

Analytical study of behavioral dimensions of retail investors towards investment decision making & performance in stock market

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Abstract

The purpose of this research study is to explore the behavioral dimensions specifically, representativeness, availability, anchoring, overconfidence, loss aversion, regret aversion, and herding biases of retail investors towards investment decision-making and their performance in the stock market. To achieve the research objectives, a survey questionnaire method was adopted to collect data from 467 retail investors using the convenience sampling technique. The study has used Structural Equation Modeling (SEM) approach to analyze the relationship between the predictor variables and investors' behavior. The findings of the study suggest that Overconfidence Bias is the most significant predictor variable for individual investors' behavior, followed by loss aversion, and then anchoring bias. In contrast, availability bias contributes the least to investors' behavior. This study will be helpful in identifying and unraveling the irrational factors that affect investors' decision-making processes, leading to better investment decisions and improved performance in the stock market.

Subject Classification: (2020) 91C15, 97M70, 97N20, 97M10.

Keywords: Behavioral dimensions, Investors' behavior, Perceptual errors, Stock market performance, Mathematical analysis, Retail investors.

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1. Introduction

The traditional theory of finance makes the assumption that investors consistently make rational decisions based on all available information, which results in the efficient functioning of financial markets. However, various studies of [12]; [4] have challenged the rationality assumption of traditional finance, leading to the emergence of behavioral finance. Behavioral finance recognizes that human emotions, biases, and cognitive errors significantly influence investment decision-making and market outcomes. Therefore, it is essential to understand the actual behavior of investors to improve the efficiency of individuals and financial markets. Investors' behavior plays a crucial role in driving the performance of financial markets and the overall economy [15]. Behavioral finance has emerged as a new discipline that aims to understand human psychological biases in financial markets and to improve market efficiency [26]; [30]. The foundation of all behavioral biases is based on heuristic, prospect, and herding theories [27]; [24]; [29]. These theories have significant implications for understanding the actual behavior of investors and the decisions they make in financial markets.

Although several studies have explored the behavioral dimensions of retail investors, many of these dimensions remain unexplored or have been investigated with little effort to improve the performance of retail investors in the stock market. Therefore, this study aims to investigate all major cognitive biases associated with Heuristics, Prospect, and Herding theories of Behavioral Finance to better comprehend investors' psychology and improve the investment performance of individuals as well as the stock market.

2. Literature Review

Majority of the modern economics research has assumed that individuals are rational agents who seek to maximize wealth while minimizing risk. To build an investment portfolio that matches their risk tolerance, these agents thoroughly evaluate the risks and returns of all potential investments. [3]. Below are some major biases associated with Heuristics, Prospect, and Herding Theories are addressed.

Anchoring bias: Anchoring bias occurs when investors base their decisions on information that is already known to them or the first information they come across [31]; [29]. Normal people place a high value on the first information they obtain while making investing decisions [28].

Availability bias: Availability bias explains people’s propensity to make decisions based on information that is quickly and easily accessible rather than after carefully examining all pertinent facts [29]; [14]; [22]; [19].

Herding bias: Herding bias is a prevalent phenomenon where investors tend to rely on the beliefs and opinions of other investors [17]. This inclination towards imitation contribute to market volatility [13].

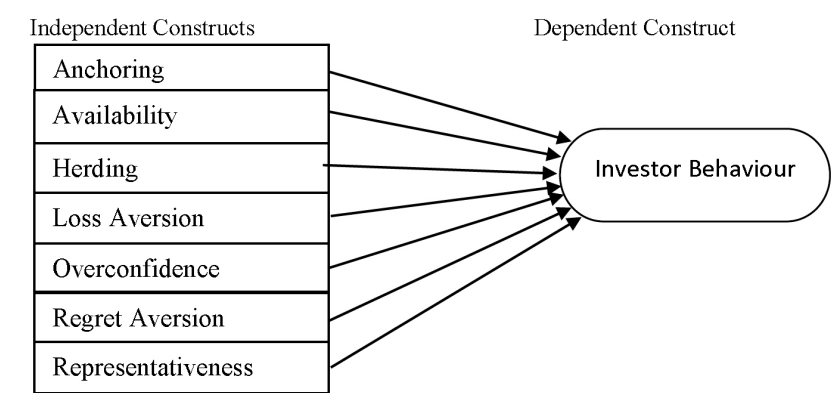
Loss Aversion bias: Loss aversion bias is a psychological phenomenon that leads to investors sell stocks that have appreciated in value above their initial investment because they fear losing money if prices fall [2].

Overconfidence bias: Overconfidence bias refers to an individual’s tendency to overestimate their abilities and knowledge [25]. Investors who suffer from overconfidence bias often fail to achieve larger returns on their investments [1]. It contributes to price volatility in financial markets [18]; [23]; [5].

Regret Aversion bias: Investors who have regret aversion bias are more likely to regret keeping onto losing equities for too long rather than selling winning stocks too quickly [21]; [16].

Representativeness bias: This is a cognitive bias that arises from over-reliance on stereotypes and beliefs that recent past performance is a good predictor of future performance [8].

3. Research Conceptual Model:



Source: The Authors

Figure 1
Conceptual Model display: Study of Behavioral Dimensions for analysis

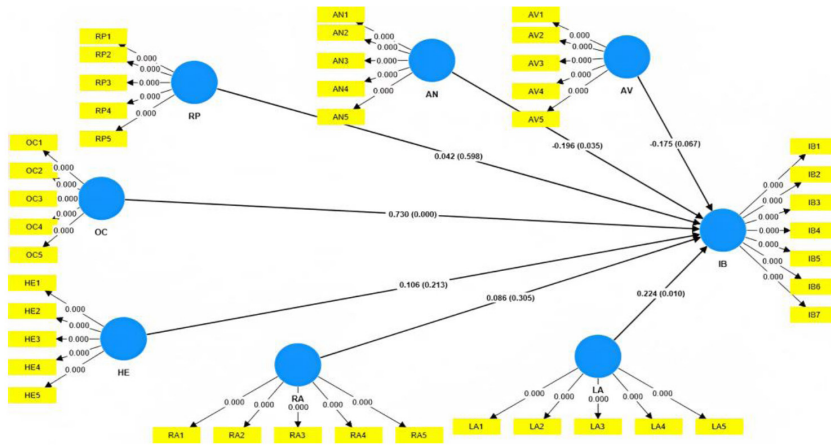
The study's conceptual model is shown in Figure 1. In line with other studies, the relationship between the endogenous construct (investors' behavior) and the major exogenous constructs (anchoring, availability, herding, loss aversion, overconfidence, regret aversion, and representativeness) is investigated.

4. Methodology for data analysis

This theoretical research model aims to evaluate how behavioral biases affect investor behavior. The study received 467 responses after removing missing and outlier responses from the targeted 700 sample size. A structured questionnaire was designed using a five-point Likert Scale to collect data from respondents. To collect sample responses, the Convenience Sampling Technique was employed in the study. The questionnaire consisted of three sections, one gathering demographic information, the second assessing behavioral biases, and the third section containing investor behavior. The acquired information was analysed using the partial least square structural equation modelling (PLS-SEM) method. Measurement model analysis was used to assess the construct quality of the questionnaire in terms of reliability, validity. Cronbach's Alpha and Composite Reliability (CR) values are > 0.7 [20]; [9]. For each construct, Convergent Validity has been calculated by Average Variance Extracted (AVE) which is > 0.5 indicating above the threshold limit of 0.5 [10]. Path coefficients, model fitness, and predictive relevance were evaluated using structural model analysis.

5. Structural Model of the Study

Figure 2 depicts the current study's structural model. The bootstrapping technique is applied in the study which is a re-sampling procedure in Smart PLS. It is run using a 5,000-subsample size to ensure a lower variance between mean and original values of path coefficients. Bootstrapping technique contributes to the predictability of estimates [7].



Source: The Authors

Figure 2

Structural Model in Smart PLS (Bootstrapping technique)

Note: Availability = AV, Herding = HE, Loss Aversion = LA, Overconfidence = OC, Risk Aversion = RA, Representativeness = RP, Investment Behavior = IB

Table 1
Result of Path Coefficients Analysis

Path	Beta Values	Std. Dev.	T-values	P-values	F-square	Remarks
AV → IB	-0.175	0.096	1.83	0.067	0.021	Low effect size
HE → IB	0.106	0.085	1.245	0.213	0.01	Zero effect size
LA → IB	0.224	0.087	2.587	0.010	0.043	Low effect size
OC → IB	0.73	0.055	13.186	0.000	0.518	Strong effect size
RA → IB	0.086	0.084	1.025	0.305	0.006	Zero effect size
RP → IB	0.042	0.08	0.528	0.598	0.001	Zero effect size

Source: The Authors

Note: P values are significant at < 0.10.

* $\sigma_s = \sqrt{1/n - 1} \sum_{i=1}^n (x_i - \bar{x})^2$

* $SE = \sigma / \sqrt{n}$

* $t = (X - \mu_0) / (s / \sqrt{n})$

5.1 *Mathematical Analysis of Data & Result:*

Table 1 displays the path analysis results. Anchoring bias has a negative significant influence on investors' behavior, with coefficient value being significant ($\beta = -0.196$, $P = 0.035$) where p value is <0.05 . Availability bias also has negative and least significant influence on investors' behavior because ($\beta = -0.175$, $P = 0.067$) where p value is >0.05 and <0.10 . As the value of coefficient is insignificant ($\beta = 0.106$, $P = 0.213$), herding bias has an insignificant impact on investor behavior. The loss aversion bias has strong and positive significant impact on investors' behavior as the value of coefficient is significant ($\beta = 0.224$, $P = 0.010$) where p value is equal to 0.01. Overconfidence bias has strongest and positive significant influence on investors' behavior because the value of coefficient is most significant ($\beta = 0.730$, $P = 0.000$) where p value is <0.01 . Regret aversion bias has no impact on investors' behavior because the value of coefficient is insignificant ($\beta = 0.086$, $P = 0.305$). Representativeness bias also has no significant impact on investor behavior because the coefficient value ($\beta = 0.042$, $P = 0.598$) is most insignificant. The effect sizes of loss aversion ($f^2=0.043$) and anchoring bias ($f^2=0.022$) are small, only the overconfidence bias's effect size ($f^2=0.518$) is high on investors' behavior. Compared to loss aversion and anchoring bias, overconfidence bias has a bigger impact on investor behavior

5.2 *Predictive Relevance*

The R^2 value under this model is 0.538 indicates that overconfidence, loss aversion, and anchoring bias account for 53.8% of the variation in investors' behavior. The value of Q^2 predicts is 0.406 which indicates high predictive relevance because it is exceeding the threshold limit 0.35 [6]. The study's model fit is also evaluated by calculating the standardized root mean square residual (SRMR) value which is 0.078. It is less than the maximum recommended threshold level of 0.08 indicating that the model fitness is at a satisfactory level [11].

6. **Conclusion and implications**

The results show that four out of the seven variables significantly affect investor behavior. Overconfidence bias contributed the most towards investors' behavior followed by loss aversion then anchoring bias and the availability bias contributed the least. Overconfidence and loss aversion biases are significantly impacting investors' behavior. While, anchoring

bias, and availability bias, on the other hand, negatively impact investors' behavior. According to the study, rather than doing an in-depth analysis of all the information available, individual investors in the Delhi-NCR region typically choose financial securities based on pre-existing facts or the first information they come across. They avoid decisions that may yield a good return but are risky. They make their judgments on current and easily obtained information rather than detailed analysis. In light of this, the current study provides a justification for investors' irrational investment behavior, which causes poor stock market performance and volatility. This study's findings have implications for retail investors, financial advisors, policymakers, and other stakeholders in the financial industry.

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