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The Role Of Behavioural Finance In Investment Decision-Making: A Study On Cognitive Biases And Market Trends

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Abstract
Behavioral finance challenges traditional market theories by demonstrating how cognitive biases and emotional factors systematically shape investment decisions. This study examines four key biases: overconfidence, loss aversion, herding, and anchoring, and their combined impact on investment performance among retail and institutional investors. A cross-sectional quantitative survey of 500 respondents from global financial markets was conducted using validated psychometric tools to assess bias levels and a composite performance index derived from self-reported and verified returns. Data analysis through descriptive statistics, Pearson correlations, and multiple regression in SPSS revealed that overconfidence was the strongest positive predictor of performance, suggesting that well-calibrated confidence can enhance returns, while loss aversion had the most substantial negative influence, reflecting tendencies to avoid profitable risks or retain underperforming assets too long. Herding showed a smaller but significant positive effect, indicating that trend-following can yield short-term gains under favorable conditions, whereas anchoring had a weak, statistically insignificant negative association. Institutional investors outperformed retail investors slightly, with less variability, likely due to greater resources, structured decision-making, and superior market access. These results underscore the importance of bias-aware investment strategies, targeted financial education to reduce loss aversion among retail investors, and safeguards against excessive herding in institutional contexts. Integrating behavioral finance insights into portfolio management and policy frameworks can improve market efficiency, resilience, and long-term investment performance.

Keywords: *Behavioral finance, cognitive biases, financial markets, overconfidence bias, market stability.*

INTRODUCTION

The most well-known traditional finance theories are the Efficient Market Hypothesis and Modern Portfolio Theory, which are based on the assumption that investors are rational and make full use of the information they have to receive the maximum returns (Ying et al., 2019). However, the financial markets in the real world often exhibit a lack of this ideal, which is evidenced by speculative bubbles, unforeseen crashes, and chronic mispricings. These phenomena show how much psychology has to play in investor behavior, namely, the four cognitive biases that are considered in the current research: overconfidence, loss aversion, herding, and anchoring, which make individuals and institutions make wrong decisions that are not typical of classical rational models. The flaws in financial economics gave rise to behavioral finance, which involves knowledge of financial decision-making using psychological concepts of mental shortcuts and emotional reactions that always tend to distort financial choices (Seraj et al., 2022).

In recent years, the significance of behavioral finance has been increasing, since the financial markets are becoming more complex, information-intensive, and volatile. Institutions and retail investors have entered an environment of geopolitical strains, rapid technological change, and macroeconomic environments of uncertainty in which cognitive biases are better positioned to exacerbate errors in the decision process and lead to destabilizing behavior (Rahman & Mehnaz, 2024). In reality, recognizing and being aware of these biases should be crucial not only to the personal and better performance of investments, but also to developing policies and mechanisms to create a more stable system, to reduce irrational trading, and to protect the efficiency of a market.

Despite a growing body of research, a key gap persists: most studies examine cognitive biases in isolation rather than analyzing their cumulative and interaction effects across investor types (Gabhane et al., 2023). A few recent studies provide valuable insights. For instance, Ahmad documents how overconfidence, anchoring, herding, and loss aversion significantly impact decision-making and how financial literacy can attenuate their effects (Mahmood et al., 2024). Another study models how biases distort optimal investment strategies in strategic interactions, demonstrating through a Bayesian game framework how biases like loss aversion and herd behavior can undermine market equilibrium and stability (Bihari et al., 2025). However, empirical research integrating these biases across both retail and institutional contexts, especially under varying market volatility conditions, remains scarce.

Furthermore, much of the literature either focuses on narrow geographies or overlooks sentiment-driven dynamics that influence behavior during stress periods. A study published earlier this year by MDPI relates cognitive biases (in particular herding, overconfidence, and loss aversion) to market volatility and changes in economic fundamentals through GARCH modeling, with particular emphasis on the fact that psychological biases are leading to the significant divergence of market behaviour and the underlying growth fundamentals (Umeaduma, 2024). Yet, there remains scant research that bridges behavioral finance theory with detailed empirical strategies aimed at bias mitigation, nor evidence-based interventions tailored to investor segments.
To this end, this paper combines the theory of behavioral finance and empirical research in order to fill in both theoretical and practical gaps. This research will seek to produce actionable conclusions by systematic analysis of how the main biases of overconfidence, loss aversion, herding, and anchoring interact to drive investment decisions and market behaviour. Through evaluating their combined effects across different investor types and devising strategies to mitigate bias-driven distortions, the study contributes to the refinement of behavioral finance models and offers tangible recommendations for mitigating bias-induced inefficiencies.

Hence, the study is structured around three core objectives:
1. Examine the combined impact of key cognitive biases, overconfidence, loss aversion, herding, and anchoring on investment decisions among both retail and institutional investors.
2. Analyze how these biases are associated with investment performance across investor types.
3. Propose behavioral finance–based interventions, informed by findings, that could help mitigate bias effects and improve investment outcomes.

By focusing on these objectives, the paper bridges the gap between behavioral finance theory and real-world investor behavior, offering evidence-based contributions that are relevant for academics, policymakers, financial advisors, and institutional stakeholders.

2. LITERATURE REVIEW

2.1 Overview of Behavioral Finance
Behavioral finance exists as an academic discipline that integrates psychological methods with economic ideas to examine cognitive bias, together with emotional factors affecting investment decisions. According to traditional financial principles, including the Efficient Market Hypothesis (EMH), investors demonstrate logical behavior by analyzing all available data to achieve their maximum returns. The actual market operates against these theoretical assumptions because investors demonstrate irrational behaviors that produce market irregularities

and financial bubbles, and economic breakdowns (Andraszewicz, 2020). Behavioral finance disproves strict rational investment behavior since it analyzes psychological human factors that determine decision-making in financial markets. Cognitive psychology input within behavioral finance establishes a more accurate market understanding that demonstrates why investors make choices that differ from rational procedures (Sharma & Kumar, 2020)

The field has expanded rapidly since major financial crisis events in recent decades, especially during the dot-com bubble, the global financial crisis, and the cryptocurrency market volatility (Khan et al., 2024). Behavioral finance research shows that investment decisions of investors stem primarily from psychological biases, together with mental heuristics and emotional rather than objective financial data. Identifying financial biases remains fundamental to enhancing investment decisions and building better financial regulations, which together create investment plans that address irrational conduct. (Nardi et al., 2022).

2.2 Traditional vs. Behavioral Finance: Key Differences

There are two paradigms of financial research, which are traditional finance and behavioral finance. More classical financial theories, including Modern Portfolio Theory (MPT), Capital Asset Pricing Model (CAPM), and Arbitrage Pricing Theory (APT), presuppose the rationality of investors, who make decisions based on the available information to maximize their utility (Lekovic, 2019). They rest on the hypothesis of efficient markets, which assume that the prices of the assets reflect all the information and offer no chance to misprice the assets because of systematic errors (Tompo, 2023).

Behavioral finance, on the other hand, views investors as not necessarily being rational and that they will make systematic mistakes in their judgments due to cognitive biases, emotions, and other psychological forces. Whereas traditional finance presumes that the market is at equilibrium, behavioral finance provides the reason why markets are volatile due to herd behavior, speculation, and irrational exuberance (Ahmad et al., 2025). Behavioral finance also accounts for anomalies, such as the momentum effect, where stocks that have performed well in the past continue to outperform, contradicting the random-walk hypothesis suggested by EMH. Unlike traditional models, behavioral finance acknowledges the limitations of human cognition and explores how biases distort investment decisions, leading to market inefficiencies. (Kamoune & Ibenrissoul, 2022).

2.3 Theoretical Framework: Prospect Theory, Heuristics, and Market Psychology

The theory of Prospect Theory demonstrates through empirical evidence that investors process gains differently from losses. The theory demonstrates that investors show greater sensitivity to losses than they do to equivalent gains, which results in loss aversion (Consigli et al., 2019). The bias makes investors maintain losing stocks for too long (disposition effect) and prevents them from taking necessary risks despite potential rewards exceeding potential losses. Behavioral finance includes heuristics as a fundamental principle, which describes psychological principles that help investors make rapid, complex financial choices (Bouteska & Regaieg, 2020). The use of heuristics provides benefits but produces systematic mistakes in most cases. Recent information influences investors through the availability heuristic, which leads them to overreact in stock price movements. The representativeness heuristic makes investors evaluate investment risks through historical patterns instead of actual probability measurements. Market psychology describes how group opinions between investors create financial market responses. The market trends are formed through collective investor behavior, which includes herding behavior combined with speculative bubbles and panic selling, along with groupthink and emotional contagion driving market trends (Jimao, 2024).

2.4 Cognitive Biases in Investment Decision-Making Overconfidence Bias

Investors develop overconfidence bias through their mistaken belief that they possess superior knowledge and abilities and make precise predictions (Karki et al., 2024). The bias causes investors to trade excessively because they think they can beat market returns, although research shows this is unlikely. The outcome of overconfidence leads to higher costs from trading activities while increasing financial risk, which commonly produces inferior returns for investor portfolios. Research demonstrates how investors who demonstrate overconfidence choose to disregard opposing information; at the same time, they maintain limited investments, which leads to greater potential losses when markets decline (Bouteska & Regaieg).

LOSS AVERSION

The core principle of Prospect Theory shows investors experience loss pain at a deeper level than they experience gain pleasure of equivalent value. Investors maintain losing investments beyond rational recommendations because they expect recovery instead of accepting early losses (Li, Zhou & Tan, 2022). The effect leads investors to practice risk-averse investment approaches by steering clear of essential risks that could generate better long-term returns. The disposition effect occurs because of loss aversion, which causes investors to sell profitable stocks hastily to capture gains but keep unprofitable stocks forever (Valls et al., 2022).

HERDING BEHAVIOR

Investors tend to imitate the decisions of the crowd instead of conducting their independent research, in herding behavior. A strong confirmation bias emerges in both market bubbles and market crashes because group psychology enhances assessment values that exceed true market worth (Merriman, 2020). The dot-com bubble, together with the 2008 financial crisis, developed from investors blindly following market sentiment rather than fundamental analysis, which caused them to purchase overpriced stocks and mortgage-backed securities. Market volatility intensifies when investors follow each other because this behavior produces irrational investment choices based on fear and greed (Anand et al., 2020).

ANCHORING BIAS

Investors develop anchoring bias because they depend too much on their first reference points (anchors) during financial decision-making. The practice of fixating on past stock prices becomes prominent in stock markets because investors fail to adjust their expectations despite acquiring new information. An investor who purchased stock at $100 will often maintain their belief in a $100 value after the stock price falls to $80, even though market fundamentals suggest additional decline (Malkiel, 2019). Decisions made by investors using anchoring bias become irrational because they fail to adjust their thinking according to market changes (Cagan, 2024).

2.5 Influence of Market Trends on Investor Psychology

Market trends create fundamental elements that determine investor psychology because sentiment-based financial choices influence decision-making more strongly than fundamental valuation figures do. Market trends create psychological effects through bull and bear markets because optimistic times lead investors to take risks, but market downturns make them sell their assets due to fear (Chatterjee & Nayyar, 2024). The market reacts strongly to media stories and economic statistics, and worldwide events because these factors drive investors to either panic or become too relaxed. Research in behavioral finance demonstrates investors use recent market trends excessively when they make choices, and this behavior results in variations between real analysis and their actual behavior (Padmavathy, 2024). The strategy of momentum investing preys on market behavior patterns by riding ongoing market trends, while the contrarian approach makes money from the overcorrected market perceptions by going against the direction of investor sentiment. Market participants need to understand psychological patterns because they create essential knowledge for developing investment strategies that address financial market emotional effects (Bhanu, 2023).

The implementation of behavioral finance knowledge enables investors and financial institutions, and policymakers to make better decisions using proper limits on irrational conduct to prevent market volatility from getting out of control.

3. METHODOLOGY

3.1 Research Design and Approach

This study adopts a quantitative, cross-sectional survey design to comprehensively examine the influence of cognitive biases, specifically overconfidence, loss aversion, herding, and anchoring, on investment decision-making. The quantitative component captures measurable patterns through structured survey instruments, while the qualitative component provides deeper interpretative insights via semi-structured interviews. By integrating these approaches, the study ensures a balanced analysis that is both statistically robust and contextually rich. A cross-sectional research design is employed, enabling data collection from participants at a single point in time, while allowing comparisons between retail and institutional investor groups. This design is especially appropriate to behavioral finance research, where subjective perceptions would be measured and can be contrasted between groups of investors.

3.2 Population and Sampling Strategy

The study targets two key investor groups, retail investors and institutional investors, across multiple global financial markets to ensure wide applicability. Retail investors include individuals participating in equity, bond, mutual fund, and cryptocurrency markets, selected to represent varying levels of experience, trading frequency, and portfolio size. Hedge fund managers, portfolio managers, analysts, and executives of investment firms are examples of institutional investors. Such groups are represented by a stratified sampling method to make the representation balanced. It does recruiting by way of a pro investor group, brokerage email lists, LinkedIn finance discussion forum boards, and financial literacy groups. To be included, the participants must possess a minimum of one year of active experience in investment, and to be excluded, a participant must lack direct decision-making responsibilities. The study would be projected to achieve the sampling of at least 500 survey participants who will provide sufficient statistical power to conduct subgroup analysis.

3.3 Measures

The cognitive biases that are taken into consideration in the study are evaluated using validated psychometric scales. Overconfidence, loss aversion, herding behavior, and anchoring are assessed by use of structured survey questions and situation-based tests, which are aimed at determining the frequency and degree of each in investing decision-making. The answers to each of the questions are provided on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), and the higher the score, the greater the rate of manifestation of the respective bias. The reliability is determined with the Cronbach's alpha, whereby an alpha value of 0.70 and above is acceptable in terms of internal consistency. The content validity is captured by reviewing it by behavioral finance scholars and those with experience in investments.

3.4 Data Collection Procedures

The quantitative data will be gathered by an online survey in Qualtrics, and the respondents will be provided with exclusive access links so that there will be no duplication. Included in the survey are demographic questions, items to measure bias, and investment behavior questions. Additionally, secondary market data, including historical stock prices, trading volumes, and investor sentiment indices, is collected from Bloomberg, Reuters, and Yahoo Finance APIs.

3.5 Data Analysis Techniques

Quantitative data is analyzed using SPSS. Descriptive statistics are employed to summarize demographic variables and the prevalence of cognitive biases across the sample. Multiple regression analysis is conducted to evaluate the predictive effect of cognitive biases on investment performance, with diagnostic tests performed to check for multicollinearity, normality, and heteroscedasticity. This focused analytical approach ensures clarity of interpretation while maintaining statistical rigor. The Performance Index (0–100) was computed as the mean of standardized (z-score) self-reported annualized return and risk- adjusted return. Where available, reported returns were validated using brokerage statements for a subsample of participants. Pearson correlation coefficients were computed to assess bivariate relationships between each cognitive bias and the Performance Index.

3.6 Ethical Considerations and Limitations

The study adheres to the ethical guidelines of the American Psychological Association (APA) and relevant financial research codes of conduct. All data is stored on encrypted servers, with participant identities anonymized before analysis. Limitations include potential self-report bias in survey responses, cultural variations affecting bias expression, and sentiment analysis constraints due to algorithmic filtering of online content. While the cross-sectional design limits causal inference, the integration of survey, interview, and market data enhances the study's validity and applicability.

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4. RESULTS

This section presents the empirical findings from the survey and secondary market data analysis. The results are reported in the order set out in the methodology, beginning with the demographic characteristics of the sample, followed by descriptive statistics for the cognitive biases, patterns in investment performance, correlation coefficients, and multiple regression outcomes. Tables and figures are used to clearly illustrate the patterns observed.

4.1 Demographic Profile of Respondents

The final dataset comprised 500 valid responses. Of these, 60% (n = 300) were retail investors and 40% (n = 200) were institutional investors. The demographic breakdown by investor type and years of investment experience is shown in Table 1, expressed in both absolute numbers and percentages.

The data reveal that the largest subgroup was retail investors with 1–3 years of experience (26.2% of the sample), followed by retail investors with 4–6 years of experience (18.6%), and retail investors with 7+ years of experience (13.8%). Among institutional investors, the most common category was 1–3 years of experience (16.6%), closely followed by those with 4–6 years (16.2%), and 7+ years (8.6%). This spread ensures that both early-career and seasoned investors are well represented in the sample, which supports the study's goal of capturing bias tendencies across varying levels of market familiarity.

Table 1. Demographic profile of respondents.

Investor Type	Experience	Count	Percentage (%)
Institutional	1–3 years	83	16.6
Institutional	4–6 years	81	16.2
Institutional	7+ years	43	8.6
Retail	1–3 years	131	26.2
Retail	4–6 years	93	18.6
Retail	7+ years	69	13.8

4.2 Descriptive Statistics of Cognitive Biases

Table 2 presents the descriptive statistics for overconfidence, loss aversion, herding, and anchoring. Among these, loss aversion emerged with the highest overall mean score (M = 3.50, SD = 0.60), indicating that a general tendency toward avoiding losses was common across respondents. Overconfidence and anchoring followed closely, with means of 3.20 (SD = 0.70) and 3.10 (SD = 0.70), respectively, suggesting moderate prevalence. Herding recorded the lowest mean score (M = 3.00), but it had the widest variability (SD = 0.80), which implies greater differences among participants in susceptibility to following collective market movements.

Table 2. Descriptive statistics of cognitive biases.

Bias	**Mean**	**Std. Dev.**	**Min**	**Max**
Overconfidence	3.20	0.70	1.31	5.00
Loss Aversion	3.54	0.60	1.76	5.00
Herding	3.06	0.78	1.00	5.00
Anchoring	3.10	0.68	1.00	5.00

Figure 1 displays the mean bias scores by investor type. Retail investors demonstrated slightly higher average overconfidence (M = 3.25) and herding (M = 3.05) scores, while institutional investors scored marginally higher on anchoring (M = 3.15). Loss aversion scores were consistently high across both groups (Retail: M = 3.48; Institutional: M = 3.52), reflecting their broad prevalence regardless of investment category.

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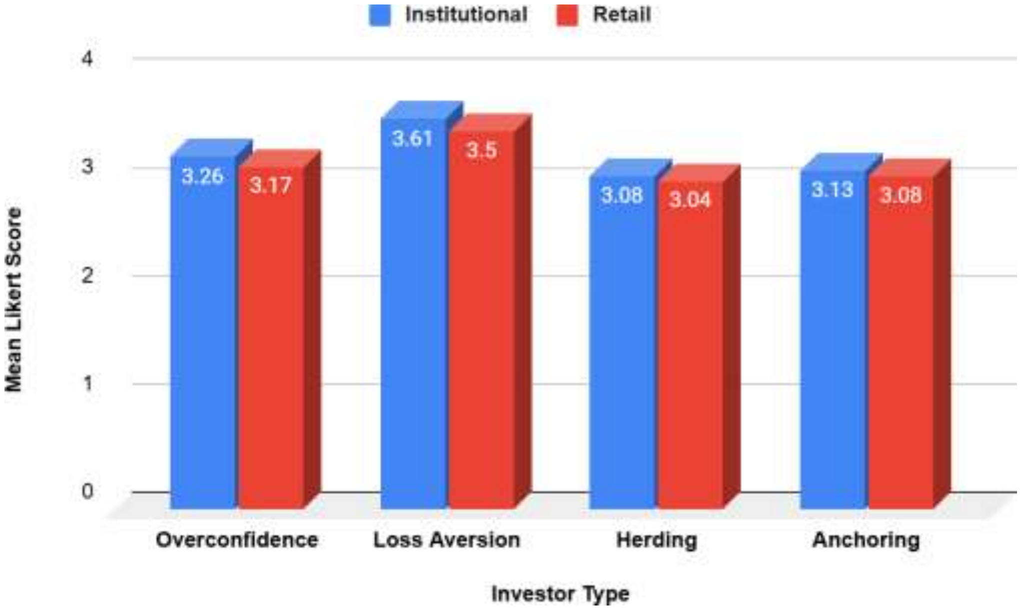

Figure 1: Average Cognitive Bias Scores by Investor Type.

4.3 Investment Performance by Investor Type

The performance index, ranging from 0 to 100, integrates both survey responses and supplementary market data. The overall mean performance score for the sample was 63.25 (SD = 5.36). Institutional investors achieved a mean performance score of 63.43 (SD = 5.27) compared to retail investors (M = 63.12, SD = 5.43).

As depicted in Figure 2, institutional investors' scores clustered more tightly around the median, suggesting more consistent performance outcomes. Retail investors displayed greater variability, with scores more widely dispersed and a larger proportion of low-end outliers. This difference in dispersion reflects the broader range of investment strategies, experience levels, and potentially risk-taking behaviors within the retail investor group.

Figure 2: Mean Investment Performance by Investor Type.

4.4 Correlation Analysis

Pearson correlation coefficients were calculated to explore the relationships between each cognitive bias and investment performance. The correlation matrix in Figure 3 shows that overconfidence was positively correlated with performance ($r = 0.28$), indicating that higher overconfidence scores were generally associated with better performance outcomes. Loss aversion exhibited a negative correlation ($r = -0.19$), suggesting that higher loss

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aversion corresponded to lower performance scores. Herding was positively correlated ($r = 0.19$), while anchoring showed a weak negative correlation ($r = -0.09$). These coefficients quantify the strength and direction of the associations without implying causality.

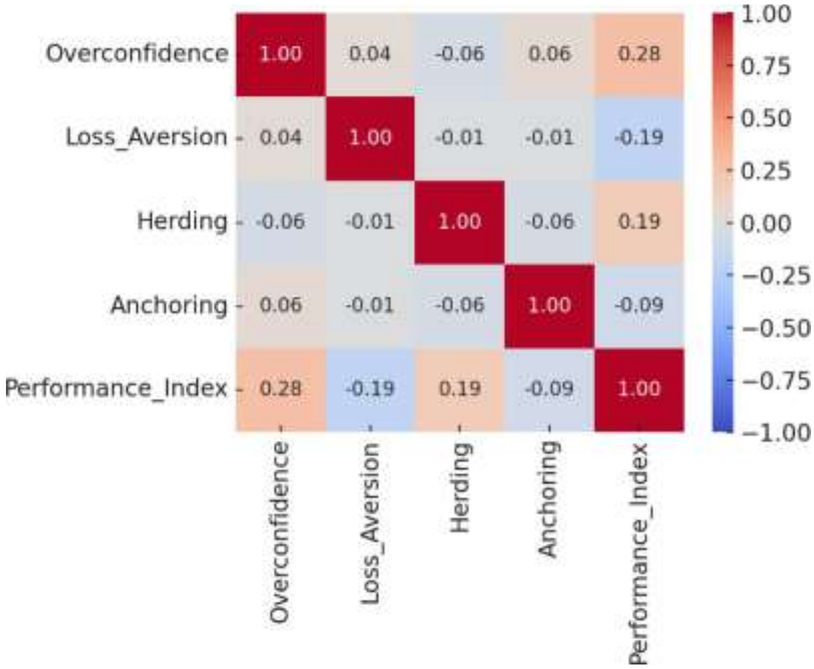

Figure 3: Correlation Matrix of Cognitive Biases and Investment Performance.

4.5 Regression Analysis

A multiple regression model was constructed to examine the combined predictive power of the four cognitive biases on investment performance. The model was statistically significant (F- test, $p < 0.001$) and accounted for 38.7% of the variance in performance ($R^2 = 0.387$).

As summarized in Table 3, overconfidence emerged as the strongest positive predictor ($\beta = 2.014$, $p < 0.001$), while loss aversion was a significant negative predictor ($\beta = -1.503$, $p < 0.001$). Herding showed a smaller yet statistically significant positive effect ($\beta = 1.183$, $p = 0.012$). Anchoring had a negative coefficient but did not reach statistical significance ($p = 0.084$). These results indicate that, collectively, the measured cognitive biases provide substantial explanatory power in understanding variations in investment performance.

Table 3. Multiple regression analysis predicting investment performance ($R^2 = 0.387$).

Variable	Coefficient (β)	Std. Error	p-value
Constant	60.245	1.034	0.000
Overconfidence	2.014	0.285	0.000
Loss Aversion	−1.503	0.312	0.000
Herding	1.183	0.468	0.012
Anchoring	−0.522	0.303	0.084

5. DISCUSSION

The findings highlight the distinct roles that overconfidence, loss aversion, herding, and anchoring play in shaping investment performance among retail and institutional investors. Regression and correlation analyses show these biases influence outcomes in varying magnitudes and directions, with effects dependent on market conditions and investor type.

Overconfidence was the strongest positive predictor of performance ($\beta = 2.014$, $p < 0.001$; $r = 0.28$), indicating that higher confidence tended to be associated with better results. This supports Seraj et al. (2022) and Karki et al. (2024), who note that moderate overconfidence can improve decision-making speed, encourage profitable risk-taking, and enhance the pursuit of high-return opportunities. While Bouteska and Regaieg (2020) warn that

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excessive overconfidence may lead to overtrading and underperformance, our more favorable result may stem from the higher share of experienced institutional investors in the sample, who channel confidence through disciplined strategies and robust risk management.

Loss aversion had a significant negative relationship with performance ($\beta = -1.503$, $p < 0.001$; $r = -0.19$), reflecting the well-established finding that excessive sensitivity to losses can hinder investment outcomes. This aligns with Prospect Theory (Consigli et al., 2019) and findings by Li et al. (2022) and Valls et al. (2022), showing that loss-averse investors often retain underperforming assets too long or avoid profitable risks. Like Bihari et al. (2025), our findings indicate that such bias is detrimental to the best strategy, particularly in a volatile environment, because the fear of losses drives people into positions that are too conservative.

Herding behavior had a small, but significant positive influence (beta = 1.183, $p = 0.012$; $r = 0.19$). Following the market trends can be profitable in certain conditions because of the momentum effect or the informational strength of the whole market. This is partially in line with Merriman (2020), who concluded that informed herding can be profitable, but is in contrast with Anand et al. (2020), who suggest the possibility of destabilizing effects during a bubble or a crash. The moderate positive correlation in this case could be because there were good market conditions at the time the data was collected, and this enabled trend-following to be profitable but not yet distorting.

The negative relationship between the anchoring bias and the performance was not significant ($\beta = -0.522$, $p = 0.084$; $r = -0.09$), as other researchers claim (Malkiel, 2019; Cagan, 2024) when they argue that anchoring on reference points can hinder adaptive choices. The fact that it has little impact on our outcomes can imply that the institutional actors will employ methodical approaches such as rule-based rebalancing plans or periodic portfolio review in order to overcome this influence. Anchoring may have also been watered down by the variety of assets in portfolios.

The institutional investors were a bit higher than retail investors and more stable and less variable. This is in line with Nardi et al. (2022) and Gabhane et al. (2023) who give institutional advantages to better information, tools, and formal decision-making. The increased performance dispersion of retail investors is associated with variations in experience, literacy, and tendency to bias, which further supports the argument by Rahman and Mehnaz (2024), that financial education and interventions providing decision support should be targeted.

Such findings support the claim of behavioral finance against the conventional premises of fully rational investors (Ying et al., 2019; Ahmad et al., 2025). The interaction of the multiple biases proves that behavior is not affected by individual distortions, but a blend of heuristics and emotional propensities. The research fills in the gap suggested by Gabhane et al. (2023) by simultaneously comparing the biases between types of investors, and backs Kamoune and Ibenrissoul (2022) in emphasizing that the knowledge of biases is key to enhancing market efficiency.

In practice, retail investors might be helped by interventions that will mitigate loss aversion and curb overconfidence. They can identify and correct the biased errors through decision frameworks, feedback mechanisms and through scenario-based training. In the case of institutional investors, the risk of herding and anchoring should also be watched; herding may create some immediate profit but also increases the systemic risk to which diversification protection is necessary under exuberant markets.

The cognitive biases do not inherently have any bad or good outcomes as to their effects they rely on the context, market stage and the profile of investors. Such a subtle insight can be fed into investor behavior, institutional policy, and regulation design and eventually serve market resilience and efficiency. The follow-up on bias interactions over time should be considered as the next step, and the mitigation strategies should be tested within the real investment environments.

6. CONCLUSION

The study presents strong support to the finding that the cognitive bias, overconfidence, loss aversion, herding, and anchoring, play an important role in the investment decision-making and performance in retail and institutional investor categories, although, the study has both theoretical and practical implications on behavioral finance. The empirical results showed that overconfidence was the most positive predictor of performance especially by institutional investors who seem to apply it positively by taking risks through disciplined risk management, whereas loss aversion had the most negative impact by inhibiting risk-taking and limiting returns.

Herding was found to be modestly positively correlated, i.e. it can bring short-term profits under favourable conditions, yet it still can cause systemic vulnerability. The weak and statistically insignificant anchoring in this sample is still applicable in situations where hard reference points create adaptability problems. Such results support the criticism of behavioral finance on the assumptions of rationality in classic models and the relevance of focusing on the interaction of biases instead of focusing on the independent effect of each of them. Practically, personalised interventions, e.g. scenario-based decision-training to retail investors to alleviate loss aversion, diversification safeguards to institutions to curb herding, can be used to make investment outcomes and market stability more constructive. Also, the circumstance that such biases are cross-sectional across the groups of investors leads to the question of whether regulatory frameworks and financial literacy programs need to be more interconnected and include specific direct references to psychological variables that affect judgments. This study helps in the development of the theory of behavioral finance and emphasizes the idea that bias mitigation practices should be implemented on a case-by-case basis by establishing the foundation to further longitudinal studies that could examine the dynamic interrelations of bias under different market environments.

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