Article

Herding Bias and Social Media Scams in the Stock Market: The Mediating Role of Overconfidence in Investment Decisions

***Md Anhar Sharif Mollah**, and
Mohammad Rokibul Kabir, Daffodil International University
Md. Meherul Islam Khan, University of Rajshahi
Friday Ogbu Edeh, Kampala International University, Uganda
E-mail: anhar.bba@diu.edu.bd

Submission received: 10 January 2025 / Revised: 21 May 2025 / Accepted: 27 June 2025 / Published: 30 June 2025

Abstract: *Behavioural biases are thought to be important influencers in explaining speculative investment, leading to irrational stock market decision-making. This study aims to assess the influence of behavioral biases called herding and social media scams on stock market investment decisions in Bangladesh with a special focus on the mediating role of overconfidence. Based on the Behavioural Bias theory and grounded in a positivist research paradigm, the study adopts a quantitative methodology. A convenient sampling technique is employed to collect data through a structured questionnaire administered to 700 investors in the stock markets of Bangladesh, achieving a response rate of 60.29% with 395 respondents. The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The study reveals that investment decisions are greatly influenced by social media scams and herding biases. Similarly, social media and herding bias greatly contribute to the development of overconfidence. Furthermore, irrational investing decisions are partially mediated by overconfidence. The study provides practical implications for policymakers and financial institutions to design behavioral interventions and educational programs aimed at mitigating the adverse effects of such behavioral biases. By understanding common cognitive biases, advisors can help clients avoid following the crowd or making decisions based on social influence. Advisors can also play a key role in promoting more independent and evidence-based investment strategies.*

Keywords: Herding bias, Social media scams, Investment decision, Stock markets, PLS-SEM

1. Introduction

The emerging field of behavioral finance research aims to comprehend how cognitive and psychological biases influence investment decision-making. One of the most important psychological phenomena in the stock market investment is herding behavior, coupled with the recent rise in social media hype and scams related to stock market investment. Individual investors have recently shown a tendency to rely on peer information and social media gossip of super gains from particular stocks, which makes them overconfident, leading to biased investment decision-making (Ammann & Schaub, 2021). The tendency to collaborate with other people instead of forming own views is known as herding bias (Gong *et al.*, 2023). They frequently take financial advice from other investors. Investors may make wrong judgments due to herding. Herding behavior is exacerbated by price bubbles, rumors, and eccentricities in the market.

----

[*]**Corresponding Author**

Herding is the convergence caused by collective imitation (Suresh, 2024). People imitate others when they are uncertain or uneducated (Ahmad et al., 2022). Herd mentality among investors can lead to poor investment decisions because of overconfidence created by others (Shah & Hussain, 2024). Anyone with an internet connection may access social media (SM), which acts as a forum for investors to share their ideas and opinions (Fitri & Hariyanto, 2024). According to Gunathilaka & Wickramasinghe (2023), social media platforms have become an essential part of our everyday lives and influence many facets of our behavior, including the way we make financial decisions. With its many frauds and thrilling news, SM life has in many instances nearly turned into an addiction (Karaiskos et al., 2010; Turel & Serenko, 2012). However, the habit of using cellphones and social media for emotional support and accessibility has a significant impact on investing markets through social impacts (Atmaningrum et al., 2021). Herding may result from social contact since individuals prefer to gather reactions and share experiences of others who are reliable to them. This can occasionally cause investors to make irrational decisions based on scams that their peers communicate on social media. In recent years, the financial sector has been influenced by the emergence of SM, especially when it comes to stock market investment decisions. Researchers have been interested in the effect of social media on investment decisions because it provides information on how user activity on social media platforms affects investment decision-making (Al Atoom et al, 2021). Thus, the SM can affect how people make decisions, especially when information is presented and accompanied by overconfidence. This can affect investors' psychological states while they are making investment decisions. Moreover, individuals may make inaccurate decisions, take unnecessary risks, and underestimate issues as a result of their overconfidence. A biased belief in an individual's abilities, expertise, or discernment is referred to as overconfidence. Many individuals exaggerate their abilities or convictions, which can result in hazardous assessments of their decision-making abilities. Cognitive activities, social media scams, and herding behaviour lead to overconfidence. Overconfident people may exaggerate their skills, knowledge, or accuracy in assessments (Al Maghrabi et al., 2024; Olawole-Scott & Yon, 2023; Neal et al., 2022). When making financial decisions, overconfidence has a significant influence on investor behavior and market outcomes (Wang & Nuangjamnong, 2022; Abideen et al., 2023), such behavior is common among investors and may have an impact on their strategies and outcomes (Newall & Weiss-Cohen, 2022). Additionally, this mindset might cause one to miss out on chances for development and advancement (Manzoor et al., 2023).

Though there are different studies on behavioral finance, the big question regarding how herding and social media scams combinedly influence stock market investment decisions mediated by overconfidence requires addressing. Hence, further study is required to fully comprehend how SM characteristics, overconfidence, and herding biases affect investment decisions (Shahani & Ahmed, 2022; Kumar & Prince, 2023). Thus, this study aims to assess the effect of herding bias and social media scams on investors' decision-making processes in the capital market of Bangladesh. It also evaluates the mediating role of overconfidence in the relationship between herding bias, social media scams, and investment decisions, with the expectation to add a new dimension to capital market research.

2. Literature Review, Underpinning Theory & Hypotheses Development

In recent decades, neoclassical finance has failed to provide a satisfactory explanation for the observed behavior of equity markets, according to financial economists and psychologists (Baker & Wurgler, 2007). Although the efficient market theory maintains that asset prices should reflect all relevant information, accurate forecasting of future price changes is not achievable (Fama, 1970). Conventional finance theories assert that investors operate rationally in the market, but, in actuality, an investor's ability to make decisions is impeded by a variety of behavioral and psychological issues. Over the years, it has been noted that investors don't always act rationally while making financial decisions (Nigam et al., 2018). They base their conclusions on their tastes, views, and experiences from the past.

2.1 Behavioral Bias Theory

Behavioral finance posits that humans, in addition to being social and intellectual entities, utilize both cognitive processes and emotions in their decision-making. Behavioural finance is defined as "a study of cognitive errors and emotions in financial decisions" (Hirschey & Nofsinger, 2008). The examination of financial decision-making affected by emotional and cognitive factors is referred to as behavioral finance. The function of emotions in decision-making is another significant issue in behavioral finance. Fear, greed, and overconfidence can all impact investor behavior and lead to poor decisions. Behavioral bias is a pattern of judgmental oscillation that occurs in specific situations. It may occasionally lead to erroneous judgment, incorrect interpretation, perceptual distortion, or what is commonly termed irrationality. According to Shefrin (2002), behavioural finance is not a science that can outwit the market. The foundation of behavioural finance is the finance and economics paradigm, which upholds psychological and cognitive behaviour in the context of making investment decisions. It investigates the psychological elements that influence irrational investment decision-making (Thakur, 2017). Investors may think incorrectly due to a variety of behavioural biases, including herding, that they are prone to. Rigorous research efforts focus on developing a valuable framework for the systematic classification of these biases. Rather than a broad theory of investment behaviour, the basis of behavioural finance research is a substantial body of evidence demonstrating the ineffectiveness of human decision-making in a wide range of economic decision-making scenarios (Pompian et al., 2021).

2.2 Herding Bias

When many investors act in the same way at the same time on the stock market, this is known as herding. According to Ranjbar et al. (2014), it is the investor's propensity to imitate other investors' actions in the financial market. Additionally, investors who engage in herding tend to make decisions based on the activities of others rather than on their private information. It exists because the logical investor begins acting irrationally in the financial market by imitating other people's choices. According to Kumar and Goyal (2015), the individual investor typically exhibits herd behavior by imitating the actions of a sizable group. Herding can initiate stock trading and increase its momentum, according to Waweru et al. (2008). According to Zahera and Bansal (2018), herding is a component of behavioral finance and refers to the collectively irrational conduct of investors who follow other traders in the stock market. Herding happens when the market is growing or falling, in general and in particular circumstances, such as bull and bear markets, high-volume trading scenarios, and market conditions. Reasonable stock market investors never follow the herd and instead make their own decisions based on the facts. However, investors tend to follow the group when they lack the expertise and information necessary to decide. Herding, often referred to as the bandwagon effect, is a bias when investors heavily rely on the choices made by those around them to appear to be like them and be connected with them. As a result, asset prices deviate from their intrinsic values (Dewan & Dharni, 2019). The tendency of an investor to imitate the activities of other investors is referred to as "herd mentality bias" in behavioral finance.

Instead of using their critical thinking, they rely more on their feelings and instincts (Chaudhary, 2013). The phrase "herd mentality" refers to a phenomenon in which reasonable investors will occasionally act foolishly to emulate the investment decisions made by other investors. This is what occurs when investors are pressured to select assets (Malik & Elahi, 2014). Herd mentality: investors typically act in this way because they think that the decisions made by the majority of investors are always going to be the right ones. This tendency may lead to unwise investment decisions. Herding investors, according to Loxton et al. (2020), base their stock purchases and sales decisions on the actions of the vast majority of other investors in the market. The study found that herd mentality persisted in the market during both price increases and decreases. The herding effect also causes a large increase in market volume and volatility. Before deciding what to buy, investors spend a great deal of time and energy carefully examining the information that the public has to provide. When making judgements, investors often disregard their expertise, no matter how precise, and unintentionally follow the herd, even when the herd may be wrong. When they digest information, they will always act like a herd, and when they do, they will find joy in mistakes made by the group as a whole as opposed to by a single individual (Ahmad & Mahmood, 2020). Herding, according to Banerjee (1992), is when "everyone follows what everyone else does, even when their private information suggests doing something different." Herding tends to repeat earlier behaviors, whether they were sensible or not (Devenow & Welch, 1996). According to research by Fernández et al. (2011), when investors rely on false information, they are more likely to accept the beliefs and choices of others. When gathering data and assessing financial problems, herding typically has an impact on individual investors. They are unable to assess the market. According to herding theory, individual speculators who can cause grouping variance on the objective market are institutional finance professionals (Ouarda et al., 2013). Herding behaviour, which typically shows up during periods of market stress, is a common practice among investors in emerging economies (Rahayu et al., 2020). Humra (2014) defines herding behaviour as the practice of a group of investors disregarding independent information in favor of group information while making investment decisions. As a result, there will be noticeable changes in market prices when the majority makes a poor decision.

2.3 Social Media Scam

Social networking sites now play a crucial role in everyday life, influencing many facets of our conduct, including how we make decisions. The financial sector has also been influenced by social media's rise, especially in regard to investing choices. According to Kariskos et al. (2010) and Turel and Serenko (2012), social media use has nearly turned into an addiction. The two most popular platforms for social sharing are Twitter, where people also share manipulated information and create financial scams (Andreassen et al., 2012), and Facebook (Karadag et al., 2015). However, the practice of using social media has led to a significant change in the accessibility and structure of information (Atmaningrum et al., 2021), and social influences have played a noteworthy role in investing markets. Social interaction may develop herding as they tend to collect responses and share experiences with similar people.

2.4 Overconfidence Bias

An example of overconfidence bias is when someone thinks highly of themselves, their knowledge, or the precision of their views and judgments. Due to this bias, people may undertake or decide to take on jobs that they cannot execute successfully (Shah et al., 2018). "Too many people overvalue what they are not and undervalue what they are," claims Chernoff (2010); these people suffer from an overconfidence bias. Overconfidence, according to Simon et al. (2000), may exist because individual investors fail to appropriately adjust their initial evaluations after receiving fresh information, failing to recognize how inaccurate those assessments may be. The cause of their overconfidence is that they believe their judgment to be overly certain. Overconfident investors exaggerate the precision of their valuation skills, as Abbes et al. (2009) effectively suggest. Consequently, they base their investing decisions on private signals, disregarding public signals. Overestimation, over-placement, and overprecision are three personality traits that Moore and Healy (2008) claim are present in people who exhibit overconfidence bias. In overestimation, individuals predominantly focus on their own capabilities, with the decision-maker's opinions of performance quality overshadowing the actual performance (Statman et al., 2006). Overestimation is a characteristic that can be quantified through overperformance, level of control, likelihood of success, and overestimating one's true talents (Duttle, 2015). Overplacement is the belief that one is superior to another. Because they are overconfident in their ability to make sound investment decisions, overly exact investors fail to consider the risk factors (Odean, 1999). Shefrin (2002) states that overconfidence "relates to how well people understand their abilities and the limits of their knowledge." Overconfident individuals frequently think they are superior to others despite their true limitations. The same is true for data. Excessively confident people often think they know more than they do. Overconfident people don't always have inadequate knowledge or abilities. Instead, it suggests that individuals think better of themselves than is the case. An investor's tendency to overestimate their ability to select stocks and know when to enter or exit a position is common. Traders who made the most trades tended, on average, to obtain yields that were much lower than the market, according to a study by Odean (1999) into these patterns. Additionally, overconfidence leads people to exaggerate their influence over events, underestimate hazards, and overestimate their knowledge, according to psychologists. Overconfidence bias as a whole is a common cognitive bias that can have important repercussions across a range of fields. People can attempt to overcome this prejudice and make better decisions if they are aware of how it affects them.

2.5 Herding Biases, Overconfidence, and Investment Decisions

By investigating herd behavior in stock exchange alliances (EURONEXT), Kallinterakis and Lodetti (2009) expand their analysis beyond the national market. They offer proof of notable herd behavior in the global securities market. However, when adjusting for the impacts of size, industry, and country, such a trend becomes weaker. German-language researchers Oehler and Wendt (2009) examine the trading actions of equity fund managers from 2000 to 2005. When fund managers see broad market-wide cash inflows or withdrawals, they discover considerable evidence of herd behavior. Additionally, fund managers who only select German equities for investment exhibit herd behavior when choosing stocks. In a more recent study, Balcilar and Demirer (2015) examined the dynamic interplay between global risk factors and herd behavior in the Turkish market utilizing the Markov regime-switching model. Important evidence of herd behavior under regimes of high and extreme volatility is found. They also demonstrate that, except for the industrial sector, factors associated with the US market have a substantial impact on such regime transitions and, consequently, herd behavior. Huang *et al.* (2015) examine how investors' actions on the Taiwan equities market are impacted by idiosyncratic volatility. They discover substantial evidence of herd behavior, which exhibits a distinct pattern in the peculiar volatility of different industries. Galariotis et al. (2016) provide additional proof of herd behavior for high-liquidity equities in the G5 market. Additionally, they demonstrate how return clustering influences equity market liquidity variance, particularly during and after crises. The herding practices in Asian stock exchanges (China, South Korea, Singapore, Malaysia, and Indonesia) were discussed by Chiang and Zheng (2010) and Zheng et al. (2017) and Chang and Cheng’s (2010) conclusion that herding acts are more common in developing countries. "Herd mentality bias" refers to investors' propensity to copy and reproduce the moves made by other investors. Their decisions are primarily influenced by instinct and emotion rather than independent thought. Lakshman et al. (2013) observed the impact of return and volatility on the herding behavior of institutional investors in the Indian capital market. The findings show that there are herding tendencies in the market. Chen and Pelger (2013) used the Black-Scholes model to ascertain how compensation affected herding behaviour. The results showed that herding was motivated by managers' risk aversion and relative compensation. Investor herding behaviour in the Pacific Basin equities market was examined by Chiang et al. (2013). The result demonstrated that different herding behaviours are associated with bullish and bearish market conditions. It also revealed a negative association with market volatility and a positive correlation with herding and market performance. Cipriani et al. (2012) examined the importance of herding behaviour in the financial markets using data from the Ashland Company, a stock traded on the New York Stock Exchange. The result showed that it affects asset prices as well as traders' decisions to buy and sell. Using individual and sector-level data, Demirer and Kutan (2006) investigated the effects of herding information in the Chinese market. Additionally, they discovered the return dispersion during market index up- and down-moving periods. The outcome demonstrated that the Chinese market did not exhibit herding behavior, and equity return dispersion was much higher during periods of major change in the overall index. The results are also consistent with the asset pricing and market efficiency models. Drehmann et al. (2005) examined the impact of herding and contrarian behavior in the financial market using an online experiment methodology. 264 consultants from international firms took part in this project. According to their findings, market prices that are flexible minimize herding tendency and price distortion caused by contrarian behavior. Using EPRF data from Latin America and Asia, Hsieh et al. (2008) investigated the effects of herding behavior and positive feedback on capital influx. The outcome showed that the herding effect exists in emerging markets where capital and good feed information exist. Kallinterakis and Kratunova (2007) examined how thin trading affected herding behavior in the Bulgarian market using the Hwang and Salmon (2004) measure. The outcome shows that thin trading lessens herding tendencies. Oehler and Wendt (2009) used manager purchasing and selling data from the years 2000 to 2005 to identify the mutual fund herding tendency in Germany. The outcome revealed that they invest 70% of their money in the stock market, demonstrating unequivocally that there is strong herding behavior in the stock market. Ornelas and Alemanni (2008) examined herding behavior in these markets using data from nine developing nations between 2000 and 2005. According to the analysis, emerging markets exhibit herding behavior. Additionally, it was shown that herding had little effect on volatility. 57 German mutual fund companies, which invest mostly in DM-dominated bonds and account for 71 percent of the market volume, provided the data for Oehler and Chao's 2000 study of institutional herding in the bond market. Their findings indicated that the bond market exhibited substantial herding behavior. Puckett and Yan (2008) used 776 institutional investors' trades from 1999 to 2004 to study the effects of short-term institutional herding on stock prices. They claimed that pricing and short-term selling driven by behavior diverged sharply from underlying worth. Redding (1996) investigated herding behavior and the noise trader. The findings demonstrated that prices drastically differed from their intrinsic value. Raddatz and Schmukler (2013) investigated the herding behavior of pension fund managers using special monthly asset-level data from the pioneer instance of Chile and came to the conclusion that herding bias significantly and favorably influenced portfolio investment choices. The outcome demonstrated that the fund managers followed one another's tactics to increase profit and minimize risk. Using data from 2000 to 2005, Arouri and Nguyen (2010) examined institutional investors' herding behavior in the French equities market. The findings indicated that tiny enterprises, as opposed to large and medium-sized firms, exhibit herding more frequently. Using a unique set of data from daily translation over four years, Venezia *et al*. (2009) explored the herding tendency of amateur and professional investors. The findings indicated that novice investors exhibit more herding behavior than professionals. Wang (2008) used state space models to investigate market index herd behavior. They looked at how people gathered around unforeseen events like the financial crisis of 1997–1998. The findings indicated that emerging markets experienced more herding than developed markets. Yao (2010) looked at the trade volume on the Toronto Stock Exchange using Hwang and Salmon's (2004) measure of herding tendency. The findings showed that there are three elements to herding. The first is the market condition indication. The second is intentional herding concerning investor expectations, and the third is present herding that is dependent on earlier herding.

H1: Herding bias has a significant direct effect on investment decision-making

H2: Herding bias has a significant positive effect on investor overconfidence.

2.6 Social Media Scam & Investment Decisions

According to Agarwal et al. (2022), SM may significantly impact how share prices respond to declarations, especially for businesses that receive a lot of attention via SM. According to Maity and Sandhu's "Evidence from Facebook and Twitter" (2021), social media has a crucial influence on stock prices. In their research, Chaitanya & Nordin (2021) claimed that investors' belief in SM scams for information and investment has a big influence on investment decisions. According to Al Atoom et al. (2021), investors participating in SM frequently imitate transactions from other people's success stories and adhere to well-liked investing techniques, suggesting a herd mentality and a lack of independent thought among them. According to Miniesy et al. (2022), members of the well-known investment community called "Seeking Alpha" tend to display confirmation bias by ignoring evidence that disputes their preexisting views on scams and only looking for evidence that confirms those ideas. According to Kaustia and Knüpfer (2012), SM scams have an impact on individual investors' stock market engagement. Furthermore, Henseler et al. (2016) offers proof that SM influences the trading habits of individual investors. According to Agarwal et al. (2022), SM users often trade with greater frequency compared to other traders and exhibit overconfidence due to SM scams, which lowers investment returns. According to Barber and Odean (2002), the internet contributes to the overconfidence of individual investors by allowing them to validate their preexisting opinions through the abundance of financial data and scams that are accessible online. Based on the above argument, the following hypotheses are formed.

H3: Social media scams have a significant direct effect on investment decision-making.

H4: Social media scams have a significant direct effect on overconfidence.

2.7 Herding, Social Media Scams and Overconfidence

Psychological traits like herd mentality and overconfidence influence stock market investment decisions. When traders follow other influential investors without conducting market research, this is known as herd behavior (Smith et al., 2023). On the other hand, overconfidence results from overestimating one's skills and knowledge, which leads to unnecessary risk-taking. Recent research looked at how herd behavior on investments is mediated by overconfidence (Lee & Ma, 2024). According to Smith et al. (2023), overconfidence and herding lead to irrational decisions, which have a big impact on market dynamics when there is uncertainty. Overconfidence causes investors to make wrong decisions in volatile markets with little information (Lee & Ma, 2024). Jain et al. (2023) found overconfidence to be a mediator of herd behavior and investment choice, which lends support to the following hypotheses.

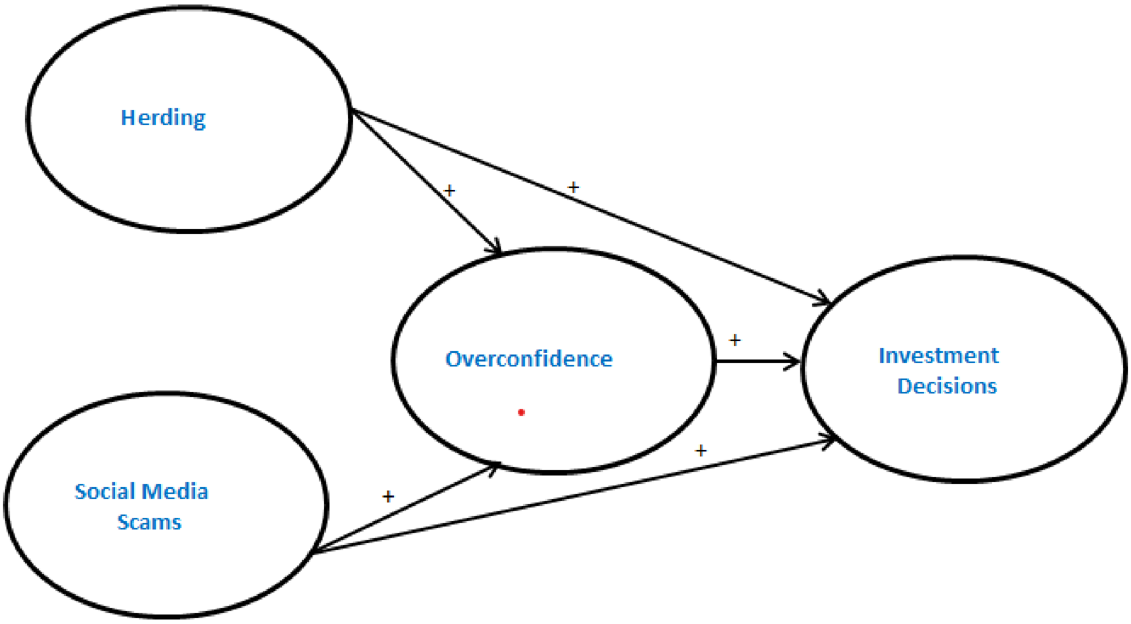
H5: Overconfidence positively influences investment decision-making.

H6: Overconfidence mediates the relationship between herding bias and investment decision-making.

H7: Overconfidence mediates the relationship between social media scams and investment decision-making.

Therefore, based on the above literature and Behavioural Finance Theory, the research framework is proposed in Figure 1.

Figure 1: Research Framework



Source: Authors' Compilation.

3. Methodology of the Study

This study used a deductive approach because its design required gathering and examining primary data from the field before attempting to draw any theoretical generalizations (Saunders et al., 2007). Put another way, the hypothesis was developed and tested in this study using primary data obtained through a questionnaire. This study's research methodology attempts to investigate how behavioral factors called prospect biases affect the performance and investment choices of individual investors.

3.1 Population and Sampling

The study's target participants for primary data collection were all active individual investors who had invested in various stocks either in the Dhaka Stock Exchange (DSE) or in the Chittagong Stock Exchange (CSE). A questionnaire survey technique was used to gather the primary data. According to the most recent information provided by Central Depository Bangladesh Limited (CDBL), the total number of domestic investors' BO (beneficiary owner) accounts in the country as of July 31, 2023, was 17,53809, which forms the population for this study. A convenience sampling technique has been chosen for this study because it is accessible to the researcher and is suitable for the study area's constantly fluctuating population size (Bell et al., 2022). Thus, convenience sampling was employed for both the survey and the primary data collection, supported by similar earlier studies incorporating convenience sampling, including Chandra and Kumar (2012), Chavali and Mohanraj (2016), and Asgarnezhad and Soltani (2017). For a large population, at a 5% standard error and a 95% confidence level, the sample size should be 384. Sekaran (2016) added that a sample size of 384 should be used if the population is more than 10,000. Hence, this research includes a sample size of 395 investors in the stock markets of Bangladesh.

3.2 Constructs and Items

The following Table 01 shows the constructs and relevant items.

Table 01: Constructs and Items

Construct	Items	Source	Measurement
Herding Bias	05	Khan & Imam (2023).	Five-point Likert scale
Social Media Scam	03	Ahmed et al. (2021).	
Overconfidence	03	Bakar & Yi (2016), Singh & Chakraborty (2024).	
Investment Decision	4	Bakar & Yi (2016), Sachse et al. (2012).	Five-point Likert scale

Source: Authors' Compilation.

3.3 Data Collection Methods and Questionnaire Design

A total of 700 questionnaires were distributed to active individual investors. The goal of distributing these 700 questionnaires was to maximize responses and enhance the generalizability of the current study. The goal of the study was explained to the participants, and they received assurances regarding the privacy of the information gathered. A cover letter that was affixed to both hardcopy and softcopy questionnaires explained this goal. These surveys were disseminated via a variety of channels, including brokers and personal connections, both in hard copy and mostly electronically. Out of 700 questionnaires, 422 were returned, of which 395 were fully replied to or finished in all respects and used for analysis. So, the current study's response rate is 60.29. Continuous follow-up by the authors and brokerage firms helps to get maximum response. A self-administered questionnaire was used in this research for data collection.

The self-administered questionnaire is regarded as one of the most effective techniques for gathering quantitative data among the several data collection methods. A closed-ended questionnaire has been used in this study, as such questions are pre-coded, making it simpler to transfer the results into another analysis (Bakar & Yi, 2016). The research has made use of questionnaires on a 5-point Likert scale. As per Menike et al. (2015) as well as Bakar and Yi (2016), this technique is frequently employed to gather data from people regarding their level of agreement. The Likert scale facilitates researchers in questioning participants about their degree of agreement or disagreement while they read statements. A 5-point Likert scale has five categories, ranging from 1 to 5: strongly disagree, disagree, agree, and highly agree. The questionnaire was broken down into behavioral aspects that influence investment decision-making, investment profile, and personal information. Measures that are nominal and ordinal are utilized in the personal information section. A 5-point Likert scale is used to rate the set of questions about behavioral factors influencing investment decisions. Investors were given guarantees that the data they provided on the questionnaire would be kept confidential. For terminology selection, term interpretation, and measurement selection, specialists in the financial sector, academics, and investment advisors were consulted. Because of the relevant instructions and questions that were clarified, individual investors were able to complete the questionnaire.

3.4 Data Analysis Techniques

Partial Least Squares-Structural Equation Modeling (PLS-SEM) has been used in the study to evaluate and investigate the relationship between investors' decision-making processes and prospect biases. There are two parts in PLS-SEM called ‘Measurement Model’ and ‘Structural Model’. The structural model expresses the causal linkages between the latent variables, whereas the measurement model elucidates the relationship between the latent variables and their component indicators.

3.5 Demographic Statistics

Table 02 displays the statistics for demographic characteristics of the sample used for analysis. The majority of investors are male, comprising 85.3% (337 out of 395) of the sample. Female investors make up 14.7% (58 out of 395). This indicates a significant gender disparity in stock market participation, with male investors overwhelmingly dominating the market. The age distribution of investors is concentrated in the 35-45 age group, which constitutes 51.2% (202 out of 395) of the sample. The next largest age group is 20-35 years, representing 31.8% (126 out of 395). Investors aged 45-55 account for 13.7% (54 out of 395), and those above 55 years make up the smallest segment at 3.3% (13 out of 395). This suggests that middle-aged individuals (35–45) are the most active participants in the stock market.

Table 02: Demographic Distribution

Demographic Variable	Investors’ Grouping	Frequency	Percentage
Gender	Male	337	85.3
	Female	58	14.7
	Total	395	100.0

Age	20-35	126	31.8
	35-45	202	51.2
	45- 55	54	13.7
	Above 55	13	3.3
	Total	395	100.0
Educational Qualification	Below HSC	11	2.7
	Undergraduate Graduate	77	19.4
	Graduate	140	35.5
	Postgraduate and above	167	42.5
	Total	395	100.00
Occupation	Business	65	16.4
	Salaried	242	61.2
	Self-employed	35	9.0
	Student or others	53	13.4
	Total	395	100.0
Marital Status	Married	290	73.9
	Unmarried	96	24.1
	Separated	9	2.0
	Total	395	100.0
Financial Advisor	Yes	110	27.8
	No	285	72.2
	Total	395	100.0
Attended Training	Yes	229	57.9
	No	166	42.1
	Total	395	100.00
Trading Experience	Less than 2 years	123	31.1
	2 to 5 years	83	21.1

	5 to 10 years	57	14.4
	Above 10 years	132	33.4
	Total	395	100.0
Annual Income	2,00,000 - 7,00,000	196	49.5
	7,00,000 - 12,00,000	134	33.8
	12,00,000 - 16,00,000	29	7.4
	Above 16,00,000	36	9.4
	Total	395	100.0
Percentage of Investment in the Stock Market	less than 20%	50	12.7
	20% - 40%	173	43.8
	40% - 60%	77	19.4
	Above 60%	95	24.1
	Total	395	100.0
Mode of Investment	Primary market	38	9.7
	Secondary Market	142	35.8
	Both Market	215	54.5
	Total	395	100.0

Source: Authors' Computation.

In terms of educational qualifications, 35.5% (140 out of 395) of the investors hold a postgraduate degree or higher, making this the largest group. Undergraduate graduates constitute 19.4% (77 out of 395), while only 2.7% (11 out of 395) have qualifications below the Higher Secondary Certificate (HSC). The total for this category sums to 42.5% (167 out of 395), indicating that a significant portion of the investors are well-educated, with a strong leaning towards higher education. The majority of investors are salaried employees, representing 61.2% (242 out of 395). Business owners account for 16.4% (65 out of 395), while self-employed individuals make up 9.0% (35 out of 95). Students or others represent 13.4% (53 out of 395). This suggests that salaried individuals are the predominant group in stock market investment. A significant proportion of the investors are married, accounting for 73.9% (290 out of 395). Unmarried individuals make up 24.1% (96 out of 395), and those who are separated represent 2.0% (9 out of 395). This data suggests that married individuals are more likely to invest in the stock market. Only 27.8% (110 out of 395) of the investors use a financial advisor, while the majority, 72.2% (285 out of 395), do not. This indicates that most investors prefer to make their own investment decisions without professional guidance. A significant 57.9% (229 out of 395) of the investors attended training related to stock market investments, while 41.1% (166 out of 395) did not. This reflects a considerable interest in education and training among investors, although a sizable portion still invests without formal training. Investors with more than 10 years of trading experience constitute the largest group, making up 33.4% (132 out of 395) of the sample. Those with less than 2 years of experience represent 31.1% (123 out of 395), followed by investors with 2 to 5 years of experience at 21.1% (83 out of 395) and those with 5 to 10 years of experience at 14.4% (57 out of 395). This shows a diverse range of experience levels among investors, with a notable portion having significant experience in the market. The majority of investors, 49.5% (196 out of 395), have an annual income between 200,000 and 700,000. Those earning between 700,000 and 1,200,000 make up 33.8% (134 out of 395), while investors with an income between 1,200,000 and 1,600,000 account for 7.4% (29 out of 395). Investors with an annual income above 160,000 represent 9.4% (36 out of 395). This suggests that the stock market attracts individuals across various income levels, with a concentration in the lower to middle-income brackets. Investors who allocate 20% to 40% of their total investments to the stock market make up the largest group at 43.8% (173 out of 395). Those investing less than 20% constitute 12.7% (50 out of 395), while 19.4% (77 out of 395) invest between 40% and 60%. A significant 24.1% (95 out of 395) invest more than 60% of their portfolio in the stock market, indicating varying levels of risk tolerance among investors. The majority of investors, 54.5% (215 out of 395), participate in both the primary and secondary markets. Those investing exclusively in the secondary market represent 35.8% (142 out of 395), while only 9.7% (38 out of 395) focus solely on the primary market. This highlights a preference for diversified investment strategies among most investors.

This analysis reveals that the typical investor in the stock market is likely to be a middle-aged, married male with a postgraduate degree, working in a salaried position and earning between 200,000 and 700,000 annually. Most investors prefer to manage their portfolios independently without a financial advisor, although a significant number have attended formal training. The majority invest a moderate portion of their income in the stock market, with a balanced approach towards primary and secondary market investments.

4. Results

4.1 Measurement Model

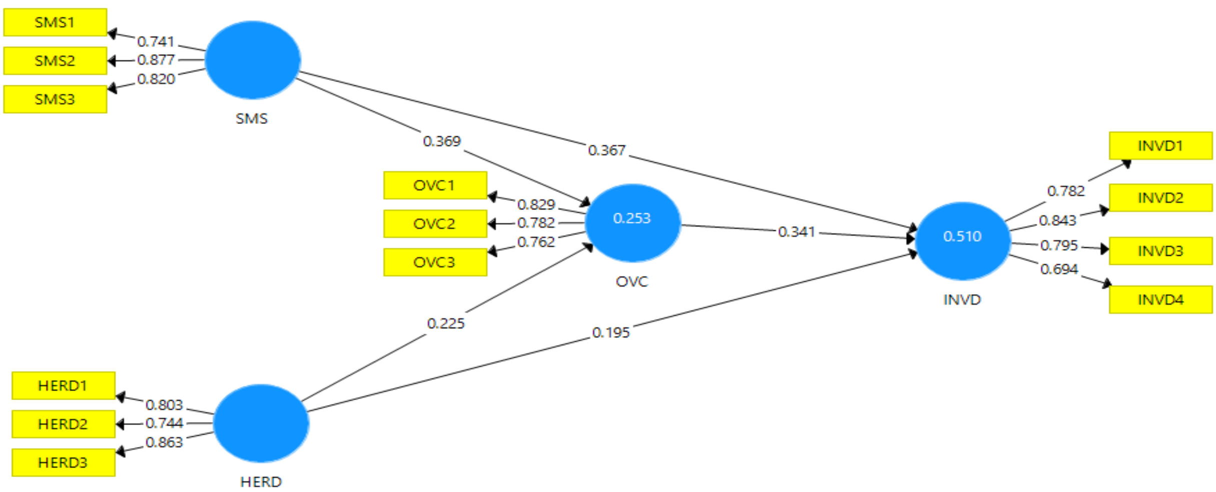
The validity, consistency, and reliability of the constructs were examined in the first phase of data analysis. Using Smart PLS 4.0 (Ouro *et al.*, 2023) and the two-stage systematic process, PLS-SEM was used. Examining the measurement model's composite reliability and convergent validity was the first step in the assessment process. Table 03 and Figure 02 show the values of factor loadings, Dillon-Goldstein's rho (rho_A & rho_C), Cronbach's alpha, average variance extracted (AVE), composite reliability (CR), and Cronbach's alpha. First, factor loadings were viewed using the cut-off value of 0.70 in order to evaluate the inter-item dependability (Munir, 2018). Factor loadings in the current study show acceptable values. The constructions' CR and rho_A & C values were greater than the 0.7 cutoff point, indicating that the model has attained internal reliability. Cronbach's alpha value is another indicator of reliability; a value of more than 0.7 denotes exceptional reliability. According to the measurement model evaluation results, all of the constructs' alpha values exceeded the 0.7 threshold meeting reliability requirements.

Table 03: Measurement Model Assessment

Variables	Items	Factor Loading	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	(AVE)
Herding Bias	HERD_1	0.803	0.731	0.754	0.846	0.648
	HERD_2	0.744				
	HERD_3	0.863				
Social Media Scam	SMS_1	0.741	0.753	0.785	0.855	0.664
	SMS_2	0.877				
	SMS_3	0.820				
Overconfidence	OVC_1	0.829	0.702	0.704	0.834	0.627
	OVC_2	0.782				
	OVC_3	0.762				
Investment Decision	INVD_1	0.741	0.784	0.793	0.861	0.609
	INVD_2	0.801				
	INVD_3	0.78				
	INVD_4	0.701				

Source: Authors' Computation.

Figure 02: Measurement Model



Source: Authors' Computation.

The average variance extracted (AVE) calculation explains convergent validity. The degree of variation and change that a latent variable can express is determined using AVE. Convergent validity is attained when AVE values are 0.5 or greater, according to Ramayah et al. (2017). The AVE values for the current investigation are greater than the threshold value of 0.50, indicating the convergent validity of the instrument. Convergent validity of the constructs was shown by AVE values greater than 0.5. Internal consistency reliability is measured using composite reliability (CR), and strong internal consistency reliability is indicated by values over the 0.70 threshold (Hair et al., 2017). Convergent validity was obtained for the constructs in this investigation based on the data presented in Table 03. The next stage was to evaluate the discriminant validity of the constructs after determining their convergent validity. Two metrics are recommended for this purpose: the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio of correlations (HTMT).

Table 04: Heterotrait-Monotrait Ratio (HTMT)

	HERD	INVD	OVC	SMS
HERD				
INVD	0.601			
OVC	0.513	0.779		
SMS	0.500	0.755	0.600	

Source: Authors' Computation.

According to the Fornell-Larcker criterion, in order to guarantee the necessary discriminant validity, the square root of a construct's AVE must be higher than the correlation coefficient of that construct with other constructs in the model (Fornell & Larcker, 1981) (Table 5).

Table 05: Assessing Discriminant Validity (Fornell-Larcker criterion)

	HERD	INVD	OVC	SMS
HERD	0.805			
INVD	0.469	0.780		
OVC	0.372	0.582	0.792	
SMS	0.400	0.601	0.458	0.815

Source: Authors' Computation.

Discriminant validity was attained because each of the constructs met the requirements outlined by Fornell & Larcker (1981). According to the HTMT criterion, all of the estimated construct values must be less than 0.9 (Henseler *et al.,* 2016). Table 04's HTMT results demonstrate that every value meets the requirements for attaining discriminant validity. The measurement model assessment's overall results indicate that the model has demonstrated sufficient validity and reliability.

4.2 Structural Model

The relevance of the hypothesis is ascertained by looking at the structural model after meeting the conditions of the measurement model. It involves figuring out the moderating impact, total effects, model fit, and effect magnitude.

4.3. Collinearity Test

The variance inflation factor (VIF) was used to verify the collinearity issue in the first phase of structural model assessment and hypothesis testing. The purpose of the VIF study was to evaluate the multicollinearity of the variables. Since all values in Table 06 are much below the generally accepted threshold value of 5, as recommended by Hair *et al.* (2017), there are no substantial multicollinearity issues, as indicated by the VIF values for all items, which ranged from 1.225 to 2.827. Furthermore, it satisfied the VIF less than 3.3 requirement established by Diamantopoulos and Siguaw (2006). As a result, the study's constructions satisfy the standard referenced by Hair *et al.* (2017), with no collinearity concerns.

Table 06: VIF Values for Assessing Multicollinearity

Items	VIF
HERD1	1.353
HERD2	1.472
HERD3	1.657
INVD1	1.573
INVD2	1.856
INVD3	1.608
INVD4	1.391
OVC1	1.488
OVC2	1.372
OVC3	1.306
SMS1	1.645
SMS2	1.944
SMS3	1.374

Source: Authors' Computation.

4.4 Model Fitness

The suggested model's goodness is assessed by looking at its model fitness as shown in Table 07. Partial least squares structural equation modeling was utilized in the current investigation, and its fitness was evaluated using several metrics. SRMR (Standardized Root Mean Square Residual) is one of the model fit metrics. Both the estimated and saturated models have an SRMR of 0.066. A good match between the model and the observed data is indicated by an SRMR score of less than 0.08. According to Ramayah *et al.* (2017), the SRMR value should be less than 0.08 as the acceptance criterion, and a 0" SRMR value can result in a flawless model fit. 4.808 is the d_ULS value for both models.

Table 07: Model Fitness Statistics

	Saturated Model	**Estimated Model**
SRMR	0.084	0.084
d_ULS	0.649	0.649
d_G	0.215	0.215
Chi-Square	493.606	493.606
NFI	0.725	0.725

Source: Authors' Computation.

The suggested model's goodness is assessed by looking at its model fitness. Partial least squares structural equation modeling was utilized in the current investigation, and its fitness was evaluated using several metrics. SRMR (Standardized Root Mean Square Residual) is one of the model fit metrics. Both the estimated and saturated models have an SRMR of

0.066. A good match between the model and the observed data is indicated by an SRMR score of less than 0.08. According to Ramayah et al. (2017), the SRMR value should be less than 0.08 as the acceptance criterion, and a "0" SRMR value can result in a flawless model fit. 4.808 is the d_ULS value for both models. This metric is less commonly used, but lower values generally indicate a better fit. The fact that both models have the same value suggests consistent fit quality. The d_G value is 1.679 for both models. Similar to d_ULS, lower d_G values suggest a better fit. The identical values for both models imply that the fit is consistent across the models. The Chi-square value is 3699.370 for both models. While the Chi-square statistic is widely used for model fit, it is sensitive to sample size. In large samples, even small differences between the observed and estimated covariance matrices can lead to a significant Chi-square, which might not necessarily indicate a poor fit. However, the consistency of this value across both models suggests that the estimated model is a good representation of the data. Here, the model is statistically fit and sound, and it meets the quality criteria of a good model. Table 07 shows the values of model fit.

4.5 Coefficient of Determination

The R-squared (R2) value indicates how much the predictor variables have a considerable effect on the criterion variable. Table 08 displays that the R-square value of 0.510 indicates that approximately 51% of the variation in investment decisions can be explained by the exogenous constructs included in the model. This is a strong indication that the model is quite effective at capturing the factors that influence investment decisions. In other words, the exogenous construct collectively accounts for nearly 51% of the variations in the investment decisions, leaving only about 49% unexplained.

Table 08: R Square

	R Square	R Square Adjusted
INVD	0.510	0.506

Source: Authors' Computation.

4.6 Hypothesis Results

4.6.1 Direct Hypothesis Results

Table 09: Structural Model Path Coefficients with p-Values (Path Analysis)

Hypotheses		**Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**	**Decision**
H1	HERD -> INVD	0.195	0.196	0.043	4.580	0.000	Accepted
H2	HERD -> OVC	0.225	0.228	0.054	4.149	0.000	Accepted
H3	SMS -> INVD	0.367	0.364	0.056	6.552	0.000	Accepted
H4	SMS -> OVC	0.369	0.370	0.055	6.715	0.000	Accepted
H5	OVC -> INVD	0.341	0.344	0.054	6.354	0.000	Accepted
H6	HERD -> OVC -> INVD	0.077	0.079	0.023	3.323	0.001	Accepted
H7	SMS -> OVC -> INVD	0.126	0.127	0.029	4.354	0.000	Accepted

Source: Authors' Computation.

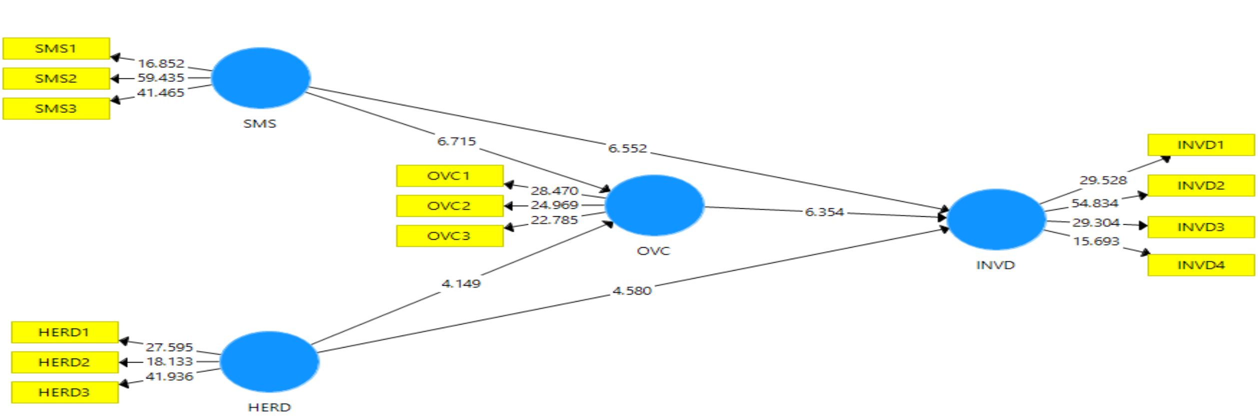
ISSN 2664-3413 (Print) 2664-3421 (Online)
Daffodil International University Journal of Business and Entrepreneurship (DIUJBE), Vol. 18. No.1, pp. 84-109, June 2025

The results of the PLS-SEM analysis reveal that all five hypothesized relationships are statistically significant, supporting the proposed research framework which is shown in Figure 3 and Table 09. Specifically, herding bias (HERD) has a positive and significant influence on both investment decisions (INVD) (β = 0.195, t = 4.580, p < 0.001) and overconfidence (OVC) (β = 0.225, t = 4.149, p < 0.001), which is supported by H1 and H2. This suggests that the behavior of others not only influences the investment decisions of investors but also contributes to their overconfidence. Similarly, exposure to social media scams (SMS) significantly impacts both investment decisions (β = 0.367, t = 6.552, p < 0.001) and overconfidence (β = 0.369, t = 6.715, p < 0.001) thus supporting H3 and H4, indicating that incorrect or misleading content and scams on social media can prompt investors to make hasty judgments and cultivate an exaggerated sense of discernment. Furthermore, the study found a positive and significant effect of overconfidence (OVC) on investment decisions (β = 0.341, t = 6.354, p < 0.001), which supported H5, suggesting that greater confidence, influenced by herd mentality and social media scams, increases the propensity to irrational investment decisions.

4.7 Mediating Hypothesis

To illustrate mediating power, the PLS-SEM bootstrapping approach is used. According to Hair et al. (2017), "bootstrapping" has the benefit of being able to function even with a smaller dataset. Preacher and Hayes's (2008) procedure should also be used when examining mediation outcomes. When indirect effects are substantial, there are mediating effects. Current mediation research focuses on two types of mediation: partial and complete mediation. Complete mediation is assumed when the indirect influence is considerable, but the direct impact is not. Conversely, partial mediation is guaranteed in cases when the direct and indirect effects are both substantial (Carrión et al., 2017). It is evident from Table 9 that overconfidence mediates the relationship between herding and investment decisions, confirming hypothesis H6. Similarly, overconfidence mediates the relationship between social media scams and investment decisions, accepting hypothesis H7. There is partial mediation (PM) because the direct impact (HERD -> INVD and SMS -> INVD) as well as the indirect impact (HERD -> OVC -> INVD) is significant. Again, when both the direct and indirect relationships are significant and show the same directions (either positive or negative), there is a complementary partial mediation (Carrión et al., 2017; Baron & Kenny, 1986). Thus, there is a complementary partial mediating effect of OVC on investment decision-making, as both direct and indirect relationships are positive.

Figure 3: Structural Model Output



Source: Authors' Computation.

5. Discussion

This research investigated the impact of herding behavior (HERD) and social media scams (SMS) on investor investment decisions (INVD) in the Bangladesh stock markets, with a focus on the mediating role of overconfidence. The findings demonstrated a positive and significant association between herding behavior, social media scams, and investor investment decisions. The study investigated the impact of herding bias and social media scams on investment decisions and found that herding bias and social media scams significantly impacted investment decisions. Due to this bias, investors tend to trust the advice of their friends, family, and peers when making investment decisions, even if they don't always have the best track record and think that the group's actions will increase the likelihood of success. This finding aligns with earlier studies by Koma and Jatiningsih (2024), Jain et al. (2022), and Kishor (2022), which imply that people often imitate the behavior of others, especially in times of uncertainty. It is common that many retail investors in Bangladesh rely heavily on social networks, family, friends, or popular investors when making decisions (Khan & Imam, 2023). This encourages herd behavior, as individuals follow the crowd without fully understanding the reasoning behind those decisions. Similarly, the results of this study indicate that the relationship between investor social media scams and herding is partially mediated by overconfidence. This finding, which was corroborated by earlier research by Adil et al. (2022), showed that overconfidence improves the correlation between investment choices and herd behavior. Thus, the results show how important herding bias, social media scams, and overconfidence are in influencing people's stock market investing decisions.

6. Conclusion and Implications

To sum up, this study looked at how herding biases and social media scams affect investment decisions and how overconfidence can play a mediating role in making investment decisions. The results imply that herding bias and social media scams significantly influence investment decisions; similarly, herding bias and social media also significantly contribute to enhancing overconfidence. Moreover, overconfidence also plays a partial mediating role in influencing irrational investment decisions. Herding behavior is common and indicates that a lot of investors are influenced by what other people do, which frequently results in illogical changes in the market. Since biases like herding are prevalent in the Bangladeshi market, financial advisors and brokerage firms need to be trained in behavioral finance. By understanding common cognitive biases, advisors can help clients avoid following the crowd or making decisions based on social influence. Advisors can also play a key role in promoting more independent and evidence-based investment strategies. The tendency of investors to rely on outdated or easily available information points to a lack of reliable and timely data in the Bangladeshi stock market. Regulatory bodies, such as the Bangladesh Securities and Exchange Commission (BSEC), should focus on improving the availability of accurate and up-to-date market information.

6.1 Limitations and Future Research Directions

This study has a number of limitations that should be noted, even if it provides insightful information. First, the study's findings may not be as applicable to the larger investor population because it mainly examined retail investors who were active on Bangladeshi social media sites. Future research could examine how behavioral biases affect different categories of investors, such as retail investors, institutional investors, and foreign investors. Second, because of the rise in retail customers' stock market investments, behavioral biases are a dynamic occurrence; as a result, the study may also be limited by the cross-sectional figures in the data. Third, the research focuses primarily on a specific set of herding biases. Other relevant biases, such as heuristics, emotional biases (e.g., fear or greed), and market factors, could also play a significant role in shaping investor behavior in Bangladesh moreover, research might look at how well investor education, digital literacy initiatives, and regulatory actions work to lessen the effects of social media fraud and herd mentality. Real-time insights on market psychology and scam propagation may be obtained by integrating sophisticated data analytics, such as sentiment analysis from social media sites.

References

1. Abbes, M. B., Boujelbene, Y., & Bouri, A. (2009). Overconfidence bias: Explanation of market anomalies French market case. *Journal of Applied Economic Sciences*, 4(7), 12-25.
2. Abideen, Z. U., Ahmed, Z., Qiu, H., & Zhao, Y. (2023). Settings order article reprints open access editor’s choice article do behavioral biases affect investors’ investment decision making? Evidence from the Pakistani Equity Market.
3. Adil, M., Singh, Y., & Ansari, M. S. (2022). How financial literacy moderate the association between behaviour biases and investment decision?. *Asian Journal of Accounting Research*, *7*(1), 17-30.
4. Agarwal, P., Al Aziz, R., & Zhuang, J. (2022). Interplay of rumor propagation and clarification on social media during crisis events: A game-theoretic approach. *European Journal of Operational Research*, *298*(2), 714-733.
5. Ahmad, M. U., & Mahmood, A. (2020). An empirical study on herd mentality in Indian investors. JIMS8M: *The Journal of Indian Management & Strategy*, 25, 58-61.
6. Ahmad, S., Islam, M., Zada, M., Khattak, A., Ullah, R., Han, H., & Araya-Castillo, L. (2022). The influence of decision making on social inclusion of persons with disabilities: A case study of Khyber Pakhtunkhwa. *International Journal of Environmental Research and Public Health*, *19*(2), 858.
7. Ahmed, F., Chowdhury, T. H., & Nahar, N. (2021). Cognitive biases and individual stock investment decision making: Evidence from Bangladesh. *Journal of Behavioral & Experimental Finance*, 31, 100571.
8. Al Atoom, S. A., Alafi, K. K., & Al-Fedawi, M. M. (2021). The effect of social media on making investment decisions for investors in Amman Financial Market. *International Journal of Innovation, Creativity and Change*, *15*(6), 934-960.
9. Al-Maghrabi, M., Mamede, S., Schmidt, H. G., Omair, A., Al-Nasser, S., Alharbi, N. S., & Magzoub, M. E. M. A. (2024). Overconfidence, time-on-task, and medical errors: Is there a relationship?. *Advances in Medical Education and Practice*, 133-140.
10. Ammann, M., & Schaub, N. (2021). Do individual investors trade on investment-related internet postings?. *Management science*, *67*(9), 5679-5702.
11. Andreassen, C. S., Torsheim, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook addiction scale. *Psychological reports*, *110*(2), 501-517.
12. Arouri, M. E. H., & Nguyen, D. K. (2010). Oil prices, stock markets and portfolio investment: Evidence from sector analysis in Europe over the last decade. *Energy policy*, *38*(8), 4528-4539.

13. Asgarnezhad N. B., & Soltani, M. (2017). Effective factors on job stress and its relationship with organizational commitment of nurses in hospitals of Nicosia. *International Journal of Management, Accounting & Economics*, *4*(2).
14. Atmaningrum, S., Kanto, D. S., & Kisman, Z. (2021). Investment decisions: The results of knowledge, income, and self-control. *Journal of Economics and Business*, *4*(1).
15. Bakar, S., & Yi, A. N. C. (2016). The impact of psychological factors on investors' decision making in Malaysian stock market: a case of Klang Valley and Pahang. *Procedia Economics and Finance*, *35*, 319-328.
16. Baker, M. & Wurgler, J. (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129-151.
17. Balcilar, M., & Demirer, R. (2015). Effect of global shocks and volatility on herd behavior in an emerging market: Evidence from Borsa Istanbul. *Emerging Markets Finance and Trade*, *51*(1), 140-159.
18. Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics*, 107(3), 797-817.
19. Barber, B. M., & Odean, T. (2002). Does online trading change investor behavior?. *European Business Organization Law Review (EBOR)*, *3*(1), 83-128.
20. Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*, *51*(6), 1173.
21. Bell, E., Harley, B., & Bryman, A. (2022). *Business research methods*. Oxford University Press.
22. Carrión, G. C., Nitzl, C., & Roldán, J. L. (2017). Mediation analyses in partial least squares structural equation modeling: Guidelines and empirical examples. *Partial least squares path modeling: Basic concepts, methodological issues and applications*, 173-195.
23. Chaitanya, D. B., & Nordin, N. (2021). The relationship between psychological factors, risk perception and social media on investment decision making. *International Journal of Advanced Research in Economics and Finance*, *3*(4), 55-72.
24. Chandra, A., & Kumar, R. (2012). Factors influencing Indian individual investor behaviour: survey evidence.
25. Chang, E. C. & Cheng, J. W. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking and Finance*, *34*(8), 1911-1921.
26. Chaudhary, A. K. (2013). Impact of behavioral finance in investment decisions and strategies–a fresh approach. *International journal of management research and business strategy*, *2*(2), 85-92.
27. Chavali, K. & Mohanraj, M. P. (2016). Impact of demographic variables and risk tolerance on investment decisions—an empirical analysis. International journal of economics and financial issues, 6(1), 169-175.
28. Chen, A., & Pelger, M. (2013). How relative compensation can lead to herding behavior. *Available at SSRN 2217715*.
29. Chernoff, S. D. (2010). *Manual for Living: Reality, A User's Guide to the Meaning of Life*. Spirit Scope LLC.
30. Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking & Finance*, *34*(8), 1911-1921.
31. Chiang, T. C., Li, J., Tan, L., & Nelling, E. (2013). Dynamic herding behavior in Pacific-Basin markets: evidence and implications. *Multinational Finance Journal*, *17*(3/4), 165-200.

32. Cipriani, M., Costantini, R., & Guarino, A. (2012). A Bayesian approach to experimental analysis: Trading in a laboratory financial market. *Review of Economic Design*, *16*, 175-191.
33. Demirer, R., & Kutan, A. M. (2006). Does herding behavior exist in Chinese stock markets?. *Journal of International Financial Markets, Institutions and Money*, *16*(2), 123-142.
34. Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European economic review*, *40*(3-5), 603-615.
35. Dewan, P., & Dharni, K. (2019). Herding behaviour in investment decision making: a review. *Journal of Economics, Management and Trade*, *24*(2), 1-12.
36. Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British journal of management*, *17*(4), 263-282.
37. Drehmann, M., Oechssler, J., & Roider, A. (2005). Herding and contrarian behavior in financial markets: An internet experiment. *American Economic Review*, *95*(5), 1403-1426.
38. Duttle, K., & Inukai, K. (2015). Complexity aversion: influences of cognitive abilities, culture and system of thought. *Economic Bulletin*, *35*(2), 846-855.
39. Fama, E. F. (1970). Efficient capital markets. *Journal of Finance, 25*(2), 383-417.
40. Fernández-Sánchez, A., Madrigal-Santillán, E., Bautista, M., Esquivel-Soto, J., Morales-González, Á., Esquivel-Chirino, C., ... & Morales-González, J. A. (2011). Inflammation, oxidative stress, and obesity. *International Journal of Molecular Sciences*, *12*(5), 3117-3132.
41. Fitri, F. A., & Hariyanto, D. (2024). The impact of social media, herding bias, gambler's fallacy, and framing effect on investment decisions among Gen Z investors in Pontianak City. *Proceedings Series on Social Sciences & Humanities*, *15*, 202-207.
42. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50.
43. Galariotis, E. C., Krokida, S. I., & Spyrou, S. I. (2016). Bond market investor herding: Evidence from the European financial crisis. *International Review of Financial Analysis*, *48*, 367-375.
44. Gong, Y., Tang, X., & Chang, E. C. (2023). Group norms and policy norms trigger different autonomous motivations for Chinese investors in cryptocurrency investment. *Humanities and Social Sciences Communications*, *10*(1), 1-10.
45. Gunathilaka, C., & Wickramasinghe, R. S. (2023). Smartphone addiction-A disease in the stock market driving herding and overconfidence–A PLS-SEM analysis. *Asian Finance Review*, *1*(01).
46. Hair Jr, J. F., Matthews, L. M., Matthews, R. L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123.
47. Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. *International marketing review*, *33*(3), 405-431.
48. Hirschey, M., & Nofsinger R. J. (2008). *Investment: Analysis and behavioral*. New York, NY: McGraw-Hill/Irwin.
49. Hsieh, S., Tai, Y. Y., & Vu, T. B. (2008). Do herding behavior and positive feedback effects influence capital inflows? Evidence from Asia and Latin America. *The International Journal of Business and Finance Research*, 2(2), 19-34.

50. Huang, T. C., Lin, B. H., & Yang, T. H. (2015). Herd behavior and idiosyncratic volatility. *Journal of Business Research*, 68(4), 763-770.
51. Humra, Y. A. S. H. B. A. (2014). Behavioral finance: An introduction to the principles governing investor behavior in stock markets. *International Journal of Financial Management*, *5*(2), 23-30.
52. Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of empirical finance*, *11*(4), 585-616.
53. Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance*, *11*(4), 585-616.
54. Jain, J., Walia, N., & Gupta, S. (2023). Evaluation of behavioral biases affecting investment decision making of individual equity investors by fuzzy analytic hierarchy process. *Review of Behavioral Finance*, *12*(3), 297-314.
55. Kallinterakis, V., & Kratunova, T. (2007). Does thin trading impact upon the measurement of herding? Evidence from Bulgaria. *Ekonomia*, *10*(1).
56. Kallinterakis, V., & Lodetti, M. (2009). Herding, nonlinearities and thin trading: Evidence from Montenegro. *Available at SSRN 1350968*.
57. Karadağ, E., Tosuntaş, Ş. B., Erzen, E., Duru, P., Bostan, N., Şahin, B. M., ... & Babadağ, B. (2015). Determinants of phubbing, which is the sum of many virtual addictions: A structural equation model. *Journal of Behavioral Addictions*, *4*(2), 60-74.
58. Karaiskos, D., Mavragani, C. P., Sinno, M. H., Dechelotte, P., Zintzaras, E., Skopouli, F. N., ... & Moutsopoulos, H. M. (2010). Psychopathological and personality features in primary Sjögren's syndrome—associations with autoantibodies to neuropeptides. *Rheumatology*, *49*(9), 1762-1769.
59. Kaustia, M., & Knüpfer, S. (2012). Peer performance and stock market entry. *Journal of Financial Economics*, *104*(2), 321-338.
60. Khan, F. A., & Imam, M. O. (2023). Herding behavior in stock market of Bangladesh: A case of behavioural finance. *Journal of Financial Markets and Governance*.
61. Kishor, N. (2022). Development and validation of behavioral biases scale: a SEM approach. *Review of Behavioral Finance*, *14*(2), 237-259.
62. Koma, D. R. A., & Jatiningsih, D. E. S. (2024). The effect of overconfidence bias, risk tolerance, and herding bias on stock investment decisions with financial literacy as a moderation variable. *KnE Social Sciences*, 303-336.
63. Kumar, J., & Prince, N. (2023). Overconfidence bias in investment decisions: a systematic mapping of literature and future research topics. *FIIB Business Review*, 23197145231174344.
64. Kumar, S., & Goyal, N. (2015). Behavioural biases in investment decision making - A systematic literature review. *Qualitative Research in Financial Markets*, *7*(1), 88-108.
65. Lakshman, M. V., Basu, S., & Vaidyanathan, R. (2013). Market-wide herding and the impact of institutional investors in the Indian capital market. *Journal of Emerging Market Finance*, *12*(2), 197-237.
66. Lee, Y. H., & Ma, W. (2024). The Relationship between financial literacy misestimation and misplacement from the perspective of inverse differential information and stock market participation. *International Journal of Financial Studies*, *12*(3), 81.
67. Loxton, M., Truskett, R., Scarf, B., Sindone, L., Baldry, G., & Zhao, Y. (2020). Consumer behaviour during crises: Preliminary research on how coronavirus has manifested consumer panic buying, herd mentality, changing discretionary

spending and the role of the media in influencing behaviour. *Journal of Risk and Financial Management*, *13*(8), 166.

68. Maity, R., & Sandhu, S. K. (2021). The impact of social media on online purchasing behaviour of consumers: an empirical study of youth in West Bengal, India. *Malaysian Journal Of Consumer and Family Economics*, *26*, 42.
69. Malik, S. U., & Elahi, M. A. (2014). Analysis of herd behavior using quantile regression: Evidence from Karachi Stock Exchange (KSE).
70. Manzoor, S. R., Ullah, A., Ullah, R., Khattak, A., Han, H., & Yoo, S. (2023). Micro CSR intervention towards employee behavioral and attitudinal outcomes: a parallel mediation model. *Humanities and Social Sciences Communications*, *10*(1), 1-14.
71. Menike, M. G. P. D., Man, W., Street, S. D., Dalian, P. R., & District, S. (2015). Stock market reactions to the release of annual financial statements case of the banking industry in Sri Lanka. *European Journal of Business and Management*, *5*(31), 75-86.
72. Miniesy, R., Elshahawy, E., & Fakhreldin, H. (2022). Social media's impact on the empowerment of women and youth male entrepreneurs in Egypt. *International Journal of Gender and Entrepreneurship*, *14*(2), 235-262.
73. Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review, 115* (2), 502-517.
74. Munir, F. F. A. (2018). Reliability and validity analysis on the relationship between learning space, student’s satisfaction and perceived performance using SMART-PLS. *International Journal of Academic Research in Business and Social Sciences*, *8*(1), 775-783.
75. Neal, T., Lienert, P., Denne, E., & Singh, J. P. (2022). A general model of cognitive bias in human judgment and systematic review specific to forensic mental health. *Law and Human Behavior*, *46*(2), 99.
76. Newall, P. W., & Weiss-Cohen, L. (2022). The gamblification of investing: How a new generation of investors is being born to lose. *International Journal of Environmental Research and Public Health*, *19*(9), 5391.
77. Nigam, R. M., Srivastava, S., & Banwet, D. K. (2018). Behavioral mediators of financial decision making–a state-of-art literature review. *Review of Behavioral Finance*, *10*(1), 2-41.
78. Odean, T. (1999). Do investors trade too much?. *American Economic Review*, *89*(5), 1279-1298.
79. Oehler, A., & Wendt, S. (2009). Herding behavior of mutual fund managers in Germany. *Available at SSRN 1343470*.
80. Olawole-Scott, H., & Yon, D. (2023). Expectations about precision bias metacognition and awareness. *Journal of Experimental Psychology: General*, *152*(8), 2177.
81. Ornelas, J. R. H., & Alemanni, B. (2008). Herding behaviour by equity foreign investors on emerging markets. *Banco Central do Brasil Working Paper*, (125).
82. Ouarda, M., El Bouri, A., & Bernard, O. (2013). Herding behavior under markets condition: Empirical evidence on the European financial markets. *International Journal of Economics and Financial Issues*, *3*(1), 214-228.
83. Ouro, A., Santos, E., Santos, E., Barreto, I., & Olave, M. (2023). Second-order PLS structural equation modeling in scientific research. *Redeca, Revista Eletrônica do Departamento de Ciências Contábeis & Departamento de Atuária e Métodos Quantitativos*, *10*, e59733-e59733.

84. Pompian, M. M., & Strock, G. W. (2021). Investor behavior and cognitive limitations. *Journal of Behavioral Finance*, 22(2), 129-136.
85. Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879-891.
86. Puckett, A., & Yan, X. S. (2008). Short-term institutional herding and its impact on stock prices. *Available at SSRN 1108092*.
87. Raddatz, C., & Schmukler, S. L. (2013). Deconstructing herding: Evidence from pension fund investment behavior. *Journal of Financial Services Research*, *43*, 99-126.
88. Rahayu, S., Rohman, A., & Harto, P. (2020). Herding behavior model in investment decision on Emerging Markets: Experimental in Indonesia. *Journal of Asian Finance, Economics, and Business, 8*(1), *53-59. https://doi.org/10.13106/jafeb.2021.vol8.no1.053.*
89. Ramayah, T., Yeap, J. A., Ahmad, N. H., Halim, H. A., & Rahman, S. A. (2017). Testing a confirmatory model of Facebook usage in SmartPLS using consistent PLS. *international Journal of Business and innovation*, *3*(2), 1-14.
90. Ranjbar, M. H., Abedini, B., & Jamali, M. (2014). Analyzing the effective behavioral factors on the investor's performance in Tehran Stock Exchange. *International Journal of Art & Humanity Science*, 1(2), 80-86.
91. Redding, S. (1996). The low-skill, low-quality trap: Strategic complementarities between human capital and R & D. *The Economic Journal*, *106*(435), 458-470.
92. Sachse, K., Jungermann, H., & Belting, J. M. (2012). Investment risk–The perspective of individual investors. *Journal of Economic Psychology*, *33*(3), 437-447.
93. Saunders, M., Lewis, P., & Thornhill, A. (2007). *Research methods for business students*. Pearson education.
94. Sekaran, U. (2016). *Research methods for business: A skill building approach*. John Wiley & Sons.
95. Shah, S. Z. A., Ahmad, M., & Mahmood, F. (2018). Heuristic biases in investment decision-making and perceived market efficiency. *Qualitative Research in Financial Markets*, *1*0(1), 85-110. doi: 10.1108/QRFM-04-2017-0033.
96. Shah, T. A., & Hussain, I. (2024). The Effect of Herding Behavior on Investment Decision: Moderating Effect of Over-Confidence. *Qlantic Journal of Social Sciences and Humanities*, *5*(3), 132-146.
97. Shahani, R., & Ahmed, K. A. (2022). Investigating the Moderating Roles of Basic and Advanced Financial Literacy between Behavioural Biases and Stock Buying Decisions. *Journal of Organisational Studies & Innovation*, *9*(1).
98. Shefrin, H. (2002). *Beyond greed and fear: Understanding behavioral finance and the psychology of investing*. Oxford University Press.
99. Simon, M., Houghton, S. M., & Aquino, K. (2000). Cognitive biases, risk perception, and venture formation: How individuals decide to start companies. *Journal of Business Venturing, 15*(2), 113-134.
100. Singh, S., & Chakraborty, A. (2024). Role of Social Media in Investment Decision-making: A Comprehensive Review and Future Roadmap. *Paradigm*, *28*(1), 45-64.
101. Smith, M., Zidar, O., & Zwick, E. (2023). Top wealth in America: New estimates under heterogeneous returns. *The Quarterly Journal of Economics*, *138*(1), 515-573.

102. Statman, M., Thorley, S., & Vorkink, K. (2006). Investor overconfidence and trading volume. *The Review of Financial Studies*, *19*(4), 1531-1565.
103. Suresh, G. (2024). Impact of financial literacy and behavioural biases on investment decision-making. *FIIB Business Review*, *13*(1), 72-86.
104. Thakur, S. (2017). The Impact of Behavioral Finance on Stock Markets. Joseph's *Journal of Multidisciplinary Studies* (JJMDS), 1(1), 44-49.
105. Turel, O., & Serenko, A. (2012). The benefits and dangers of enjoyment with social networking websites. *European Journal of Information Systems*, *21*(5), 512-528.
106. Venezia, I., Nashikkar, A. J., & Shapira, Z. (2009). Herding in trading by amateur and professional investors. *Available at SSRN 1358623.*
107. Wang, P., & Nuangjamnong, C. (2022). Determinant Factors of Overconfidence, Herding Behavior, and Investor Elements on Investment Decision Making in China. *Universal Journal of Financial Economics*, *1*(1), 23-42.
108. Wang, Q. (2008). A generic model for guiding the integration of ICT into teaching and learning. *Innovations in Education and Teaching International*, *45*(4), 411-419.
109. Waweru, N. M., Munyoki, E., & Uliana, E. (2008). The effects of behavioral factors in investment decision-making: A survey of institutional investors operating at the Nairobi Stock Exchange. *International Journal of Business and Emerging Markets*, 1(1), 24-41.
110. Yao, S. (2010). New Sight of herding behavioural through trading volume. *Economics Discussion Paper*, (2010-11). Accessed on 21 January, 2025.
111. Zahera, S. A., & Bansal, R. (2018). Do investors exhibit behavioral biases in investment decision making? A systematic review. *Qualitative Research in Financial Markets*, *10*(2), 210-251.
112. Zheng, D., Li, H., & Chiang, T. C. (2017). Herding with industries: Evidence from Asian stock markets. *International Review of Economics and Finance*, *51*, 487-509.