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Impact of Behavioral Biases on Investors' Stock Trading Decisions: A Comprehensive Quantitative Analysis

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Abstract

Objective: This paper aims to investigate the impact of specified behavioral biases on investors' stock trading decisions in North India. It has been observed that most of the research works are based on financial theories, which affect investment decisions. But besides the theories nowadays, behavioral biases also play an important role in investment decisions, which was less focused in the previous literature. **Methods:** The study used primary data collected from a sample from North Indian States (Uttar Pradesh, Delhi, Haryana, and Punjab) through a structured questionnaire to analyze the impact of specified behavioral biases on investors' stock trading decisions. We used structural equation modelling to find out the significant impact of behavioral biases on stock trading and investment decisions. **Findings:** The investigation determined that the majority of the designated cognitive biases, such as the Overconfidence Bias, the Representativeness Bias, and the Herding Bias, exert a significant influence on the decisions about stock trading and investment made by investors. **Novelty:** The ample research in this domain has primarily occurred in various countries, with only a limited number of studies conducted specifically at the Indian level. Nevertheless, based on the literature review, it is evident that this study is groundbreaking in North India. The objective of this research is to enhance the effectiveness of financial advisors by gaining a deeper understanding of the psychological aspects of clients. This, in turn, will aid in developing portfolios tailored to individual behavior, aligning with client preferences. Recognizing and addressing behavioral biases is crucial for individual investors as they strive to make informed and successful financial decisions.

Keywords: Behavioral Biases; Overconfidence (OC) bias; Representativeness Bias (RB); Herding Bias (HB); Structural Equation Modelling

1 Introduction

Traditional investment theories state that investors seek to maximize profits. Numerous studies showed that investors are not always rational[1]. People become confused when presented with financial decision-making ambiguity. Due to the inconsistent nature of market operations, people's logic and justifications are frequently missing. The study of behavioral finance looks at the reasons behind people's illogical behavior and potential solutions. A branch of finance known as behavioral finance studies how financial market participants behave and how psychological factors affect their decisions to purchase or sell on the market, which affects pricing[2]. Science's goal is to illuminate the reasons why it is reasonable to assume that markets are inefficient. A relatively new paradigm in finance called behavioral finance seeks to integrate fundamental finance ideas by considering behavioral factors while making decisions.

Behavioral bias, often called irrational behavior, is how a person evaluates a situation, leading to perceptual alterations, errors in considering circumstances, and illogical interpretations. Behavioral bias can drive investors to act irrationally, harming their investments and leading to losses rather than gains profits[3]. Due to rapid shifts in security prices and the influence of psychological and behavioral manifests on investor choices, investment behavior has evolved. In understanding how behavioral biases impact market participants' decision-making, the main objective is to study financial behavior. Investors commonly make irrational decisions when trading stocks on capital markets because subconscious psychological influences affect their decisions. Overconfident investors are highly susceptible to severe losses due to aggressive trading without adequate financial education, which frequently leads to investors suffering considerable financial loss. Due to herding effects, investors could purchase overpriced stocks[4].

In the dynamic realm of financial markets, the impact of behavioral biases on investors' decision-making processes has emerged as a pivotal area of study[5]. Investors often navigate through an intricate landscape shaped by economic fundamentals and cognitive and emotional factors that can significantly influence their stock trading decisions. Behavioral biases, rooted in psychological tendencies, can lead investors to deviate from rational decision-making, affecting market dynamics and individual financial outcomes[6]. This study delves into the intricate interplay between behavioral biases and investors' stock trading decisions, seeking to unravel how psychological factors shape investment behavior. By understanding these influences, we aim to provide valuable insights that can contribute to developing strategies for more informed and resilient decision-making in financial markets. Having studied the above, the following research questions can be concatenated:

RQ.1: How do overconfidence bias, representativeness bias, and herding bias impact investors' stock trading decisions?

By addressing these research questions, this study aims to contribute to a deeper understanding of the intricate relationship between behavioral biases and investors' stock trading decisions, offering valuable insights for both academics and practitioners in the field of finance. Recent studies have shown that psychological and emotional factors, such as overconfidence bias, herding bias, and representativeness bias, can substantially stimulate investment decisions due to technical and fundamental analysis limitations for individual investors[7]. This research's output looks at how these factors—overconfidence, representative bias, and herding behavior, affect the decisions made by individual investors.

Metawa et al.[8] found that investors' sentiment, underreaction and overreaction, overconfidence, and herd behavior substantially impacted investing decisions. Additionally, gender, age, and education level affect investor investing judgments considerably favorably. Expertise did not significantly affect financial decisions, but investors prefer to overlook emotional elements as they gain expertise. Parveen et al.[9] explained that evidence reveals that behavioral biases, such as the fixing heuristic, the impudence bias, and the disposition effect, influenced investors' judgments negatively. Wu, Q.[10] analyzed that driving bias has a noteworthy detrimental impact on investment performance and perceived market efficiency and has a pivotal impact on individual investor road ahead.

Nareswari et al.[11] explained that investors' sentiment, overconfidence, salience, overreaction, and herd bias positively influence stock trading and investment decision-making. The study's decisions have substantial significance for investors in understanding themselves and anticipating bias in investment decision-making. According to Ahmad, M.[12], investors frequently use mental heuristics to minimize the risk of fatalities in undefined and volatile circumstances, but this leads to judgment faults; as a result, investors face biased and unreasonable decisions, causing the market to underreact or overreact - in either case, the marketplace befits incompetent. El-Hussein, N. H. A. & Abdelgadir[13] explained that behavioral biases significantly impact individual investment decision-making regardless of the stock market's state. Research in established, emerging, or developing countries shows investors are vulnerable to psychological biases when deciding whether to purchase, sell, or hold. Weixiang S et al. in[14], found analytical significant relationship between heuristic and behavioral bias development in the process of decision-making.

Karmacharya et al.[15] explained that the herding variable influences investing decisions positively. Nepalese investors rely significantly on the advice and ideas of others while making investment decisions without conducting thorough market research. Investment performance and heuristics have the highest value among the latent constructs' relationships, followed by herding

and market factors. Jain et al. explained that individual investors' decision-making was found to be significantly influenced by financial literacy[16]. Herding and overconfidence bias were discovered to be serially mediated by the link between financial literacy and investor decision-making. Wang & Nuangjamnong observed that investor sentiment, overconfidence, and risk tolerance all influence investing decisions to varying degrees. Finally, overconfidence affects investors' risk tolerance[17]. Quang et al.[18] explained that investors' overconfidence, and emotions, were vital to be studied by new-age investors. Furthermore, investors' investment decisions are heavily influenced by their age, gender, and level of education.

Hirdinis, M. et al. observed that herding positively and considerably impacts investment decisions made by investors[19]. Overconfidence influences investment decisions in the Jakarta area in a good and important way. This suggests that rising herding and overconfidence among investors can influence investment decisions in the Jakarta area. Fitri and Cahyaningdyah[20] explained that overconfidence significantly influences derivative investment in the international market. Wibowo et al. indicated that herding and overconfidence biases in investors can impair the quality of stock trading and investment decisions[21]. Furthermore, herding bias and overconfidence bias might lower investors' risk perception. Investors' risk perception can impact investment decisions and boost the advantages of the investing process[22]. Risk perception can act as a buffer between over-optimism and herding prejudice on venture choices. The findings of this study imply that investors should avoid prejudice while making investing decisions and diversify their portfolios to reduce risk. Saxena & Chawla and Vaya et al.[23,24] found a link between demographic features and financial behavior biases, as well as a link between investment decisions and financial behavior bias. The findings also demonstrated a significant link between demographic variables and differences in investment behavior.

Most of the research works in this field connect to national and worldwide levels, as seen from the literature review. And a very tiny number covers bigger cities and smaller geographic areas. Studies in India are primarily undertaken in Mumbai, Delhi, Chandigarh, Indore, etc. In the North India, this kind of research has not been done. Therefore, our work is unique in this field[25]. To measure the influence of behavioral biases on investors' stock trading decisions in North India, this study will focus on investors in this region. The conceptual framework serves as a roadmap for comprehending the relationships between study variables. A practical frame was created after synthesizing the literature on various subjects, guiding ideologies, and separating the manifests from it. It is a chart that shows how dependent and independent variables are related. Three main biases employed in the study and stock trading decisions have been linked in various ways. It was decided to do a statistical analysis to explain the relationship's consistency based on the relationships and the diagram's flow. The current conceptual framework is depicted in the following diagram.

Fig 1. Conceptual Framework

One of the essential ideas that govern and oversee financial markets worldwide, including India, is volatility. Excessive dynamism in the stock values of different companies in the stock market has become more complicated for sensible investors due to irrational investors' predictions and restlessness. The swings of the financial markets are so blatant that they switch quickly from bullish to bearish and back to positive within a day, a week, or a month. To develop better strategies and client portfolios, financial counseling organizations may benefit from better information and understanding of investor responses to market changes. Therefore, it is crucial for market participants today to comprehend investors' illogical conduct as well as the causes of it. With the context mentioned above in mind, the following list contains the precise objectives of the current research.
- To understand and explore the basic concept of behavioral finance and behavioral biases.
- To examine the impact of specific behavioral biases on stock trading decisions.

2 Methodology

The research has been separated into two sections based on the current study's nature. Because the study constructed a model in the first phase and tested it in the second, the first phase utilized an exploratory research design, while the second phase used a causal research design.

2.1 Sample

A sample is a subset of the larger universe which reflects the entire universe. This is a single element or collection of elements subject to universe selection. The research samples consisted of all capital market investors residing in North India. The samples were selected through snowball sampling technique. The sample was collected from four significant states of north India Uttar Pradesh, Haryana, Delhi, and Punjab.

The study observed the conduct of these samples by employing a self-administered questionnaire, focusing on various behavioral biases. The aim was to comprehend how behavioral biases play a role in the decision-making processes of investors engaged in capital market activities or stock trading. The combined behavior of samples from the four states of North India was considered indicative of the overall trends in the capital market. Following this premise, responses were gathered to delineate the nature of the sample's investment decisions, taking into account their behavioral patterns. Since the primary objective is to explore the impact of behavioral biases on investors' stock trading decisions, the sample selection utilized the snowball sampling technique (non-probability). A satisfactory number of sample units were chosen based on the study's theme to ensure that the fundamental elements of the investigation accurately reflected the characteristics of the broader population. We collected data from 627 respondents, yielding a total of 484 valid responses. We employed structural equation modelling to examine the impact of specific behavioral biases on investors' stock trading decisions.

2.2 Research Tool

The research employed a questionnaire that participants filled out on their own accord. Designing and implementing the questionnaire is a difficult job involved in researching. It is challenging to gather the responses as an illustration of human behavior. A questionnaire was created after thoroughly investigating the literature to support the study's research goal. The questionnaire combines self-developed questions with those posed by different researchers. The questions' format and language have been slightly modified according to the study requirements. A pilot study was done, and some changes in the questionnaire were made as per inputs from a pilot study and the expert in this area.

3 Results and Discussion

The path analysis results unveil valuable insights into the structural relationships within the examined model. Notably, the paths emanating from OC, RB, and HB to STD demonstrate positive estimates, signifying the presence of significant associations. The critical ratios (CR) for these paths—3.304, 3.33, and 3.394, respectively—alongside the low p-values (0.002, 0.001, and 0.000) firmly establish their statistical significance. This suggests that the variables OC, RB, and HB exert meaningful influences on the dependent variable STD. The accepted paths underscore the importance of considering these inter-variable dynamics in the broader context which has been documented in past studies.

Furthermore, the model delves into the subcomponents of OC and HB, revealing additional noteworthy relationships. The paths leading from OC1 to OC2 and OC3, as well as from HB to HB5, all exhibit positive estimates of 1.047, 1.021, and 1.122, respectively. The corresponding critical ratios of 12.504, 11.928, and 4.727, coupled with p-values of 0.002, 0.000, and 0.006, underscore the robustness and significance of these relationships. These findings contribute to a nuanced understanding of how the specific components within OC and HB contribute to the structural model's overall dynamics as observed in previous work.

However, amidst the overall acceptance of paths, a notable exception is found in the second path from RB1 to RB. While this path bears a significant estimate of 0.869 and a critical ratio of 4.443, the associated p-value of 0.000 indicates a substantial relationship. Despite being the only non-accepted path in the model, its significance prompts a closer examination of the relationship between RB1 and RB, warranting further investigation into the potential implications of this pathway on the broader structural dynamics.

- **Hypotheses**

H1: Overconfidence bias has a significant explicit influence on stock trading decisions.
    H2: Representativeness bias has a significant influence on the stock trading decisions.
    H3: Herding bias has a significant negative influence on stock trading decisions.

- **Analysis of Data**

This section examines the data gathered from the study via a standardized questionnaire. It explores the role of behavioral biases on stockholder stock trading decisions in the capital market pertaining to North India. The analysis was done in SPSS and AMOS and based on the respondents' opinion; the interpretation of the results was done. The analysis of data has been categorized into three parts. The first part is related to the analysis of the descriptive profile of demographic data. The second part is related to the development of the model (exploratory analysis), and the third part is related to hypothesis testing.

Table 1. Descriptive Analysis

Factors	Classification	Freq.	%
	Male	348	71.9
Gender	Female	136	28.1
	Total	484	100
	18-28 Yrs.	261	53.9
	29-39 Yrs.	174	36
Age	40-50 Yrs.	30	6.2
	51-60 Yrs.	13	2.7
	Above 60 Yrs.	6	1.2
	Total	484	100
	Undergraduate	184	38
Education Level	Postgraduate	196	40.5
	Professional Manager	104	21.5
	Total	484	100
	Private	142	29.4
	Public	158	32.6
Occupation	Professional	90	18.6
	Retired	94	19.4
	Total	484	100
	Married	202	41.7
Marital Status	Unmarried	270	55.8
	Widowed/others	12	2.5
	Total	484	100
	< 50,000	155	32
Monthly Salary	50,000-1,00,000	200	41.3
	>1,00,000	129	26.7
	Total	484	100
	< 2 Yrs	217	44.8
	2-5 Yrs.	129	26.7
Trading Experience	5-8 Yrs.	54	11.2
	> 8 Yr.	84	17.4
	Total	484	100

Table 1 offers valuable insights into the demographic and socio-economic characteristics of the survey respondents. When considering the gender distribution, the data indicates a significant majority of male respondents, constituting approximately 71.90% of the sample. This gender imbalance raises questions about the representation of women in the study and the potential impact of gender-related factors on the research findings. Regarding age, most respondents fall within the 18-28 years category, comprising 53.90% of the sample, while other age groups are represented in smaller proportions. The data also sheds light on the respondents' educational backgrounds, with a notable number holding postgraduate degrees (40.50%), followed by undergraduate (38.00%) and professional manager qualifications (21.50%).

The occupation data reflects a diverse mix of respondents, with individuals categorized into private, public, professional, and retired roles. The most prevalent category is "unmarried" among the marital status options, representing 55.80% of respondents.

Additionally, the monthly salary distribution highlights that a substantial portion of respondents earns between 50,000 and 1,00,000, making up 41.30% of the sample. Finally, the data on trading experience reveals a significant number of respondents with less than two years of experience (44.80%), suggesting that many participants are relatively new to trading. These statistics provide a comprehensive profile of the respondents, which will be instrumental in understanding their perspectives and responses to the research questions. Some items and constructs have been removed during exploratory factor analysis to achieve discriminant and convergent validity. The above variables and constructs have been finalized and further taken for the final study and model development.

Fig 2. SEM of Investors' Stock Trading Decisions

Table 2 presents a set of model fit statistics used to evaluate the goodness of fit of a statistical model, particularly in the context of structural equation modelling. The "Default Model" demonstrates a reasonably good fit with values indicating the model's ability to explain a substantial portion of the variance in the data, as seen in the NFI (0.937), RFI (0.892), IFI (0.957), TLI (0.925), and CFI (0.956). In contrast, the "Saturated Model" perfectly fits the data, reflected in its perfect fit values (1.000). The "Independence Model," which assumes variable independence, unsurprisingly has fit indices close to 0. These fit statistics are crucial for researchers to assess the adequacy of their statistical models and guide decisions on potential model modifications on investors' stock trading decisions (see Figure 2).

Table 2. Model Fit Statistics

Particular	N'F'I	R'F'I	I'F'I	T'L'I	C'F'I
Default Model	0.937	0.892	0.957	0.925	0.956
Saturated Frame	1.000	-	1.000	-	1.000
Independence Frame	0.000	0.000	0.000	0.000	0.000

Table 3 presents crucial validity criterion statistics for the examined constructs in the context of structural equation modelling. Composite Reliability (CR) values, which determine internal consistency reliability, range from 0.664 to 0.775, demonstrating acceptable reliability for the constructs. Average Variance Extracted (AVE) values, which assess construct validity, fall between 0.519 and 0.658, indicating that the constructs capture a significant portion of their variance relative to measurement error. Additionally, the table reveals the correlations between the constructs, highlighting their interrelationships within the measurement model.

Table 3. Validity Criterion of the constructs

Variables	CR	AVE	STS	OC	HB	RB

Table 3 continued

STD	0.749	0.609	0.780			
OC	0.775	0.536	0.525	0.725		
HB	0.686	0.519	0.625	0.589	0.625	
RB	0.664	0.658	0.748	0.668	0.748	0.625

Table 4. Testing of Hypotheses

Path	Estimate	SE	CR	P	Label
STD ← OC	0.156	0.47	3.304	0.002	Accepted
STD ← RB	0.224	0.67	3.330	0.001	Accepted
STD ←HB	0.169	0.050	3.394	0.000	Accepted
OC1 ←OC	1.000	-	-	-	-
OC2 ←OC	1.047	0.084	12.504	0.002	Accepted
OC3 ←OC	1.021	0.086	11.928	0.000	Accepted
HB3 ←HB	1.000	-	-	-	-
HB5 ←HB	1.122	0.237	4.727	0.006	Accepted
STD3 ← STD	1.000	-	-	-	-
STD5 ←STD	1.607	0.278	5.868	0.002	Accepted
RB1 ← RB	1.000	-	-		-
RB1 ← RB	0.869	0.202	4.443	0.000	Accepted

The estimate represents the depth and direction of the relationship between the constructs. Positive estimates indicate a positive relationship, while negative estimates suggest a negative relationship. For example, STD ← OC has an estimate of 0.156, indicating a positive relationship between the constructs. The standard error measures the precision of the estimate. Smaller standard errors indicate greater precision. The critical ratio measures the strength of the relationship relative to its standard error. Higher CR values indicate more significant relationships. For instance, CR values for STD ← OC, STD ← RB, and STD ← HB are 3.304, 3.330, and 3.394, respectively, indicating strong and significant relationships. The p-value assesses the statistical significance of the relationship. Smaller p-values (usually below a significance level, e.g., 0.05) indicate statistical significance. In this table, all relationships with p-values below the significance level (0.05) are marked as "Accepted," indicating that these paths are statistically significant. The measurement model is used for analyzing the goodness of fit of model and used for analyzing the reliability and validity of model. It can be observed that value of composite reliability is more than 0.7 in some constructs and in the remaining constructs, it is close to 0.7, which is fair.

This novel attempt surpasses conventional analyses by intricately scrutinizing these behavioral biases, presenting a nuanced viewpoint on how psychological factors interact with financial decision-making. The uniqueness of this approach lies in its capacity to untangle the complex dynamics influencing market behavior, providing a deeper understanding of investor inclinations. Accordingly, the research contributes an exclusive perspective for interpreting and addressing the intricacies involved in the impact of behavioral biases on stock trading decisions, proving valuable for both academic discussions and practical applications in the financial sector.

- **Implications of the study**

Recognizing and understanding the role of behavioral biases, such as overconfidence, herding behavior, and loss aversion, can lead to more informed and rational investment decisions. This awareness can result in improved risk management, better portfolio diversification, and ultimately, enhanced financial outcomes for individual investors. Furthermore, the financial industry can leverage these insights to design tailored products and services, while regulators and educators can use this knowledge to enhance market stability and financial literacy. This research highlights the critical need to address and mitigate behavioral biases to promote wiser and more successful stock trading decisions in the investment landscape.

4 Conclusion

Quantitative analysis of the impact of behavioral biases on investors' stock trading decisions, focusing on overconfidence bias, herd bias, and representativeness bias, illuminates the intricate interplay between psychological factors and financial choices.

Recognizing the pervasive influence of these biases provides valuable insights for market participants, enabling the development of informed strategies to navigate the complexities of the financial landscape. As we continue to delve into the nexus of human psychology and investment behavior, a clear understanding of these biases becomes essential for fostering a more resilient and rational approach to stock trading in an ever-evolving stock market. Hence, behavioral biases play a role in shaping decisions related to capital market investing and stock trading, causing investors to diverge from the rational thinking process traditionally emphasized in finance. This research specifically delved into the effects of biases like overconfidence, herding, and representativeness on investors' decision-making process in stock trading. Regardless of their relative importance, these elements contribute to a better understanding of investor behavior. Investors' decisions also have an impact on the economy. It depends on the government's initiatives to expand the financial market and adopt significant improvements to boost investors' finances. When investors make informed decisions, carefully assess their risk tolerance, choose to allocate more funds to the equity market, and reduce their exposure to the debt market, it contributes to economic development and improves their prospective financial well-being. The proposed model confirms the pervasive impact of chosen biases, while the nuanced findings highlight the importance of considering specific dimensions within each bias. These insights can inform investment strategies, risk management, and financial education programs aimed at mitigating the potential negative effects of cognitive biases on investors' decision-making.

- **Limitations and future scope**

With a sample size of 484, it's important to acknowledge that this study's findings might not be universally applicable. The investor population is incredibly diverse, and the sample may not fully represent the full spectrum of investor demographics, risk tolerances, or investment goals. Moreover, the study might be subject to selection bias, as investors who voluntarily participate in such research may differ significantly from those who do not. Additionally, using self-reported data could introduce recall bias, as investors may not accurately remember or report their past trading decisions. Furthermore, the study might not capture the nuances of specific behavioral biases or their interactions, which could vary across market conditions and investment scenarios. Hence, future research should incorporate more extensive and diverse samples to enhance the external validity of the findings. The study's scope is limited to North India. Given the vast size of India, it's important to note that this study doesn't claim to represent the typical Indian investor comprehensively. The primary focus was on participants from four states in Northern India. Whether investors in other regions exhibit similar behavior to those observed in this study is still an open question. This study's scope is limited to analyse impact of selected behavioural biases on stock trading decisions, in future studies mediating role of gender and experience of investors can be also analysed along with behavioural biases.

As we advance, researchers could explore various opportunities to expand the knowledge base regarding the impact of behavioral biases on stock trading decisions. Larger and more diverse samples should be considered, and using big data analytics and machine learning techniques could help uncover patterns and relationships that might be missed with traditional statistical methods. Longitudinal studies tracking individual investors' decisions over extended periods could provide insights into how biases evolve and impact portfolio performance. Qualitative research, including interviews and case studies, can provide a deeper understanding of the psychological and emotional factors that underlie trading decisions. Additionally, research that delves into interventions and strategies to mitigate the adverse effects of behavioral biases in real-world investment scenarios could be particularly valuable for both individual investors and financial professionals.

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