European Economic Letters
ISSN 2323-5233
Vol 15, Issue 1 (2025)
http://eelet.org.uk

BEHAVIOURAL FINANCE AND ITS BIASES: A STUDY ON INVESTORS INVESTING THROUGH STOCK TRADING PLATFORMS

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ABSTRACT
Finance has been a vital aspect of everyone's life, but everyone tends to behave differently while managing finance. Some work for money, and very few put their money into work. Traditional finance has been inefficient in concluding why behaviour with money and finance differs among individuals. Behavioural finance has been considered sound in defining the underlying factors that result in unpredictable financial decisions. This study tried to explain the same using four behavioural biases: overconfidence bias, recency bias, anchoring bias, and herding bias. The study also tried to explain the role of stock trading platforms in encouraging investment habits among individual investors. A questionnaire was developed using Likert scaling techniques to find who among males and females is more sceptical of these four biases. Data has been analysed using Excel data analysis tools and techniques. After analysing the collected data, it can be summarised that out of four biases, only herding bias has the potential to impact the investment decisions of individual investors and that too is more prominent in male than female individual investors.

KEYWORDS: Behavioural finance, Behavioural Biases, Stocks, Investors, Stock Trading Platforms.

1. INTRODUCTION

The human brain is so complex that it can process 1,000 to 3,000 words per minute. It possesses remarkable reasoning and decision-making abilities but often exhibits irrational behavior. This irrational behavior can manifest in various useful and useless aspects of our daily lives. This paper will discuss one such area of life: investment, specifically in stocks. Traditionally, investment has been viewed as rational behavior, with the belief that investors aim solely to maximize their profits. However, numerous studies worldwide have demonstrated that much more goes on in investors' minds when they begin investing and throughout their investment journey. This paper will primarily focus on these aspects.

The concept of "Behavioural Finance" was first introduced in George Seldon's book *Psychology of the Stock Market* in 1912 and gained significant attention in 1979 when Daniel Kahneman and Amos Tversky proposed that most investors make decisions based on subjective reference points rather than objectively selecting the best option. Behavioural finance is a field of study that merges psychology and economics to explore how emotional, cognitive, and social factors influence the financial decisions of individuals and institutions. This differs from traditional finance, which assumes people act rationally and in their best interests. Traditional finance theory is built on two key principles: one suggests that investors are rational beings, and the other is the Efficient Market Hypothesis, which posits that markets are fully efficient. As per this hypothesis, investors have access to market information and asset prices, which are considered rational. Even after the progressive growth of modern finance, researchers are still puzzled as to why investors act irrationally while dealing with money(Madaan & Singh, 2019). The growing discipline of behavioural finance has identified several biases that significantly impact individual investors' actions. These biases are believed to directly impact investment decisions, ultimately leading to reduced investment gains in the stock market. (Schulz, 2023). One reason these biases exist is that, in practice, investors often rely on simple heuristics or 'thumb rules' instead of engaging in lengthy and complex mental calculations, which can lead to suboptimal decisions and contribute to market inefficiencies. Furthermore, investors are not always rational and lack the infinite cognitive capacity needed to consider all possible scenarios for making sound investment decisions.

Research has been conducted on behavioural finance and its implications for investors and their decision-making process. This study will show the implications of behavioural finance biases on investors investing through stock trading platforms in the Indian stock market. The paper has been divided into four chapters, which consist of an introduction, which majorly explains behavioural finance and its related issues and biases; a literature review; the research methodology; and, finally, results and discussions. The conclusion summarises the findings and future scope for research.

1.1 Behavioural Finance

Behavioural finance is a field of finance that examines the influence of psychological and emotional factors on the behavior of investors and financial markets(Rani, 2024). Behavioural finance is one such field that examines the irrationality of investors and the biases to which they are prone(Suresh G, 2024). It explores how emotions, cognitive biases, and social and cultural factors affect the investment patterns of investors, particularly in volatile environments like the stock market. Traditionally, it was assumed that investors make decisions solely to maximize profits. However, the introduction of behavioural finance challenged the Efficient Market Hypothesis and uncovered numerous biases that hinder rational thinking. These biases often lead investors to misjudge the market, resulting in losses in many cases. Some well-known biases in behavioural finance include confirmation bias, overconfidence bias, herding bias, recency bias, anchoring bias, loss aversion, greed aversion, the endowment effect, authority bias, conformity bias, and regret aversion, among others. This study focuses on four of these biases: overconfidence, recency, herding, and anchoring.

1.2 Behavioural Bias

In everyday activities, individuals are required to make numerous decisions, which involve a combination of factors such as motives, intentions, anticipated impacts, and social relevance. Investment decisions are no exception, as they also involve a blend of these considerations. According to various theories, individuals are expected to make rational decisions when dealing with financial matters; however, this is often not the case, especially in contexts where there are high prospects for both gains and losses. In such volatile markets, human rationality is frequently compromised by the allure of high-risk, high-reward opportunities. Many investors fail to adequately analyze company-specific variables and factors before investing, which leads to missed profits and booked losses. This issue is particularly pronounced in futures, options, and intraday trading, where it is reported that only approximately 7% of traders achieve consistent profits. This study primarily focuses on the following four biases:

- Overconfidence bias
- Recency bias
- Anchoring bias
- Herding bias

1.2.1 Overconfidence Bias

Overconfidence is a psychological trait that significantly influences human behavior. Overconfidence bias leads to the consideration of deceptive data and makes investors believe that they are better than others, leading them to overestimate their capabilities and success quotient(Čuláková et al., 2017). Overconfidence in relation to decision-making and economics was probably used for the first time by Adams and Adams (1960)(Čuláková et al., 2017). The theory of overconfidence suggests that individuals tend to exaggerate their abilities and the accuracy of their predictions, often leading to overconfidence and risky investment decisions(Rani, 2024). It is also considered one of the most influential biases in Behavioural Finance, particularly impacting the investment decisions of stock market investors. This is because the stock market is prone to volatility, driven by various factors such as economic booms or downturns, wars, or natural and artificial disasters. Overconfidence can make financial markets inefficient by causing mispricing, leading to excessive volatility and variability in returns(Odean, 1998). Self-attribution theory (given by Fritz Heider) is also considered impactful in explaining overconfidence bias. This theory suggests that individuals tend to attribute their successes to personal skills and abilities, while external factors or bad luck are often blamed for failures. Further, in a study, Bastian Schulz (2023) found that overconfidence bias majorly disrupts the quality of investment decisions among male German investors compared to female investors.

1.2.2 Recency bias

As the name suggests, this bias is supposed to have occurred when investors rely too much on recent information they have come across through recently happened events. In financial contexts, recency bias is also explained by the Adaptive Market Hypothesis (given by Andrew W. Lo), where market participants adapt to changing environments and often overemphasize recent trends when making decisions, especially under uncertain conditions. This bias tries to understand the tendency for individuals to give more weight to recent events while making decisions, resulting in myopic thinking and potentially misjudging long-term trends(Rani, 2024). Recency bias convinces investors regarding the significance of recently happened events, assuming recent trends will continue indefinitely, ignoring historical context and long-term patterns, and making decisions based on short information. This bias can affect various aspects of life, from finances to personal relationships. Timely recognizing and addressing this bias can lead to more informed decisions and a more nuanced understanding of the world.

1.2.3 Anchoring bias

Anchoring bias occurs when investors rely predominantly on the initial information they receive, using it as a reference point for subsequent investment decisions. This bias is one of the most widely studied psychological phenomena in finance. Although professionals may be less susceptible to anchoring effects, individual or lay investors are often influenced by initial information, leading to skewed stock return estimates and biased decision-making in online markets, such as auctions. The anchoring effect is a psychological phenomenon in which individuals tend to rely on an initial figure, even when it is unrelated to the subject they are estimating (Georgiana, 2024). Dual Process Theory (given by William James) also offers an explanation for anchoring bias, positing that human cognition operates through two systems: System 1: Fast, automatic, and intuitive decision-making. System 2: Slow, deliberate, and analytical thinking**.** System 1 is quick and relies on heuristics, such as the anchoring heuristic, where people tend to adjust their estimates or decisions based on an initial anchor point. This happens almost reflexively, without deep cognitive processing. For example, when an investor sees a specific price for a stock as a reference point, they might unknowingly anchor their expectations to that price without fully assessing current market conditions. A study by Bastian Schulz (2023) revealed that male German investors' investment decisions are majorly impacted by anchoring biases compared to female investors.

1.2.4 Herding bias

Herding bias is the tendency of individuals to align their actions with those of a larger group, often disregarding their own information or analysis. This cognitive bias is especially prominent in financial markets, where investors frequently replicate the buying or selling behaviors of others instead of making independent decisions grounded in personal research. Decisions influenced by herding bias are rooted in herd behavior, where individuals conform to the group's actions, even when doing so contradicts their personal judgment or access to superior information. Information Cascade Theory (Sushil Bikhchandani**,** David Hirshleifer**,** and Ivo Welch) provides a framework for understanding how individuals make decisions based on the observed actions of others rather than on private information or signals. This phenomenon is particularly prevalent in uncertain environments, such as financial markets. A study on German investors has shown that women are more likely than males to fall victim to the herding bias(Schulz, 2023).

This concept is central to behavioural finance, a field that examines how psychological factors shape investor behavior and contribute to market inefficiencies. Notable historical examples of herding behavior include the 1929 stock market crash, commonly known as the Great Depression. During this period, widespread panic selling triggered a sharp decline in the American stock market, with inadequate financial data reporting later identified as a major contributing factor to the crisis. Similarly, the 2008 financial crisis witnessed a wave of investors hastily selling their assets out of fear, intensifying the market decline as many sought to exit simultaneously.

The theory of social learning also provides a valuable framework for understanding herding behavior. In his foundational work on social learning theory, Bandura (1960) highlighted the roles of observation, modeling, and imitation in the development of behaviors, attitudes, and emotional responses. He demonstrated that learning occurs through observing others, with key factors such as attention, retention, reproduction, and motivation impacting the effectiveness of this process.

1.3 Investors and Stock Trading Platform

Stock trading platforms are digital systems that enable individuals and institutions to buy and sell financial securities, primarily stocks, through an online interface. These platforms have revolutionized trading by making it more accessible, efficient, and cost-effective. They are largely responsible for the influx of investors into the stock market, as these brokers have simplified the investment process. Investors can now trade shares or invest in mutual funds using their mobile devices with minimal complications, making the process significantly easier. These platforms provide an investor-friendly interface where investors can check the financial statements of companies on a yearly or quarterly basis; investors can check the shareholding pattern, debt, assets, and liabilities of companies. A comparative analysis can be done with companies in similar sectors. Given all the above-mentioned facilities by stock trading platforms, it also results in irrational behavior among tyro investors because readily available information related to stocks and the market is sometimes misjudged by retail investors, resulting in purchasing unwanted stocks and ignoring useful ones.

Stock trading platforms have become a focal point for studying behavioural biases in investment decisions. Research indicates that various cognitive biases significantly influence investor's stock trading choices (Shukla et al., 2024). Overconfidence, representativeness, and herding biases are particularly prevalent among investors (Shukla et al., 2024). Loss aversion and familiarity biases also play crucial roles in shaping investment decisions (Bhatnagar & Aggarwal, 2021). These biases often lead to suboptimal investment choices, potentially disrupting market health (Bhatnagar & Aggarwal, 2021; Khan et al., 2023). Financial literacy has been identified as a moderating factor in the relationship between behavioural biases and investment decisions (Khan et al., 2023). To mitigate the impact of these biases, researchers suggest promoting financial literacy and providing guidance from financial professionals (Khan et al., 2023; Chhapra et al., 2018). Understanding this behavioural aspect can help financial advisors develop tailored portfolios and improve the quality of investment decision-making (Shukla et al., 2024; Chhapra et al., 2018).

2. LITERATURE REVIEW

The literature on behavioural finance, behavioural biases, and investment decision-making has been extensively explored in prior studies. Behavioural finance has emerged as a significant area of study, offering explanations regarding volatile markets, which earlier theories, like the efficient market hypothesis, failed to address. It is a relatively new approach to explaining the volatility of the financial market, which is contrary to the efficient market hypothesis(Madaan & Singh, 2019). The efficient market hypothesis, as proposed by Eugene F. Fama, states that investors act rationally, whereas behavioural finance considers that investors are not always rational and explains their behaviour from a psychological and sociological perspective(López-cabarcos et al., 2020).

The importance of behavioural finance began to gain significant recognition in the 1970s and 1980s, as traditional economic theories, such as the Efficient Market Hypothesis, struggled to explain some real-life phenomena like stock market crashes, irrational investor behaviour, and stock market bubbles. The importance of behavioural finance became more evident in 1990 when some researchers shifted from using econometric models that analysed price or dividend time series to adopting financial models rooted in psychology(Shiller, 2003). In 1996, the book "The Econometrics of Financial Market" by Campbell, Lo and MacKinlay empirically explained key concepts and laid the foundation for a revolution in finance(Shiller, 2003).
One of the earliest theories within the pool of behavioural finance is the price-to-price feedback theory. It is one of the oldest theories whose mention was noticed in newspapers and magazines way back, even before it was mentioned in scholarly articles(Shiller, 2003). When the speculative price goes up, investment gains are created for some investors, which in turn attracts public attention, promotes word-of-mouth enthusiasm, and raises expectations for further positive momentum in prices(Shiller, 2003).

Behavioural finance examines how psychological factors influence investors' decision-making in financial markets. Several studies have identified key behavioural biases affecting stock trading decisions, including overconfidence, representativeness, and herding (Shukla et al., 2024). These biases significantly impact investment choices and shape future decision-making patterns (Mangala & Sharma, 2014). Behavioural finance encompasses both micro-level examination of individual investor biases and macro-level analysis of market anomalies (Gill & Bajwa, 2018). Research in this field has evolved significantly since its introduction in 1974, with recent studies focusing on seven distinct types of biases (Ansari et al., 2020). Understanding these biases is crucial for investors, financial advisors, and academics to develop more effective investment strategies and portfolios tailored to individual behaviours (Shukla et al., 2024). The growing body of literature in behavioural finance continues to provide valuable insights into the psychological aspects of financial decision-making.

Studies have revealed that biases in behavioural finance affect gender differently. A study on German investors revealed that women are more prone to herding bias, while male investors are more susceptible towards anchoring and overconfidence bias, demonstrating that behavioural biases do not impact both genders equally(Schulz, 2023). Another study examining the impact of behavioural biases on investment decisions revealed that overconfidence and herding bias significantly positively impact investment decisions(Madaan & Singh, 2019). Out of all biases, overconfidence bias is one of the primary building blocks in the discipline of behavioural finance(Madaan & Singh, 2019). Overconfidence is the vigorous outcome of psychology, which is considered one of the principal reasons for market anomalies(Ko & (James) Huang, 2007). Overconfidence bias has been backed by the Self-Attribution theory, which is a psychological concept that explains how individuals attribute their success and failures to internal and external factors.

Recency bias is another bias that has an influential impact on investment decisions. In a financial context, recency bias is also explained by the Adaptive Market Hypothesis, where market participants adapt to changing environment and time and again emphasise recent trends while making their investment decisions, especially in dynamic markets like the stock market. Hogarth and Einhorn's model, earlier known as the belief-adjustment model, is a psychological framework that describes how individuals mould their understanding in response to new information. Investors do not use information properly because they tend to consider the most recent information for decision-making(ALVIA, 2010).

Anchoring bias, a cognitive influencing investment decisions, has gained significant attention in behavior finance research. Studies have shown that this bias affects stock market decisions, impacting individual stock prices (Jiang et al., 2023). Systematic literature reviews have highlighted the prevalence of anchoring bias among other heuristic biases in investment decision-making (Kumar & Goyal, 2019). These reviews emphasise the need for more research on anchoring bias in emerging economies and its role in shaping investor behaviour. The COVID-19 pandemic has further underscored the importance of understanding behavioural biases in stock market participation, as financial uncertainty may exacerbate their effects (Sood & Sharma, 2022). Recognising and mitigating the impact of anchoring bias is crucial for investors, traders, and financial analysts to make more rational investment decisions in stock trading platforms (Jiang et al., 2023).

Herding bias, a key concept in behavioural finance, refers to investors imitating others' actions in financial markets, often disregarding fundamental information (Gupta, 2018; Kumar & narwhal, 2022). This behaviour is more prevalent in developing nations, during crises, and in the short term (Kumar& jarwal, 2022). It is frequently observed in emerging and frontier capital markets (Gusni et al., 2023). Herding can be detected using micro data for specific stocks or aggregate market data through stock price movements (Gusni et al., 2023). The concept extends beyond finance to online consumer behaviour, where social influence affects information search, evaluation, and purchasing decisions (Ali et al., 2021). Research on herding spans multiple disciplines, with a focus on economics and finance, but there is growing interest in its application to marketing, particularly in the online buying context (Ali et al, 2021). Understanding herding behaviour is crucial for comprehending market dynamics and investor decision-making processes.

The rise of fintech has revolutionised stock trading, particularly through mobile platforms and algorithmic trading. Mobile trading apps have increased market accessibility and liquidity in India, attracting a broader demographic of investors (Choudhary et al., 2024). These platforms offer real-time data, streamlined processes, and cost-effective services, leading to a surge in demand accounts and trading volumes. Algorithmic trading has enhanced efficiency and precision in the market (Hasnain et al. 2023). Fintech companies have become attractive investment alternatives, showing greater growth capacity in the stock market compared to traditional financial firms (Gil-cobacho et al., 2023). However, their performance is influenced by economic conditions. The forecasting of fintech stock prices using methods like Random forest has shown promising results, with high accuracy rates (Meher et al., 2023). As the industry evolves, there is a need for robust regulations, financial literacy initiatives, and responsible investing practices to sustain growth and protect investors (Choughary et al., 2024).

From the above theoretical analysis, it can be assumed that investor sentiments are important and play a vital role in shaping the direction of their investment portfolio. This evidently proves that biases in behavioural finance can't be ignored and should be studied thoroughly in order to clarify the underlying factors behind any investment decision, especially in volatile markets.

2.1 Research gap

After thoroughly reviewing numerous research papers in the field of behavioural finance, the author observed that while various behavioural biases have been extensively explored in different studies, there is a notable lack of focus on the demographic factors influencing investors' decisions and their contribution to the occurrence of behavioural biases. Although one study examined the impact of gender on investment decisions among German investors (Schulz, 2023), no similar research has been conducted on Indian investors. Additionally, the influence of stock trading platforms on behavioural finance has not been sufficiently explored. Therefore, these two aspects have been emphasised in this study.

2.2 Research hypothesis drawn from the above literature review:

H1: Male investors are more likely to be prone to overconfidence bias compared to female investors.
H2: Male investors are more inclined to be influenced by recent events (recency bias) than female investors.
H3: Female investors are more likely than male investors to fall victim to Anchoring bias.
H4: Female investors are more likely to be influenced by herding bias than male investors.

H5: The introduction of stock trading platforms has significantly increased investors in the stock market. (H_1: $p > p_0$), p0 = 0.5 (p = sample proportion, p0 = hypothesized proportion) (one-tailed test)
H6: Stock trading platforms are considered more convenient than other ways of purchasing stocks. (Hypothesized Mean - 5)

3. RESEARCH OBJECTIVES

1. To investigate gender differences in the susceptibility to overconfidence bias in stock trading.
2. To analyze the influence of recency bias on both male and female investors.
3. To study the gender-specific susceptibility to anchoring bias in investment decisions.
4. To assess the prevalence of herding bias among male and female investors.
5. To examine the impact of stock trading platforms on investor participation in the stock market
6. To evaluate the perceived convenience of stock trading platforms in comparison to traditional methods of purchasing stocks.

4. RESEARCH METHODOLOGY

To investigate the impact of gender differences on the susceptibility to behavioural biases and to examine the impact of stock trading platforms on investor participation and relative convenience as compared to other ways of investing, the required data was collected from individual investors through a questionnaire in the Google form. The questionnaire consisted of 33 self-assessment questions, of which 20 questions were related to behavioural biases, 6 questions to justify the factor of stock trading platforms, and 7 questions were related to the socio-economic conditions of respondents. The questionnaire was divided into three parts- the first part covers demographic variables of gender, age, and occupation, followed by the second part, which collected information related to investment and their experience with stock trading platforms. The last part is related to behavioural biases.

The data were collected from 91 individual investors through convenience sampling. The primary criteria for sample selection were that the investor should actively invest in stocks exclusively through stock trading platforms and reside in either the Delhi-NCR region or Uttarakhand. The questionnaire was developed utilizing comprehensive resources from scholarly sources, tailored to measure each specific bias accurately. Academic professionals reviewed it, and only after receiving their satisfactory feedback was it distributed to respondents.

The sample size aligns with Jackson’s guidelines for determining sample size based on parameters to estimate, which recommend at least 20 cases per parameter(Suresh G, 2024). In this study, the primary focus is on estimating four parameters—specifically, the biases themselves—which suggests a minimum sample size of 80 cases. However, to achieve more robust results, given the constraints of financial resources, time, and reach, data were collected from 91 individual investors. All responses were fully completed due to the questionnaire's mandatory field policy, allowing for the inclusion of all 91 cases without any missing data.

To effectively examine gender susceptibility to specific biases and the convenience of stock trading platforms, data analysis was conducted using Excel tools and techniques. Excel data analysis tools have been helpful in finding the normality of the data (through the Shapiro-Wilk Test), reliability (Cronbach alpha), correlation coefficient matrix (Spearman’s Rank correlation), and testing of hypothesis (Man Whitney U-test). Graphs have also been used to explain the convenience of stock trading platforms and to show who has started investing after the introduction of stock trading platforms.

5. RESULT AND DISCUSSION

5.1 Socio-economic background

The questionnaire asked respondents to provide their socio-economic details, such as age, gender, investment experience, and occupation. Table 1 describes the socioeconomic background of individual investors. With respect to gender, about 76.1% are male, and only 23.9% are female investors. Age reveals that 67.4% are in the less than 30 years of age group, 25% are in the 30–40 year age group, 5.4% are in the 40-50 year age group, and 2.2% are more than 50 years of age. Occupation confirms that 6.5% have their own business, 6.5% are professionals working in different fields, 66.3% are salaried, and 20.7% are students/scholars. The survey data shows that 26.1% of investors have less than 1 year of experience, 59.8% of them have 1–2 years of experience, 10.9 % of them have 5-10 years of experience, and 3.3% of them have more than 10 years of experience in investments.

Table 1. Socio-economic Background.			
Serial Number	**Socio-economic Background**	**Variables**	**Frequency**
1	Gender	Male	76.10%
		Female	23.90%
2	Age	Under 30	67.40%
		30-40	25%
		40-50	5.40%
		50 and above	2.20%
3	Occupation	Business	6.50%
		Professional	6.50%
		Salaried	66.30%
		Student/Scholars	20.70%
4	Investment Experience	Less than 1 year	26.10%
		1-5 years	59.80%
		5-10 years	10.90%
		10 years and above	3.30%
5	Investment objective	Capital Growth	25%
		Income Generation	27.20%
		Long-Term Wealth Building	45.70%
		Retirement Planning	2.20%
6	Year of investment	Before 2010	1.09%
		2011-2015	4.35%
		2016-2020	39.13%
		2021-2024	47.82%
		Could not track	7.61%

Source: Survey data

5.2 Normality test

Before proceeding further with the Coefficient correlation matrix and hypothesis testing, it is vital to find the normality of the collected data. The Shapro-wilk test has been used to find the normality of the data since there are 91 respondents, and this test is the best fit here. This test was introduced by Samuel Sanford Shapiro and Martin Wilk in 1965. Below is the table showing the p-value, W-stat, alpha at 0.05% and decision regarding normality (table 2).

Table 2. Shapiro-Wilk Test				
Biases	**W-stat**	**P-value**	**Alpha**	**Normality**
Overconfidence bias	0.964074594	0.012995294	0.05	No
Recency Bias	0.983111713	0.287554888	0.05	Yes
Anchoring Bias	0.977096128	0.108797557	0.05	Yes
Herding Bias	0.978933904	0.147235915	0.05	Yes

Source: Calculated by author

The results of the Shapiro-Wilk test for the three biases, namely recency bias, anchoring bias and herding bias, consistently indicate that the data follows a normal distribution. For each bias, the p-values are greater than the significance level (alpha = 0.05). Specifically, the p-values are 0.1472**,** 0.1088**,** and 0.2876, which means that the null hypothesis—stating that the data is normally distributed—cannot be rejected for any of the biases. Furthermore, the W-statistics for all three biases are close to 1, which further confirms the normality of the data, as a W-statistic closer to 1 indicates a stronger fit to the normal distribution. Therefore, it can be concluded that the data for all three biases meets the assumption of normality, making it suitable for parametric statistical tests that require normally distributed data. However, the results of the Shapiro-Wilk test for overconfidence bias indicate that the data does not follow a normal distribution. The test produced a W-statistic of 0.9632 and a p-value of 0.0120, which is less than the significance level (alpha = 0.05). Since the p-value is below 0.05, the null hypothesis, which assumes that the data is normally distributed, is rejected. Therefore, it can be concluded that the data deviates from normality, suggesting that non-parametric tests or data transformations may be more appropriate for further analysis. Since the assumption of normality is not met for one of the biases, there are two options: either apply non-parametric tests for all biases to maintain consistency across analyses or use parametric tests for the biases that meet normality assumptions and non-parametric tests for the one that does not. Non-parametric tests, such as the Mann-Whitney U Test, are robust and can handle both normal and non-normal data. However, if maintaining consistency is a priority, it is recommended to use non-parametric tests for all four biases, as this avoids violating statistical assumptions and ensures a uniform approach to hypothesis testing. Hence, the researcher has decided to use a non-parametric test (Mann-Whitney U Test) for hypothesis testing.

5.3 Reliability Test

To access internal consistency/reliability for the survey data, cronbach alpha has been used. Cronbach's alpha is a widely used statistical measure of reliability in psychometric testing and research (Jain & Angural, 2017). It assesses the internal consistency of a scale or questionnaire, with values greater than or equal to 0.07 generally considered acceptable (Klllc, 2016). However, very high values (greater that 0.9) may indicate redundant items (Klllc, 2016). Bonett & Wright (2015) propose a confidence interval method for Cronbach's alpha that does not require equal variances or covariances, outperforming traditional methods in simulations.

Table 3. Cronbach Alpha

Independent Variable	Latent Variable	Dependent variable	Cronbach Alpha
Gender	Heuristic bias	Overconfidence bias	0.778190927
		Recency bias	0.89142624
		Anchoring bias	0.89069982
		Herding bias	0.90698318
Stock Trading Platforms	Investor experience with stock trading	Increased stock market investors	-
		Investment convenience	-

Source: Calculated by author

Table 3 reveals that all variables in the study exhibited Cronbach's alpha coefficients exceeding 0.70. This result indicates that the measured dimensions demonstrated high reliability and internal consistency in assessing the intended constructs. The elevated Cronbach's alpha values observed in this study further substantiate the reliability of the measured variables.

5.4 Correlation Coefficient Matrix (To access the strength and direction of the relationship)

After measuring the reliability of the data through Cronbach alpha, the correlation coefficient matrix table has been formulated with the gathered data using Spearman's Rank Correlation (since data is not normally distributed). The correlation coefficient matrix is an essential statistical tool for summarizing the relationship between various variables considered in the study. It is considered helpful in drawing the direction and degree of the relationship between variables. It tells whether two variables are moving in the same direction (positive correlation) or in opposite direction (negative correlation), which in turn informs about the relevance of various variables or if there is a need to combine variables to reduce dimensionality. Below is the table (table 2) showing the values of various variables considered in this study. The table shows Spearman's rank correlation because the data is not normally distributed, otherwise, Pearson's rank correlation could have been used.

Table 4. Correlation Coefficient Matrix (Spearman's Rank Correlation)

Variable	Overconfidence Bias	Recency Bias	Anchoring Bias	Herding Bias	Investment Convenience	Increased Stock Market Investors	Gender
Overconfidence Bias	1	0.799468	0.79105694	0.74788	0.1132302	0.11086043	-0.51717
Recency Bias	0.799468455	1	0.86201355	0.8646	0.109084047	0.15385097	0.153851
Anchoring Bias	0.791056935	0.862014	1	0.91383	0.065491185	0.14101569	-0.43873
Herding Bias	0.747880171	0.864599	0.91383346	1	0.052387009	0.19448509	-0.41856
Investment Convenience	0.1132302	0.109084	0.06549118	0.05239	1	0.06131572	0.094955
Increased Stock Market Investors	0.110860434	0.153851	0.14101569	0.19449	0.061315715	1	0.122996
Gender (Male/Female)	-0.517165611	0.153851	-0.4387327	-0.41856	0.094955137	0.12299641	1

Source: Calculated by author

Table 4. reveals strong positive correlations among the biases of Overconfidence, Recency, Anchoring, and Herding, with a notable example being the correlation of 0.8646 between Recency Bias and Herding Bias, suggesting a propensity for individuals to exhibit multiple biases simultaneously. In contrast, perceived convenience in using stock trading platforms shows minimal correlation with these biases, indicating little to no relationship. Similarly, the variable indicating an increase in stock market investors shows only weak associations with biases, such as a 0.1539 correlation with Recency Bias and 0.1945 with Herding Bias. Gender analysis reveals negative correlations between female respondents and certain biases, specifically Overconfidence (-0.5172) and Anchoring (-0.4387), suggesting that females may be less prone to these biases compared to males.

5.5 Hypothesis testing

After measuring the coefficient correlation matrix, the most vital portion of this research paper comes next, i.e., finding what our data actually depicts. Mann Whitney U-test was used to test the hypothesis created for the first four biases (Table 5). The said test has been used because data is ordinal, not normally distributed, the sample size is small, and there are two independent groups (Male and female).

Table 5. Testing of hypothesis using Mann Whitney U Test

Test Details	Test 1 (OB)	Test 2 (RB)	Test 3 (AB)	Test 4 (HB)
Median (Male)	2.25	2.175	2.15	2.3
Median (Female)	2.4	2.4	2.325	2.6
One-Tailed p (Exact)	0.3595	0.1670	0.0617	**0.0138**
Two-Tailed p (Exact)	0.7191	0.3341	0.1233	**0.0276**
Interpretation	No significant difference (p>0.05)	No significant difference (p>0.05)	Approaching significance (p≈0.06 approx)	**Significant difference (p<0.05)**

Source: Calculated by author

The rigorous analysis of data through Excel data analysis tools and methods presents the findings of a statistical analysis examining the impact of gender on various cognitive biases in investment decision-making, specifically focusing on overconfidence bias, recency bias, anchoring bias, and herding bias. The data collected through a questionnaire using a Likert

European Economic Letters
ISSN 2323-5233
Vol 15, Issue 1 (2025)
http://eelet.org.uk

scale has been tested using a non-parametric test (Mann-Whitney U Test), and the p-values have been mentioned in Table 4. The analysis of behavioural biases reveals the following gender-specific observations: For overconfidence bias (Test 1, p = 0.3595) and recency bias (Test 2, p = 0.1670), no significant differences were found between males and females, indicating that both genders are equally inclined to these biases. For anchoring bias (Test 3, p = 0.0617), the result approaches significance (p≈0.06p \approx. 0.06p≈0.06), suggesting a possible trend where males may exhibit slightly higher anchoring bias than females, though the difference is not statistically significant. For herding bias (Test 4, p = 0.01238), a significant difference was observed, with females (Median: 2.6) being less inclined to this bias compared to males (Median: 2.3). Hence, it can be concluded that herding bias is more prominent in stock investing, particularly among men. These results suggest that while gender does not significantly affect overconfidence, recency, or anchoring biases in investment behaviour, it does appear to play a crucial role in influencing herding bias. This finding highlights the need for further research to explore the underlying mechanisms that contribute to gender differences in susceptibility to herding behaviour, thereby enhancing our understanding of how demographic factors shape investment decisions and inform strategies to mitigate cognitive biases in financial contexts.

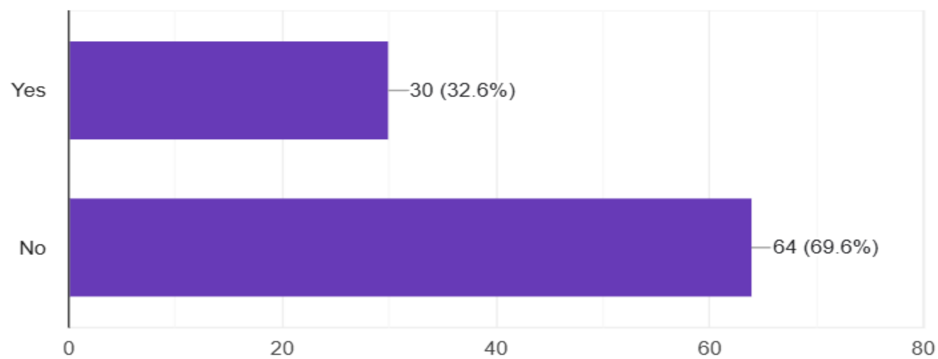

Figure 1: Chart depicting investors' entry prior to stock trading platforms.

Source: Survey data

Yes: Started Investing prior to stock trading Platforms; No: Started Investing after introduction of stock trading platforms

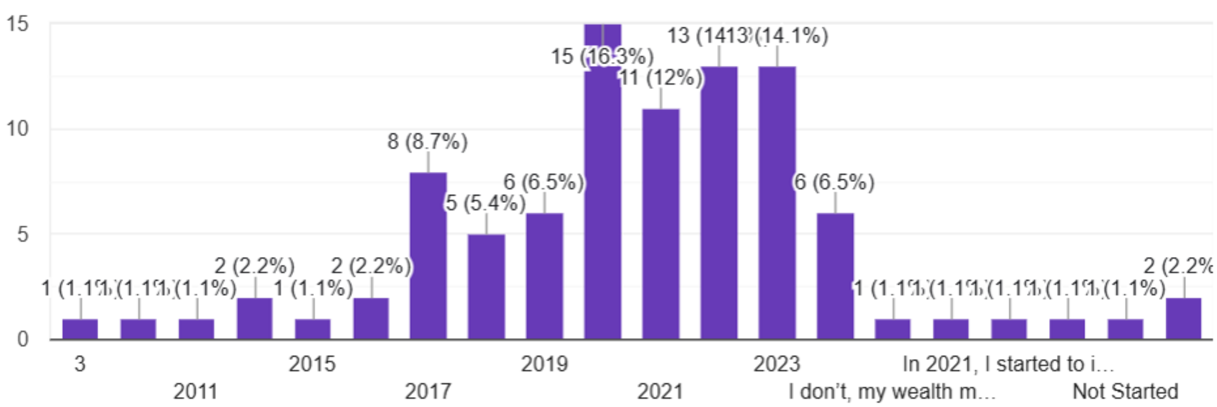

Figure 2: Chart depicting the initiation years of investors' engagement with stock trading platforms.

Source: Survey data

Figures 1 and 2, based on survey data, illustrate whether investors began investing in stocks prior to or following the introduction of stock trading platforms (Figure 1) and depict the years in which investors commenced stock investments through these platforms (Figure 2). The data indicate that 69.6% of respondents began investing after the introduction of stock trading platforms, while 32.6% had invested prior to their awareness of these platforms. This suggests that a substantial majority of current retail investors in the stock market are influenced by stock trading platforms. To confirm these results, a hypothesis test was conducted using a z-test to determine the p-value through Excel data analysis methods. Utilising the observed proportion (0.696), the hypothesised proportion (0.5), and a sample size of 91, it can be subsumed that the observed proportion is significantly greater than the hypothesised proportion, stating that a great percentage of respondents have started investing only after the introduction of stock trading platforms, which in turn provides strong evidence against the null hypothesis (reject H0), thus supporting the acceptance of the alternative hypothesis. Consequently, it is reasonable to conclude that the introduction of stock trading platforms has significantly increased investor participation in the stock market, corroborating the acceptance of Hypothesis H5.

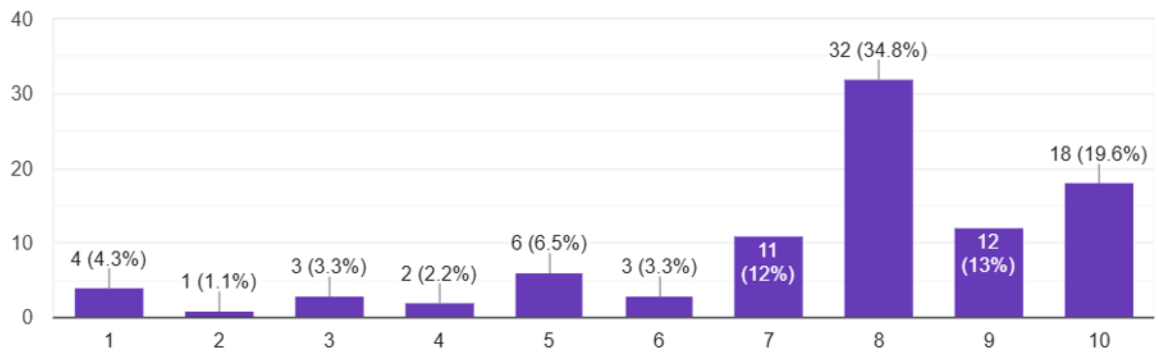

Figure 3: Chart depicting the convenience of stock trading platforms.

Source: Survey Data

Figure 3, derived from survey data, illustrates investors' perceptions of convenience with stock trading platforms on a scale from 1 to 10 (where 1 represents 'not convenient at all' and 10 signifies 'highly convenient'). The data indicate that over 82% of respondents perceive stock trading platforms as convenient, with 6.5% expressing neutrality and 10.9% finding them either less convenient or not satisfactory. Consequently, these findings support the acceptance of H6, suggesting that stock trading platforms are more convenient than other stock purchasing methods. A hypothesis test was conducted using a one-tailed t-test with an alpha level of 0.05 and a hypothesised mean of 5 to confirm these results. The analysis reveals a significant difference between the sample mean convenience rating for stock trading platforms (7.49) and the hypothesised mean (5). With a mean score of 7.49, respondents, on average, rated trading platforms as much more convenient than the midpoint (5) on the scale, indicating a strong preference.

6. CONCLUSION

The primary aim of this study is to examine whether certain behavioural biases are more prominent in male or female investors, specifically identifying which gender is more susceptible to these biases when investing in volatile markets like the stock market. Additionally, the study explores the relative convenience of stock trading platforms and their role in attracting new investors to the market. The research includes six hypotheses: four addressing the relationship between gender and specific behavioural biases (overconfidence, recency, anchoring, and herding), and two focusing on the impact of stock trading platforms.

The findings indicate that behavioural biases such as overconfidence, recency, and anchoring influence investment decision-making equally among male and female investors. Notably, herding bias emerged as a significant influence, with men showing a higher propensity to fall prey to this bias than women. Additionally, stock trading platforms have been considered convenient while investing, and among the respondents, the majority of investors have started their investments only after the introduction of stock trading platforms.

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