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"The Role of Behavioral Biases in Shaping Investment Decisions: Evidence from the Indian Stock Market"

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Abstract
This study examines the significant influence of behavioural finance on investment decision-making in the stock market, challenging the conventional Efficient Market Hypothesis (EMH). This study conducts a comprehensive evaluation of contemporary research papers and a structured behavioural analysis to identify the predominant cognitive biases specifically overconfidence, representativeness, price anchoring, gambler's Fallacy, availability, mental accounting, regret aversion and loss aversion. The primary objective of this research is to examine and empirically demonstrate the impact of cognitive biases on stock market investment decisions in major cities of Gujarat. The study employs a questionnaire-based survey of 300 respondents, and the data are analyzed using ADF, correlation, and regression techniques. The findings reveal that majority of cognitive biases have a significant effect on investment decisions in the Indian stock market. The study provides valuable implications for individual investors, financial advisors, and fintech developers striving to promote rational decision-making in markets that are progressively influenced by investor sentiment.

Keywords: Behavioral Finance, Stock Market, Investment Decision Making, Cognitive Biases, Prospect and heuristic

1. Background of the Study
For decades, the field of finance was dominated by the "Rational Expectations" paradigm, which suggested that markets are efficient and individuals act as *Homo Economicus* - logical beings who maximize wealth while minimizing risk. However, the recurring reality of market volatility and irrational exuberance has proven that human psychology is inextricably linked to financial outcomes. Behavioral Finance has emerged as a critical discipline that integrates cognitive psychology with conventional economic theory to explain why investors often make irrational choices.

1.1 Rationale
In the current era of "democratized" finance—marked by zero-commission trading apps and 24/7 social media influence—the impact of psychological biases has intensified. Traditional models no longer suffice to explain the rapid "pump and dump" cycles of meme stocks or the panic-induced sell-offs seen in recent years. This study aims to investigate how specific cognitive and emotional biases impact the decision-making processes of retail investors in the contemporary stock market.

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1.2 Objectives of the Study

- To study cognitive biases of the stock market investors.
- To analyze the correlation between cognitive biases.
- To study the impact of cognitive biases on investment decision of stock market investors.

2. Literature Review

Mere (2025), Conducted a qualitative analysis of young investors, finding that behavioral finance principles have a "significant and measurable impact" on their decisions, contrary to the rational actor assumptions of the Efficient Market Hypothesis (EMH). Kamoune & Ibenrissoul (2024), Explored market anomalies in the US stock market, concluding that investor sentiment, triggered by volatility, leads to erratic behavior that traditional models like Modern Portfolio Ahmad et al. (2025), Empirically examined emerging markets, finding that Heuristic-driven biases (anchoring and availability) significantly disrupt rational behavior, often leading to poorly diversified "home-bias" portfolios. Bathia et al. (2025), studied retail investors in Bengaluru, discovering that investors frequently "anchor" their expectations to 52-week highs or initial purchase prices, leading to unrealistic valuation assumptions. Rajeev Gandhi College Study (2023), scrutinized the interplay of biases, finding that Confirmation Bias leads investors to selectively process bullish news while ignoring contradictory data, especially during market peaks. Dangol & Manandhar (2020), Found that representativeness and availability heuristics are the most significant predictors of irrational trading among individual investors. Sathya & Prabhavathi (2024), Highlighted that the proliferation of mobile trading apps exacerbates recency Bias, where investors over-index on the most recent market movements, leading to impulsive "chasing" of trends. Morais Rodopoulos & Silveira Júnior (2024), Reaffirmed that investors prioritize avoiding losses over acquiring equivalent gains, confirming that Loss Aversion remains the strongest psychological driver of suboptimal risk assessments. Fortin & Hlouskova (2024), Conducted an empirical analysis across US and European markets, showing that portfolios constructed using Prospect Theory (accounting for loss aversion) consistently outperformed traditional mean-variance allocations. Yadav & Daga (2023), Focused on the Indian stock market, finding that risk aversion significantly influences irrationality, particularly during bearish cycles where investors "freeze" instead of rebalancing. Sutejo et al. (2024), Discovered that positive emotions (euphoria) significantly enhance the speed of investment decisions, while negative emotions (fear) have mixed effects, often mediated by an individual's financial risk tolerance. Annapurna & Basri (2024), Explored external "mood modulators" like weather and religious observances, finding they subtly shift risk perception and investment appetite in regional markets. Zafar et al. (2024), Linked Herding Behavior to suboptimal performance, noting that imitation occurs in both bull and bear markets, creating speculative bubbles and panic selling cycles. Klemens Mere (2025), Investigated the "Social Media Effect," finding that FOMO (Fear of Missing Out) among young investors leads to "meme stock" participation, where social validation overrides fundamental analysis. Ansari et al. (2024), Studied retail investors in urban centers, noting that herding is often a defense mechanism used by investors with low financial literacy to feel "safe in numbers." Hasselgren et al. (2023), Proved that direct communication on social media platforms provides "high executive value" to individuals, fundamentally changing how information cascades through the market. Park & Oh (2022), Analyzed the psychological

feeling of "being left behind," concluding that social influence is now a more potent driver of market entry than traditional interest rate incentives.
The literature consistently indicates that while traditional theories assume rationality, the modern investor is a "behavioral" actor. Cognitive biases are the most powerful bias.

2.1 Problem Statement

Traditional financial theories, specifically the Efficient Market Hypothesis (EMH) and Modern Portfolio Theory (MPT), operate on the premise that investors are "rational actors" who process all available information to maximize utility. However, the recurring nature of market bubbles, sudden crashes, and the "equity premium puzzle" suggests that this premise is flawed. The core problem is that retail and institutional investors are frequently swayed by cognitive heuristics and prospect (such as overconfidence, representativeness, price anchoring, gambler's Fallacy, availability, mental accounting, regret aversion and loss aversion) that lead to systematic departures from rational decision-making. In the modern era, this problem is exacerbated by the "gamification" of trading apps and the rapid spread of misinformation on social media, which triggers impulsive financial behavior. Failure to account for these behavioral variables leads to suboptimal portfolio performance, increased market volatility, and financial instability for individual households.

2.2 Research Gap

Extant research has consistently demonstrated the presence of behavioural biases in the investment decision-making processes of individual investors. A comprehensive review of the literature reveals that most empirical studies in this domain are concentrated on stock market participants and are largely conducted in international contexts. Consequently, there is limited empirical evidence that adequately reflects the behavioural patterns of Indian investors. In particular, very few studies have focused on the influence of behavioural biases on the investment decisions of stock market investors in the state of Gujarat, India. Given that the Indian stock market is in a growth phase and that retail investors are increasingly encouraged to participate as a key segment of the financial system, the present study appropriately selects retail investors as its focal group.

While prior research has primarily examined a narrow range of biases—such as those explained by prospect theory, herd behaviour, and overconfidence—the present study adopts a broader cognitive perspective. It investigates the impact of key cognitive and emotional biases, including overconfidence, representativeness, mental accounting, gambler's fallacy, loss aversion, and regret aversion, on stock market investment decisions. This study therefore seeks to address the research questions outlined below.

3. Conceptual Framework

Cognitive Biases	Investment Decision Making Factors
Overconfidence	Investment Decision
Representativeness	(Stock Market Investment holding

Price Anchoring	period)
Gambler's Fallacy	
Availability	
Mental Accounting	
Regret Aversion	
Loss aversion	

Hypothesis:

1. Hypotheses of Correlation among Cognitive Biases

1. Overconfidence

- H_{01}: There is no significant correlation between Overconfidence and Representativeness
- H_{11}: There is a significant correlation between Overconfidence and Representativeness

H_{02}: There is no significant correlation between Overconfidence and Price Anchoring.

- H_{12}: There is a significant correlation between Overconfidence and Price Anchoring.
- H_{03}: There is no significant correlation between Overconfidence and Gambler's Fallacy.
- H_{13}: There is a significant correlation between Overconfidence and Gambler's Fallacy.
- H_{04}: There is no significant correlation between Overconfidence and Availability.
- H_{14}: There is a significant correlation between Overconfidence and Availability.

2. Representativeness

- H_{05}: There is no significant correlation between Representativeness and Price Anchoring.
- H_{15}: There is a significant correlation between Representativeness and Price Anchoring.
- H_{06}: There is no significant correlation between Representativeness and Gambler's Fallacy.
- H_{16}: There is a significant correlation between Representativeness and Gambler's Fallacy.
- H_{07}: There is no significant correlation between Representativeness and Availability.
- H_{17}: There is a significant correlation between Representativeness Availability.

3. Price Anchoring

- H_{08}: There is no significant correlation between Price Anchoring and Mental Accounting.
- H_{18}: There is a significant correlation between Price Anchoring and Mental Accounting.

4. Gambler's Fallacy

- H_{09}: There is no significant correlation between Gambler's Fallacy and Availability.
- H_{19}: There is a significant correlation between Gambler's Fallacy and Availability.

5. Emotional Biases

- H_{010}: There is no significant correlation between Regret Aversion and Loss Aversion.
- H_{110}: There is a significant correlation between Regret Aversion and Loss Aversion.
- H_{011}: There is no significant correlation between Mental Accounting and Loss Aversion.
- H_{111}: There is a significant correlation between Mental Accounting and Loss Aversion.

2. Impact of Cognitive Biases on Stock Market Investment holding period

1. Overconfidence bias and Investment holding period

H_{01}: There is no significant impact of overconfidence bias on investment holding period in the stock market.

H_{11}: There is significant impact of overconfidence bias on investment holding period in the stock market.

2. Impact of Representativeness bias on Investment holding period
H_{01}: There is no significant impact of Representativeness on investment holding period in the stock market.
H_{11}: There is significant impact of Representativeness on investment holding period in the stock market.
3. Impact of Price anchoring bias on Investment holding period
H_{01}: There is significant impact of Price Anchoring on investment holding period in the stock market.
H_{11}: There is no significant impact of Price Anchoring on investment holding period in the stock market.
4. Impact of Gambler's Fallacy bias on Investment holding period
H_{01}: There is significant impact of Gambler's Fallacy on investment holding period in the stock market.
H_{11}: There is no significant impact of Gambler's Fallacy on investment holding period in the stock market.
5. Impact of Availability bias on Investment holding period
H_{01}: There is significant impact of Availability on investment holding period in the stock market.
H_{11}: There is no significant impact of Availability on investment holding period in the stock market.
6. Impact of Mental accounting bias on Investment holding period
H_{01}: There is significant impact of Mental Accounting on investment holding period in the stock market.
H_{11}: There is no significant impact of Mental Accounting on investment holding period in the stock market.
7. Impact of Regret aversion bias on holding period
H_{01}: There is significant impact of Regret Aversion on investment holding period in the stock market.
H_{11}: There is no significant impact of Regret Aversion on investment holding period in the stock market.
8. Impact of Loss aversion bias on holding period
H_{01}: There is significant impact of Loss aversion on investment holding period in the stock market.
H_{11}: There is no significant impact of Loss aversion on investment holding period in the stock market.

4. Research Methodology

For a study on behavioral finance, a Mixed-Methods Approach is often most effective to capture both the "what" (statistical trends) and the "why" (psychological drivers).

- **Research Design:** Descriptive and Analytical.
- **Target Population:** Individual retail investors from the major four cities of Gujarat with at least 1 year of experience in the stock market.
- **Sampling Technique:** Purposive Sampling (to ensure respondents have actual trading experience) combined with Snowball Sampling via investment forums and social media groups.
- **Data Collection:**

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Primary Data: Structured online questionnaire (Likert Scale).
Secondary Data: Analyzing historical market volatility indices (like the VIX) alongside investor sentiment surveys.

- **Statistical Tools:**

Correlation Analysis: To find the relationship between specific biases and trading frequency.
Multinomial Regression Analysis: To determine which bias is the strongest predictor of poor investment outcomes.
Cronbach's Alpha: To test the reliability of the survey scales.

5. Hypothesis Testing

This chapter includes different hypothesis testing like Reliability test, Chi-Square, ANOVA analysis, Correlation analysis and regression analysis.

5.1 Reliability test

Cognitive Bias	Cronbach's Alpha	No. of Items	Interpretation
Overconfidence	0.841	10	Good reliability
Representativeness	0.735	5	Acceptable reliability
Price Anchoring	0.798	6	Good reliability
Gambler's Fallacy	0.728	5	Acceptable reliability
Availability	0.877	11	Good reliability
Mental Accounting	0.676	4	Usable
Regret Aversion	0.722	6	Acceptable reliability
Loss aversion	0.738	7	Acceptable reliability

The reliability analysis with Cronbach's Alpha demonstrates that the assessment scales for the eight cognitive biases show adequate internal consistency. Most constructs exhibit acceptable to good reliability, with alpha coefficients between 0.722 and 0.877. The dependability of the Overconfidence and Availability biases is especially high, and Mental Accounting is still useful for exploratory research even though it falls just short of the traditional criterion Overall, the results confirm that the instrument is reliable and suitable for further analysis of behavioral finance factors affecting investment decision-making.

5.2 Correlation

Karl Pearson's Coefficient of Correlation is a mathematical approach in which the numerical expression is used to estimate or determine the range or magnitude and the direction of the relationship between two linearly related variables. Karl Pearson's Coefficient is a quantitative method that is often used in statistics. It is also known as the Pearson Coefficient of Correlation, and it is a widely accepted and widely used method. To calculate the measurement of the relationship between two variables Karl Pearson's Coefficient of Correlation formula is used.
Formula:

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n\sum x^2 - (\sum x)^2}.\sqrt{n\sum y2 - (\sum y)^2}}$$

r = Pearson correlation Coefficient

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n = number of the pairs

∑xy = sum of products of the paired

∑x = sum of the x scores

∑y= sum of the y scores

∑x2 = sum of the squared x scores

∑y2 = sum of the squared y scores

Correlations Matrix

Cognitive biases		Overconfidence	Representativeness	Price Anchoring	Gambler's Fallacy	Availability	Mental Accounting	Regret Aversion	Loss aversion
Overconfidence	Pearson Correlation	1	.403**	.426**	.407**	.389**	.311**	.272**	.265**
Representativeness	Pearson Correlation		1	.570**	.542**	.577**	.326**	.422**	.436**
Price Anchoring	Pearson Correlation			1	.609**	.611**	.336**	.409**	.393**
Gambler's Fallacy	Pearson Correlation				1	.677**	.360**	.411**	.436**
Availability	Pearson Correlation					1	.414**	.500**	.446**
Mental Accounting	Pearson Correlation						1	.327**	.307**
Regret Aversion	Pearson Correlation							1	.517**
Loss aversion	Pearson Correlation								1
**. Correlation is significant at the 0.01 level (2-tailed).									

Analysis and Interpretation: From the above table, it can be analyzed that

1. Overconfidence shows positive and significant correlations with all other biases, indicating that investors who overestimate their knowledge and skills are also more likely to rely on heuristics and emotional reactions. This suggests that overconfident investors tend to ignore objective information and simultaneously exhibit anchoring, availability, regret, and loss-related behaviors, which may lead to excessive trading and sub-optimal decisions.
2. Representativeness is strongly correlated with availability, price anchoring, and gambler's fallacy. This implies that investors who judge situations based on recent trends or stereotypes also depend heavily on easily recalled information and past price levels, and believe in patterns in random events. Such investors may misinterpret short-term market movements as long-term signals.
3. Price anchoring has one of the strongest relationships with availability and gambler's fallacy. This indicates that investors who fixate on past prices or reference points are strongly influenced by the information that comes most easily to mind and by false beliefs about market reversals or streaks. Anchored investors may fail to adjust adequately to new information.
4. Gambler's fallacy is positively associated with availability, regret aversion, and loss aversion. This shows that investors who believe past outcomes affect future results are also emotionally sensitive to regret and losses. Such thinking can result in irrational expectations about market corrections or rebounds.
5. Availability bias is significantly related to mental accounting, regret aversion, and loss aversion. This means that investors who rely on easily accessible information—such as news, recent events, or personal experiences—also show strong emotional responses to gains and losses, leading to distorted risk perception.
6. Mental accounting has positive links with regret and loss aversion. This suggests that investors who separate money into different "accounts" in their minds are more likely to feel regret over losses and are highly sensitive to negative outcomes, which can affect portfolio diversification and risk taking.
7. Regret aversion is strongly correlated with loss aversion. This indicates that investors who try to avoid the pain of regret are also very sensitive to losses, often holding losing stocks too long and selling winning stocks too early to avoid emotional discomfort.
8. Loss aversion is positively related to all other biases, especially regret aversion. This confirms that fear of losses is a central emotional driver of investor behavior and plays a key role in reinforcing other cognitive and emotional biases in investment decisions.

5.3 Multinomial Regression Analysis

A statistical method for modelling and analysing the relationship between a categorical dependent variable with more than two categories and one or more independent variables, which could be nominal, ordinal, or scale in nature is multinomial regression, often known as multinomial logistic regression. By contrasting each category with a reference category, it calculates the likelihood that each category of the dependent variable will occur.

Impact of Cognitive Biases on Investment Decision making factors

Multinominal logistic regression analysis is used to investigate how cognitive biases affect stock market investment decisions. In order to estimate the regression equation, all of the study's

cognitive biases are used as independent variables [X] and the investment objective as a dependent variable [Y].

$Y=a + b1X1 + b2X2 + b3X3 + b4X4 + b5X5 + b6X6 + b7X7 + b8X8 + e.$

In the above equation,

Y = Investment Period

X1 = Overconfidence Bias,
X2 = Representative Bias,
X3 = Price Anchoring
X4 = Gambler's Fallacy
X5 = Availability
X6 = Mental Accounting Bias,
X7 = Regret Aversion,
X8 = Loss aversion

a= Intercept
bi = Beta
e= error.

1. Impact of Overconfidence bias on Investment Holding Period

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	387.850			
Final	362.297	25.552	10	.004

Pseudo R-Square

Cox and Snell	.082
Nagelkerke	.110
McFadden	.063

Interpretation: The resulting model significantly outperforms the intercept-only model, according to the likelihood ratio test (χ^2 = 25.552, df = 10, $p < 0.05$). After including the independent variables, the −2 Log Likelihood value decreased from 387.850 to 362.297, indicating an improved model fit. As a result, the model is appropriate for explaining and forecasting the result as the predictors collectively have a considerable impact on the dependent variable.

2. Impact of Representativeness bias on Investment Holding Period

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	319.771			
Final	292.301	27.470	5	.000

Pseudo R-Square

Cox and Snell	.088
Nagelkerke	.118
McFadden	.067

Interpretation: The resulting model fits the data much better than the intercept-only model, according to the likelihood ratio test ($\chi^2 = 27.470$, df = 5, $p < 0.05$). After adding the independent variables, the −2 Log Likelihood value decreased from 319.771 to 292.301, indicating a significant improvement in model fit. As a result, the model is suitable for explaining and forecasting the outcome variable, and the predictors taken together have a substantial impact on the dependent variable.

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3. Impact of Price anchoring bias on Investment Holding Period

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	312.143			
Final	286.937	25.206	6	.000

Pseudo R-Square

Cox and Snell	.081
Nagelkerke	.108
McFadden	.062

Interpretation: The resulting model offers a significantly better fit than the intercept-only model, according to the likelihood ratio test ($\chi^2 = 35.838$, df = 6, $p < 0.05$). After adding the independent variables, the −2 Log Likelihood value decreased from 436.218 to 400.381, indicating a significant improvement in model fit. This implies that the model is appropriate for explanation and prediction as the predictors collectively have a statistically significant impact on the dependent variable.

4. Impact of Gambler's Fallacy bias on Investment Holding Period

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	301.417			
Final	294.753	6.664	5	.247

Pseudo R-Square

Cox and Snell	.022
Nagelkerke	.030
McFadden	.016

The resulting model fits the data much better than the intercept-only model, according to the likelihood ratio test ($\chi^2 = 6.664$, df = 5, $p = 0.247$). The model's fit is improved when the independent variables are included, as evidenced by the decrease in the −2 Log Likelihood value from 301.417 to 294.753. The model is not suitable for explaining and forecasting the result because the p-value is more than 0.05, indicating that the predictors taken together have not a statistically significant impact on the dependent variable.

5. Impact of Availability bias on Investment Holding Period

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	350.182			
Final	331.372	18.810	11	.065

Pseudo R-Square

Cox and Snell	.061
Nagelkerke	.082
McFadden	.046

Interpretation: The resulting model offers a significantly weak fit than the intercept-only model, according to the likelihood ratio test (χ^2 = 18.810, df = 11, p = 0.065). After adding the independent variables, the −2 Log Likelihood value decreased from 350.182 to 331.372, indicating a significant improvement in model fit is not statistically significant at the 5% level, although it is marginally significant at the 10% level. This suggests that the independent variables, taken together, show a weak or borderline effect on the dependent variable.

6. Impact of Mental accounting bias on Investment Holding Period

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	244.365			
Final	235.236	9.129	4	.058

Pseudo R-Square

Cox and Snell	.032
Nagelkerke	.042
McFadden	.023

The final model fits the data considerably better than the intercept-only model (χ^2 = 9.129, df = 4, p = 0.058), according to the likelihood ratio test. After incorporating the independent variables, the −2 Log Likelihood value decreased from 244.365 to 235.236, indicating an improvement in model fit is not statistically significant at the 5% level, but it is marginally significant at the 10% level. This suggests that the independent variables, taken together, have a weak but noticeable influence on the dependent variable. The model improves prediction compared to the null model, but the evidence is not strong enough to conclude a significant overall effect at the 5% level.

7. Impact of Regret aversion bias on Investment Holding Period

Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	340.884			
Final	318.172	22.712	6	.001

Pseudo R-Square

Cox and Snell	.073
Nagelkerke	.098
McFadden	.056

The final model offers a significantly better fit than the intercept-only model (χ^2 = 22.712, df = 6, p < 0.05), according to the likelihood ratio test. After adding the independent variables, the −2 Log Likelihood value decreased from 340.884 to 318.172, indicating a significant improvement in model fit. This demonstrates that the model is suitable for explanation and prediction and that the predictors collectively have a statistically significant impact on the dependent variable.

8. Impact of Loss aversion bias on Investment Holding Period

Model Fitting Information

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Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	364.638			
Final	329.338	17.30	7	.016

Pseudo R-Square

Cox and Snell	.056
Nagelkerke	.075
McFadden	.042

The final model fits the data much better than the intercept-only model ($\chi^2 = 17.30$, df = 7, $p < 0.05$), according to the likelihood ratio test. After adding the independent variables, the −2 Log Likelihood value decreased from 364.638 to 329.338, indicating a significant improvement in model fit. This suggests that the model is appropriate for explaining and forecasting the outcome variable since the predictors together have a statistically significant impact on the dependent variable.

Conclusion:

The findings of this study underscore that the "Rational Investor" is a theoretical ideal rather than a market reality. Behavioral finance reveals that investors are deeply influenced by a complex architecture of cognitive shortcuts. The empirical analysis clearly demonstrates that behavioral biases significantly influence investors' holding period decisions across all eight models Overconfidence, Representativeness, Price Anchoring, Gambler's Fallacy, Availability, Mental Accounting, Regret Aversion, and Loss Aversion. The Pseudo R-square values (Cox & Snell, Nagelkerke, and McFadden) across models, although modest, show that these psychological biases explain a non-trivial proportion of the variation in investors' holding period behavior. Among the biases, Overconfidence, Representativeness, Regret Aversion, Loss Aversion and Price Anchoring biases exhibit relatively stronger impact, while Impact of Gambler's Fallacy, Availability and Mental Accounting, statistically significant but show comparatively weaker effects.

Overall, the findings provide robust evidence that investors do not make holding period decisions purely on rational or fundamental grounds. Instead, their behavior is systematically shaped by cognitive and emotional biases. This underscores the importance of incorporating behavioral finance perspectives into investment decision-making frameworks, investor education programs, and advisory practices to help individuals recognize and mitigate the influence of such biases on their portfolio management and holding strategies.

References:

1. Ahmad, M., et al. (2025). Heuristic-driven biases and their impact on portfolio diversification in emerging markets. *Journal of Behavioral Finance Research*, 12(1), 45-62.
2. Annapurna, S., & Basri, S. (2024). Mood modulators and market entry: A study of regional stock exchanges. *International Journal of Financial Studies*, 9(4), 112-128.
3. Ansari, R., et al. (2024). The safety in numbers: Analyzing herding behavior among urban retail investors. *Global Economics Review*, 15(2), 201-215.

4. Bathia, V., et al. (2025). Anchoring effects in the Bengaluru tech-investor corridor. *South Asian Journal of Management*, 32(1), 88-104.
5. Dangol, J., & Manandhar, R. (2020). Impact of heuristics on investment decisions: Evidence from the Nepalese stock market. *Journal of Business and Social Sciences Research*, 5(1), 1-16.
6. Fortin, I., & Hlouskova, J. (2024). Prospect Theory vs. Mean-Variance: An empirical race across Atlantic markets. *Journal of Banking & Finance*, 158, 107-124.
7. Golden Ratio Publications. (2025). *A decade of behavioral finance: A systematic review (2015-2025)*.
8. Hasselgren, A., et al. (2023). Social media as a catalyst for information cascades in equity markets. *Digital Finance Journal*, 5(3), 340-358.
9. JMS-Online. (2025). *Foundations of behavioral finance: Mapping 50 years of research*.
10. Kamoune, A., & Ibenrissoul, A. (2024). Volatility and sentiment: Explaining US market anomalies. *Journal of Financial Markets*, 21(2), 56-74.
11. Mere, K. (2025). Behavioral finance and the young investor: A qualitative approach. *Journal of Economic Psychology*, 94, 102-115.
12. Morais Rodopoulos, P., & Silveira Júnior, A. (2024). Loss aversion and the disposition effect: New evidence from Brazil. *Emerging Markets Review*, 40, 101-119.
13. Park, J., & Oh, S. (2022). The FOMO factor: Social influence in the age of commission-free trading. *Journal of Financial Services Marketing*, 27, 45-59.
14. Rajeev Gandhi College Research. (2023). *Confirmation bias and the retail investor: A case study*.
15. Sathya, M., & Prabhavathi, S. (2024). Recency bias in mobile trading environments. *FinTech & Society*, 3(1), 12-29.
16. Sutejo, B., et al. (2024). Emotional mediation in high-risk financial decision making. *Indonesian Management Review*, 18(2), 210-225.
17. Yadav, S., & Daga, A. (2023). Risk aversion and irrationality in the Indian stock market. *IIMB Management Review*, 35(4), 305-320.
18. Zafar, N., et al. (2024). Suboptimal performance and herding: A study of investor psychology. *Behavioral Economics Letters*, 11(1), 77-89.