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Cognitive Biases and Investor Behavior: A Behavioral Finance Perspective on Stock Market Investment Decisions

Dr. Karthik Reddy[1], Dr. Dasari Rajesh Babu[2], Dr. Mutyala Subramanyam[3], Satish Kumar K[4],
[1]Assistant Professor, Department of Management Studies, Nitte
Meenakshi Institute of Technology, Bangalore, Karnataka, Email: mbaskreddy@gmail.com
[2]Associate Professor, School of Commerce and Management,
Department of Management, Mohan Babu University, Tirupati. email:
rajeshdasari100@gmail.com
[3]Professor, School of Management, CMR University (Lakeside Campus), Bangalore. Email:
drmutyala2013@gmail.com
[4]Assistant Professor, Department of Commerce,
Government First Grade College, Kunigal-572130 , and Research Scholar, School of Commerce, REVA University, Bengaluru
Email: satish2024dce@gmail.com

Abstract
this study examines how personality traits, prospect theory elements, and heuristic factors affect stock market investment choices. By drawing on behavioral finance theories, the study highlights the critical role of individual traits, emotional inclinations, and cognitive biases in influencing investor behavior. Representativeness, herd behavior, overconfidence, anchoring, and availability heuristics are among the heuristic factors that have been examined. Along with personality variables, including self-esteem, emotional experience, optimism, and risk tolerance, prospect theory components like loss aversion, regret aversion, mental accounting, and cognitive dissonance were also investigated.
The primary data was collected from individual investors with a sample size of 1200, 600 samples from Anantapur town and 600 samples from Bangalore city. The paper aims to understand cognitive biases in investment decisions in geographic areas.
According to multivariate regression analysis, heuristic factors together explain 47% of the variance in investor behavior. Representativeness (β = 0.255) and overconfidence (β = 0.270) were the most significant predictors. Validation by statistics (R2 = 0.470, F(5,1194) = 211.92, p < 0.001) demonstrates how vital these biases are in influencing investment choices. The availability, anchoring, herd behavior, and overconfidence heuristics substantially impact behavior.
The results highlight the importance of comprehending behavioral patterns to reduce cognitive biases and enhance investment methods. The study offers investors, legislators, and financial advisors' important information by emphasizing the part played by emotional considerations and heuristic biases. It concludes that to handle the complexity of contemporary market dynamics; behavioral aspects must be incorporated into classic financial theories.
Keywords:
Behavioral finance, stock market, investment decisions, investor behavior, Cognitive Biases, Stock Market Decisions

INTRODUCTION

A complex interplay of behavioral, cognitive, and emotional factors shapes investment decisions in the stock market. While traditional financial theories emphasize rational decision-making, behavioral finance highlights the significant role of heuristics, prospect theory factors, and personality traits in influencing investor behavior. These factors not only impact individual investment choices but also affect overall market dynamics.

Heuristic factors such as representativeness, herd behavior, overconfidence, anchoring, and availability heuristics simplify decision-making processes but often lead to systematic biases. Prospect theory factors,

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including loss aversion, regret aversion, mental accounting, and cognitive dissonance, explain how investors evaluate risk and respond to potential losses and gains. Furthermore, personality traits such as self-esteem, emotional experience, ability to invest, optimism, self-efficacy, ambitions, and risk tolerance influence individual risk perceptions, confidence, and long-term financial planning.

This study explores how these heuristic, prospect, and personality factors interact to influence stock market investment decisions. By understanding these dynamics, the research aims to provide financial advisors, policymakers, and investors insights to optimize decision-making strategies and improve market outcomes.

Decisions about investments are influenced by several heuristic, psychological, and personality aspects. Investors frequently misread market trends and mispricing due to heuristic variables, such as the representativeness heuristic, which causes them to assess probabilities based on stereotypes. Because few investors tend to follow the herd without question, herd behavior increases market volatility, particularly during bubbles and crashes. While anchoring biases investors in the direction of first information or reference points, such as past stock prices, which impact their judgments, overconfidence in one's expertise or prediction ability frequently results in excessive trading and unfavorable outcomes. Similarly, availability heuristics lead to a reliance on current or striking data, which might skew risk evaluations. These heuristic inclinations highlight how biases and cognitive shortcuts affect market performance and behavior. Personality and psychological aspects also influence investment choices. According to prospect theory, investors who are regret-averse adopt conservative measures to prevent regret in the future. In contrast, loss-averse people are more motivated to avoid losses than to pursue comparable gains. Mental accounting influences risk-taking and portfolio management by causing people to divide their money according to arbitrary standards.

When they justify previous behavior, investors may make biased decisions due to cognitive dissonance. Self-efficacy, optimism, and self-esteem are important personality traits that encourage resilience and confidence, allowing for proactive and consistent investing behavior. Risk perception is Significantly impacted by emotions, with caution fostered by negative emotions and risk-taking encouraged by positive ones. Investment goals and tolerance for risk are also important, as they influence portfolio investment strategies and encourage investors to seek more significant returns. Together, these elements show how personality, emotions, and cognition interact to influence investing behavior.

LITERATURE REVIEW

1. Heuristic Factors

Representativeness Heuristic

Using the representativeness heuristic, chances are assessed by comparing an event to a well-known stereotype.. Research shows that investors often overreact to recent trends, assuming they represent long-term patterns, leading to market mispricing (Kahneman & Tversky, 1974).

Herd Behavior

Herd behavior reflects the tendency of investors to follow the majority, often ignoring their analysis. Shiller (2000) found that herd behavior amplifies market volatility, particularly during bubbles and crashes.

Overconfidence

Overconfidence leads to excessive trading and less-than-ideal results because it causes investors to overestimate their knowledge or capacity to forecast changes in the market (Odean, 1998).

Anchoring

Anchoring occurs when investors rely too heavily on initial information or specific reference points, such as past stock prices, to make decisions (Tversky & Kahneman, 1974).

Availability Heuristics

Availability heuristics involve making decisions based on readily available information, often overemphasising recent or vivid events (Barberis et al., 1998).

2. PROSPECT THEORY FACTORS

LossAversion

Loss aversion drives investors to avoid losses more strongly than they seek equivalent gains. This bias influences portfolio allocation and the reluctance to sell losing investments (Kahneman & Tversky, 1979).

RegretAversion

Regret aversion causes investors to avoid decisions that might lead to regret, often resulting in conservative investment strategies (Zeelenberg & Pieters, 2007).

Mental Accounting

Mental accounting is the propensity to divide funds among several accounts according to arbitrary standards, which influences risk-taking and investing decisions (Thaler, 1985).

Cognitive dissonance

Cognitive dissonance occurs when investors experience discomfort due to conflicting beliefs, often leading to biased decision-making to justify past actions (Festinger, 1957).

3. PERSONALITY FACTORS

Self-Esteem

High self-esteem promotes confidence in decision-making, reducing the likelihood of impulsive reactions to market fluctuations (Rosenberg, 1965).

Emotional Experience

Emotions influence risk perception and investment persistence. Positive emotions encourage risk-taking, while negative emotions encourage cautious behavior (Loewenstein et al., 2001).

Ability to Invest

The ability to invest, driven by financial knowledge and resources, determines market engagement and sophistication in investment strategies (Lusardi & Mitchell, 2007).

Optimism

Optimism fosters proactive investment decisions and resilience during market downturns, though excessive optimism may lead to overconfidence (Puri & Robinson, 2007).

Self-Efficacy

Self-efficacy enhances risk-taking and persistence by fostering confidence in one's ability to achieve financial goals (Bandura, 1997).

Ambitions

Ambitions motivate investors to pursue higher returns and explore diverse investment opportunities (Zaleskiewicz, 2001).

Risk Tolerance

Risk tolerance reflects an investor's willingness to bear uncertainty in pursuit of higher returns, shaping portfolio composition and investment strategy (Grable & Lytton, 1999).

- **H01: Behavioral investment factors** Heuristic factors are representativeness, Herd Behavior, overconfidence, anchoring, and avail Ability Heuristics positively influence the investment decisions of stock market investors.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.686[a]	.470	.468	.11067	1.511

a. Predictors: (Constant), Availability Heuristics, Representativeness, Herd behavior, Anchoring, Overconfidence
b. Dependent Variable: Investor's behavior

A multiple regression analysis evaluated the influence of heuristic factors—availability heuristics, representativeness, herd behavior, anchoring, and overconfidence—on investor behavior. The results are summarized as follows:

The model showed a moderate to strong positive correlation between the predictors and the dependent variable (R=.686R = .686R=.686), with the predictors accounting for 47% of the variance in investor behavior (R2=.470R^2 = .470R2=.470). The adjusted R2R^2R2 value (Radj2=.468R^2_{\text{adj}} = .468Radj2=.468) indicates a slight difference of 0.2% between the two, suggesting good generalizability of the model. The standard error of the estimate was SE=.11067SE = .11067SE=.11067, indicating the average deviation of observed values from the regression line.

The Durbin-Watson statistic (DW=1.511DW = 1.511DW=1.511) suggests mild positive autocorrelation in the residuals.

INTERPRETATION

These findings indicate that heuristic factors, such as availability heuristics, representativeness, herd behavior, anchoring, and overconfidence, collectively explain 47% of the variation in investor behavior. This highlights the significant role these cognitive biases play in shaping investment decisions.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.978	5	2.596	211.920	.000[b]
	Residual	14.625	1194	.012		
	Total	27.603	1199			

a. Dependent Variable: Investor's behavior

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b. Predictors: (Constant), Availability Heuristics, Representativeness, Herd behavior, Anchoring, Overconfidence

An ANOVA was conducted to assess whether the model using heuristic factors—availability heuristics, representativeness, herd behavior, anchoring, and overconfidence—significantly improves the prediction of investor behavior compared to using the mean as a baseline.
The results indicated that the model was statistically significant, F(5,1194)=211.92,p<.001F(5, 1194) = 211.92, p < .001F(5,1194)=211.92,p<.001, demonstrating that the heuristic factors collectively provide a significant improvement in explaining the variance in investor behavior.

Interpretation
The significant F-ratio confirms that including heuristic factors significantly enhances the ability to predict investor behavior, emphasizing the importance of cognitive biases in investment decision-making.

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.336	.061		38.587	.000	2.218	2.455
	REPRESENTATIVENESS	.100	.009	.255	11.647	.000	.083	.117
	HERD BEHAVIOR	.079	.009	.195	8.384	.000	.060	.097
	OVERCONFIDENCE	.135	.013	.270	10.315	.000	.110	.161
	ANCHORING	.083	.010	.197	8.152	.000	.063	.103
	AVAILABILITY HEURISTICS	.059	.008	.172	7.595	.000	.044	.074

a. Dependent Variable: Investor's behavior

H01: Stock market investment decisions are impacted by Heuristic factors (representativeness, Herd Behavior, overconfidence, anchoring, availability Heuristics).
H0a: Investment decisions are positively impacted by representativeness
H0b: Investments are positive decisions impacted by Herd Behavior
H0c: Investments are positive decisions impacted by overconfidence
H0d: Investments are positive decisions impacted by Anchoring
H0e: Investments are positive decisions impacted by Availability of Heuristics

A multiple regression analysis assessed the impact of heuristic factors—representativeness, herd behavior, overconfidence, anchoring, and availability heuristics—on investor behavior. The results are summarized below:

- The model revealed that all heuristic factors significantly predicted investor behavior.
- Representativeness (b = .100, β=.255\beta = .255β=.255) had the highest standardized coefficient, indicating that investor behavior changes significantly as representativeness increases.
- Overconfidence (b = .135, β=.270\beta = .270β=.270) had the second-highest standardized coefficient, suggesting a notable influence on investor behavior.
- Herd behavior (b = .079, β=.195\beta = .195β=.195) and anchoring (b = .083, β=.197\beta = .197β=.197) were also significant predictors, with anchoring influencing investor behavior more strongly than herd behavior.

- Availability heuristics (b = .059, β=.172\beta = .172β=.172) showed the most miniature standardized effect but still significantly predicted investor behavior.

All predictors were statistically significant (p<.005p < .005p<.005) with the following t-values:

- Representativeness, t(11.647) = 11.647, p < .005
- Herd Behavior, t(8.384) = 8.384, p < .005
- Overconfidence, t(10.315) = 10.315, p < .005
- Anchoring, t(8.152) = 8.152, p < .005
- Availability Heuristics, t(7.595) = 7.595, p < .005

Interpretation

These findings suggest that all the heuristic factors significantly influence investor behavior, with overconfidence and representativeness having the most potent effects. Cognitive biases, such as herd behavior, anchoring, and availability heuristics, also play essential roles in shaping investment decisions, confirming the significant impact of heuristics on investor behavior in the stock market.

1. **Significance of Heuristic Factors**:
    - Representativeness and overconfidence emerged as the strongest predictors of investor behavior, with standardized coefficients (β = 0.255 and β = 0.270, respectively). These factors indicate that investors rely on patterns or perceived knowledge to make decisions, which may lead to systematic biases.
    - Anchoring and herd behavior were also significant influences, demonstrating that reliance on reference points or following the majority impacts decision-making.
    - Availability heuristics, while having the slightest effect, still significantly influenced behavior, suggesting that easily accessible information impacts investment choices.
2. **Statistical Validation**:
    - The overall regression model was statistically significant ($F(5,1194) = 211.92$, $p < 0.001$), confirming that the inclusion of heuristic factors provides a meaningful explanation of investor behavior.
    - The Durbin-Watson statistic (1.511) suggests mild positive autocorrelation, which is acceptable in behavioral finance research.
3. **Impact on Decision-Making**:
    - The significant t-values for all predictors affirm the individual contributions of heuristic factors to investor behavior, underscoring their critical role in shaping investment decisions.
4. **Practical Implications**:
    - Financial advisors and policymakers can use these insights to design strategies to mitigate the effects of cognitive biases. Educating investors about these biases can lead to more informed decision-making and improve market efficiency.

CONCLUSION:

The study's results prove that heuristic considerations significantly impact stock market investor behavior. The R-squared value of 0.470 shows that representativeness, herd behavior, overconfidence, anchoring, and availability heuristics explain 47% of the variance in investor behavior. The analysis highlights the following significant findings: The research highly supports the hypothesis (Ha4) that heuristic variables majorly impact act on stock market investors' investment decisions. These results highlight how crucial it is to comprehend behavioral patterns and incorporate them into investment strategies to counteract the cognitive biases that influence market dynamics. The study concludes that personality traits, prospect theory components, and heuristic considerations significantly impact investment choices in stock market participants. The research explains that cognitive bias factors, emotional tendencies for investments, and individual traits substantially impact investor behavior, challenging traditional financial theories. It was discovered that heuristic biases, including availability, herd behavior, representativeness, overconfidence, and anchoring heuristics, were highly predictive of investor behavior. The most significant influences were overconfidence and representativeness, highlighting how simplified cognitive shortcuts influence market judgments.

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