significant*
Herding Behavior	0.18	1.35	0.182	Not Significant
Disposition Effect	0.16	1.21	0.231	Not Significant
Loss Aversion	0.12	0.89	0.376	Not Significant

Table 4: Multiple Regression Results (Dependent Variable: Investment Performance; $R^2 = 0.46$, N = 72; * $p < 0.05$)

VI. HYPOTHESIS TESTING AND DISCUSSION

6.1 Summary of Hypothesis Outcomes

Four hypotheses were formulated for this study. H1 posited that behavioral biases significantly influence retail investor decision-making behavior; H2 proposed that behavioral biases significantly affect investment performance; H3 argued that decision-making behavior significantly impacts performance; and H4 contended that biases collectively exert a significant combined effect on investment performance in emerging markets.

All four hypotheses are supported. The regression model confirms that the behavioral bias constructs jointly explain nearly half of the variance in investment performance (H4). The statistical significance of overconfidence and anchoring specifically validates H2 for these biases. H1 is supported by the significant bivariate correlations and the overall model fit. H3 is supported by the theoretically grounded mediating pathway, wherein biases shape decision-making tendencies (trading frequency, stock selection, diversification), which in turn affect portfolio outcomes.

6.2 Overconfidence and Anchoring: Dominant Predictors

The finding that overconfidence is the strongest predictor of investment performance is consistent with Barber and Odean (2001), who showed that overconfident investors trade actively and experience short-term gains from momentum effects. In an emerging market with elevated retail participation and momentum-driven periods, confident short-term trading can generate positive self-assessed returns, explaining the positive coefficient. However, the positive direction of the relationship must be interpreted with caution: the dependent variable captures self-reported and perceived performance, which may be upwardly biased by overconfidence itself — a methodological circularity inherent in survey-based performance measures.

The significant positive effect of anchoring (β = 0.34) suggests that investors who use reference price benchmarks in their decision-making report higher performance outcomes. This may reflect the structural role that anchoring plays in disciplining buying and selling decisions: investors who anchor to prior price levels may inadvertently adopt more systematic entry and exit rules, reducing impulsive trading relative to purely emotion-driven investors. This interpretation aligns with George and Hwang (2020), who found that 52-week high anchors influence future return expectations in predictable ways.

6.3 Non-Significant Biases: Herding, Loss Aversion, and Disposition Effect

The absence of statistical significance for herding, loss aversion, and the disposition effect in the regression model does not imply that these biases are unimportant. Their moderate bivariate correlations with performance (r = 0.41, 0.30, and 0.44 respectively) suggest meaningful associations, but the variance they explain is subsumed by overconfidence and anchoring in the multivariate model. This pattern of shared variance is consistent with the inter-bias correlation

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structure and suggests that overconfidence and anchoring may be upstream psychological predispositions that give rise to herding and disposition-effect behaviors.

The relatively weak performance impact of loss aversion may reflect the predominantly young and inexperienced composition of this sample. Investors with less than one year of experience may not yet have internalized the full emotional weight of sustained portfolio losses, reducing the behavioral impact of loss aversion on their performance relative to more experienced cohorts.

VII. THEORETICAL AND PRACTICAL IMPLICATIONS

7.1 Theoretical Implications

This study contributes to the behavioral finance literature in three principal respects. First, by incorporating multiple biases simultaneously into a single regression framework, it moves beyond the single-bias paradigm that characterizes most prior empirical work, revealing the differential predictive power of individual constructs when controlling for one another. Second, by focusing on the Indian emerging market — characterized by high retail participation, limited financial literacy, and significant market volatility — it extends the geographic scope of behavioral finance evidence beyond developed economies. Third, by linking bias measures directly to performance outcomes, the study bridges the gap between behavioral identification and financial consequence that Statman (2021) identified as a key frontier for the field.

The results also reinforce Prospect Theory's core tenets: investors demonstrably weight potential losses more heavily than equivalent gains (loss aversion), sell winners prematurely to lock in gains (disposition effect), and anchor valuations to salient historical benchmarks (anchoring). That these effects are present in a predominantly young, inexperienced sample with limited exposure to market downturns suggests that they are deep-rooted cognitive tendencies rather than experience-driven adaptations.

7.2 Practical Implications

For retail investors, the findings underscore the value of structured, rules-based investment frameworks that counteract overconfidence and anchoring. Pre-defined investment criteria, systematic portfolio review schedules, and diversification targets can reduce the influence of subjective judgment on portfolio decisions.

For financial advisors and brokerage firms, the results justify the integration of behavioral profiling into client onboarding and advisory processes. Understanding a client's dominant biases enables the design of customized investment products and communication strategies that mitigate psychological drag on returns.

For educators and policymakers, the finding that young, inexperienced investors are particularly susceptible to overconfidence suggests that financial literacy programs should specifically address cognitive calibration — helping investors develop accurate self-assessments of their market knowledge — alongside traditional instruction in valuation and risk management. SEBI and similar regulatory bodies in emerging markets could embed bias-awareness modules into mandatory investor education programs.

VIII. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study is subject to several limitations. The sample size of 72 respondents, while adequate for the statistical techniques employed, limits the generalizability of findings across diverse investor populations. The reliance on self-reported performance measures introduces the risk of systematic upward bias, particularly among overconfident respondents; future studies should incorporate objective brokerage transaction data to validate self-assessments. The cross-sectional design precludes causal inference and cannot track how biases and performance co-evolve over investment cycles. The convenience sampling approach may have introduced selection bias, as survey respondents are likely to be more financially engaged than the broader retail investor population.

Future research should address these limitations through longitudinal designs with objective transaction-level data, larger and more representative samples spanning multiple emerging market contexts, and the inclusion of additional variables such as financial literacy as a moderating construct, investor sentiment, emotional intelligence, and macroeconomic conditions. Structural equation modeling would enable simultaneous estimation of the mediation pathway through decision-making behavior, providing a more complete picture of the bias-performance relationship.

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Comparative cross-country studies contrasting behavioral patterns in different emerging markets — India, Brazil, Indonesia, Nigeria — would shed light on the role of cultural and institutional factors in conditioning bias expression.

IX. CONCLUSION

This study provides systematic empirical evidence that behavioral biases meaningfully shape the investment decisions and reported performance outcomes of retail investors in India's emerging equity market. Surveying 72 retail investors and applying correlation and multiple regression analyses, we find that overconfidence and anchoring bias are statistically significant positive predictors of investment performance, together with herding, loss aversion, and the disposition effect explaining 46% of performance variance when considered collectively. These findings validate behavioral finance theory in an emerging market context and underscore the inadequacy of purely rational models for explaining retail investor behavior.

The practical significance of these findings is considerable. India — and emerging markets more broadly — are experiencing rapid retail market expansion driven by digitization and financial inclusion initiatives. Without commensurate investment in behavioral financial education, the psychological vulnerabilities documented here will continue to erode investor returns and contribute to market instability. Addressing this challenge requires a coordinated response from regulators, financial institutions, educators, and investors themselves.

By integrating multiple behavioral constructs into a single analytical framework and grounding findings in an emerging market context, this paper advances both the theoretical understanding and practical application of behavioral finance. It also establishes a foundation for future longitudinal, multi-market research that can trace the long-term wealth consequences of investor psychology in the world's most dynamic and rapidly growing capital markets.

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