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DO SOCIAL MEDIA INTERACTION DRIVE BEHAVIORAL BIAS AND TRADING TENDENCIES OF RETAIL INVESTORS? A MODERATED-MEDIATION APPROACH

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ABSTRACT

The present study examined the association between overconfidence bias and retail investors' trading behaviour driven by the mediating effects of miscalibration and disposition effect. The study also examined interaction moderation of social media between behavioral biases and investor behavior of 376 retail investors in North India. The data was collected with snowball sampling technique in this descriptive study and data was analysed with variance-based partial least square structural equation modeling. The main findings of this study revealed that the concurrent mediating effects of miscalibration and disposition effect between overconfidence bias and investors' trading decisions. The study also explored that social media has a stronger effect on overconfidence bias and stock market participation tendencies of investors. The association between miscalibration and the disposition effect of investors' trading activity was attenuated by social media influence. This study offered a novel approach for identifying the growing anxieties of retail investors on social media platforms for information acquisition under the environment of behavioral biases in emerging financial markets like India.

Keywords: Moderated-mediation, Overconfidence bias, Miscalibration, Disposition effect, social Media

1. Introduction

The financial market's rationality has evolved as a result of the evolution of investment decisions (Duxbury et al., 2015; Jain et al., 2020; Pradhan, 2021). Previous research studies emphasised the significance of investigating diverse investor biases and established their influence on investor behaviour (Chong et al., 2021; Gong et al., 2021; Mittal, 2022; Kartini and Nahda, 2021). Overconfidence bias seems to be the significant predictor of trading behaviour under these uncontrolled circumstances (Jain et al., 2020; Parhi and Pal 2022). Chi and Li (2019) examined how retail investors frequently lack confidence in their ability to make decisions that need to be incorporated into the stock market, underreact to the information, and ultimately end up constructing a mountain out of a hill. In this regard, behavioural economics has to be applied in several aspects of the industries, such as savings, loans, and insurance, according to a report by Ernst and Young (2021). Investors are portrayed as irrational individuals with behavioural biases driven with attitudes and conceptions influencing their financial decisions (Ferreira and Dickason - Koekemoer, 2020).

The early research on various cognitive biases, such as overconfidence bias (Kahneman and Tversky, 1973), anchoring bias (Tversky and Kahneman, 1974), miscalibration (Skala, 2008), disposition bias (Shefrin and Statman, 1985), and miscalibration (Skala, 2008) recognised the influence of these irrational beliefs among investors. The dominance of the market system, which makes it difficult for investors to make decisions, can be inferred as the source of behavioural biases (Jain et al., 2021). The influence of investor biases was specifically investigated in the past literature as the primary source of explanations for market anomalies in the stock market (Parmitasari et al., 2022; Mukherjee and Tiwari, 2022). Recent research has also confirmed that investors' self-enhancement can impact behavioural biases, indicating that even financially competent persons are susceptible to behavioural biases (Rieger et al., 2022). Additionally, these studies noted that the stock market's reformation was ultimately a result of investor prejudices (Gupta and Shrivastava, 2021). Fear of missing out (FOMO) (Gupta and Shrivastava, 2021) and investor-FOMO (Shiva et al., 2020) are recent behavioural biases, which are considered novel stock market anomalies.

Previous studies on trading behaviour have focused primarily on past performance (Jagongo and Mutswenje 2014), information acquisition (Tauni et al. 2015), and various behavioural biases like herding (Qasim et al. 2019), disposition effect (Trejos et al. 2019), and overconfidence bias (Paisarn et al. 2021). Additionally, previous research has demonstrated the importance of miscalibration and the disposition effect on investor overconfidence bias (Bias, 2005; Kahneman, 2011). However, there is a dearth of research examining how investors' use social media for information acquisition in stock market that affects their trading decisions. To address this research gap, this study addresses the critical research question, 'does social media moderate the relationship between overconfidence and trading behaviour?' Considering this research gap in the academic literature pertaining to behavioural biases and trading behavior of retail investors, the present study address the following research objectives:

RQ1. Does miscalibration and disposition effect accentuate the relationship between overconfidence bias and trading behaviour?

RQ2. How social media moderates the relationship between overconfidence bias, miscalibration, disposition effect and trading behaviour?

2. Literature review and hypotheses development

2.1 Theoretical contribution

According to Markowitz's Portfolio Theory (MPT) (1952), investors urge to maximise rewards while reducing risks in financial markets. MPT was used to derive the basic tenets of accurate returns and historical investment returns. Additionally, MPT research applied trading frequency, volume, and performance of investors to understand their behavior. According to Langer's Illusion of Control (IOC) theory (1975), an investor's subjective chances of success are substantially higher than their actual chances. This gives overconfident investors more justification for believing they may profit from larger profits on the financial markets. The IOC was used to gather information about perceived control and positive illusions.

2.2. Conceptual Framework

2.2.1 Overconfidence Bias and Trading Behaviour

Overconfidence is described as "an unjustified faith in one's intuitive reasoning, judgment, and cognitive ability." (Pompian, 2006, p.51). According to Jain et al. (2022) overconfidence among investors refers to the false belief that they are knowledgeable about the market regardless of the danger. Investors get overconfident when trading on the stock market due to their accuracy rate and believe that they are superior to others (Parhi and Pal, 2022). Investors' rationality was twisted by this behavioural bias, causing them to be influenced by these cognitive characteristics (Naveed and Taib, 2022).

Perceived control, which is defined as a person's belief that he has influence over another person's environment, behaviour, feelings, or actions (Hilton, 2006), was used to analyse overconfidence bias among investors. Additionally, the degree to which traders had success in predicting the future correctly was utilised to assess overconfidence bias (Liu & Tan, 2021). Wang et al. (2022) confirmed the conviction that forecast accuracy was a critical factor in decision-making. They also came to the conclusion that excessive investor confidence was associated with poor prediction accuracy. The third element of overconfidence is positive delusion, as opposed to self-deception, where investors adopt an idealistic perspective on specific concerns (Hilton et al., 2006). According to Labajova et al. (2022), illusion of control refers to a person's inflated perception that they have the power to affect random events. These people's upbeat fantasies cause them to become overconfident in their trading behaviour (Parmitasari and Syariati, 2022). Past investment success, which assessed an investor's success based on earlier market returns, was the third factor of overconfidence bias (Huang et al., 2022). Depending on the investor's characteristics and the success of their prior investments, different information is sent to them (Kim et al., 2020).

Trading Behavior

In terms of volume, overconfident investors were more likely to sell their stock when the price decreased (Kourtidis et al., 2011; Shah 2016; Mudalige et al., 2016). This was one of the factors that was handled by an investor's trading behaviour. Trading performance was the second element that influenced trading behaviour, and it was discovered that excessively aggressive trading by overconfident traders ultimately resulted in lower earnings (Dorfleitner and Scheckenbach, 2022; Aydemir and Aren, 2017). According to Boutseka (2020), price premiums and investor attitudes have an impact on performance. Trading frequency was the final factor that influenced trading behaviour, and investors with more experience tended to hold onto their shares for shorter periods of time (Paisarn et al. 2021). The fact that overconfident traders frequently sell shares fast, leading to aggressive trading, disproves this claim (Wang et al., 2022; Glaser and Weber, 2007).

In line with the above findings, we hypothesize that:

H1. Overconfidence bias influences the trading behaviour of retail investors

2.2.3. Overconfidence, Miscalibration and Trading Behavior

Miscalibration is "the difference between the accuracy rate and probability assigned (that a given answer is correct)" (Skala, 2008, p. 34). Various personality traits are known as behavioural biases and are responsible for investors' miscalibration (Glaser et al., 2013). Overconfidence can be characterised as a mismatch of investor expectations and is connected to the accuracy with which such expectations are calibrated (Graham et al., 2009; Lovric et al., 2010). Investors are less likely to trade because of their greater tendency to think they are more knowledgeable than everyone else (Antonelli-Filho et al., 2021a; Hamurcu and Hamurcu, 2021; Mundi and Nagpal, 2022). As a result, we offer an additional set of hypotheses based on these studies:

H2. Overconfidence bias influences miscalibrated decisions of retail investors.

H3. Miscalibration influences the trading behavior of retail investors.

H4a. Miscalibration mediates the relationship between overconfidence bias and trading behaviour

2.2.4. Overconfidence, Disposition Effect, and Trading Behavior

According to Baker et al. (2021, p. 355), the disposition effect is "the tendency of investors to keep losers for too long and sell winnings too quickly." As a result, it can be understood as the investors' unwillingness to sell losing shares and readiness to sell winning shares (Max and Liêu, 2022). These biases in stock trading mostly effect investors (Mushinada and Veluri, 2018b; Raut et al., 2018). Due to their overconfidence bias, traders eventually fall victim to loss aversion bias or mental accounting bias. They fail to sell these shares as a result of this bias because they are afraid of losing money (Hala et al., 2020). The investor does anticipate making a profit when he sells these shares, given his trust in returns and lack of fear for losing money (Hala et al., 2020). We can speculate, in light of these results, that overconfidence, the disposition effect, and trading behaviour have important relationships.

H4. Overconfidence bias influences the disposition effect of retail investors.

H5. The disposition effect influences the trading behavior of retail investors.

H4b. The disposition effect mediates the relationship between overconfidence bias and trading behaviour

2.2.5 Social Media Influence

The new era of the financial market tends to be influenced by social media to understand and identify the transactions in the stock market (Jayasuriya and O'Neil, 2021). Previous studies had identified the influence of social media on the pricing structure of financial assets(Hong *et al.*, 2004). Numerous studies enumerated the significance of social media being used as a tool to analyse the financial structure and the information effects of these on the financial markets (Paul, 2015; Jiao *et al.*, 2020; Chen *et al.*, 2014). The studies also found that the processing time when social media is used is comparatively lesser than traditional media usage (Jiao *et al.*, 2020). Researchers had attempted to identify the influence of social media when investors are affected by miscalibration as well as disposition effect (Lee *et al.*,2022; Jin *et al.*, 2021; Max and Liêu, 2022). The current study caters to understanding the impact of social media on the relationship of overconfidence bias, miscalibration and disposition effect and trading behaviour.

Thus, it is hypothesized as:

H6a. Social Media will moderate the relationship between miscalibration and trading behaviour such that the relationship weakens the investors' trading behaviour.

H6b. Social Media will moderate the relationship between the disposition effect and trading behaviour such that the relationship weakens the investors' trading behaviour.

H6c. Social Media will moderate the relationship between overconfidence bias and investors' trading behaviour such that the relationship is strengthened.

The proposed model is as follows:

3. Research Methodology

The variance-based partial least square structural equational modelling (PLS-SEM) in SmartPLS 4.0 software was used to analyse the data (Ringle et al., 2015). In order to demonstrate that common method bias was not a problem in this study, the total variance for Harman's single factor was 32.43 percent, which was below the threshold value of 50 percent (Podsakoff et al., 2003). Examining the inner values of the variance inflation factor (VIF) also allowed the full collinearity test to be applied (Kock, 2015). The maximum VIF inner value for each build was found to be 3.0, which is considerably less than the 3.3 threshold value. Thus, CMB was not viewed as an issue in this investigation. A 7-point Likert scale, ranging from strongly disagree (1) to strongly agree (7), was used to develop the questionnaire for this study. The lowest number of responses needed was calculated using the G*Power software (Faul et al., 2009), which resulted in 121 responses. The present study complies with the sample size requirements because the final analysis was conducted with 376 respondents.

The data were analysed using SmartPLS 4.0 software's variance-based partial least square structural equational modelling (PLS-SEM) (Ringle et al., 2015). The overall variance for Harman's single component was 32.43 percent, which was within the threshold value of 50 percent, to show that common method bias was not an issue in this study (Podsakoff et al.,

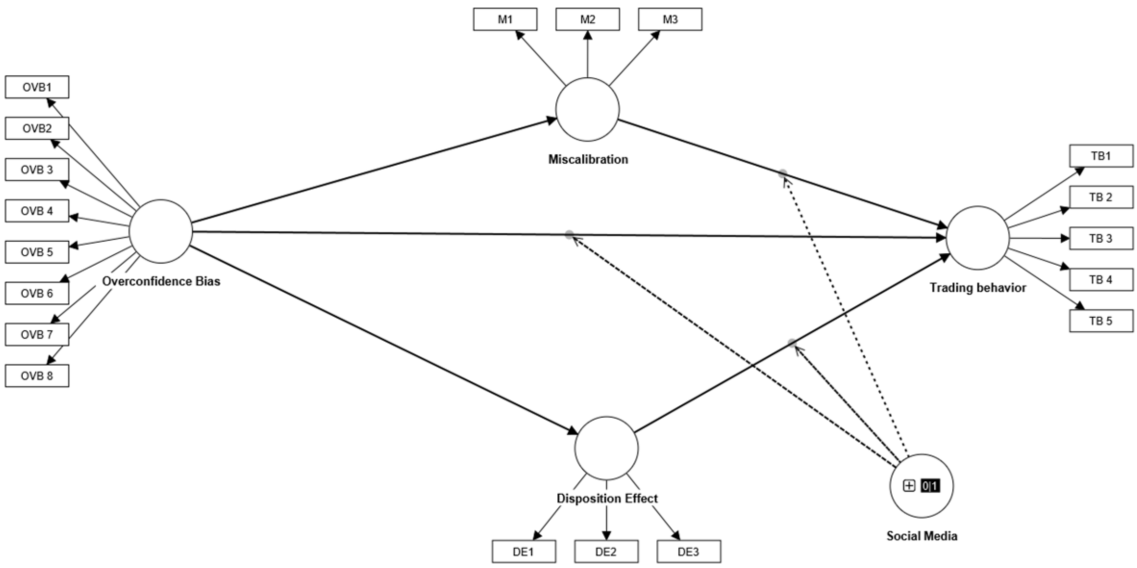

Figure 1: Proposed Model

2003). The entire collinearity test could be conducted by looking at the inner values of the variance inflation factor (VIF) (Kock, 2015). Each build's highest VIF inner value was discovered to be 3.0, which is significantly lower than the 3.3 threshold value. CMB was therefore not considered a problem in our investigation.

4. Data Analysis

4.1 Descriptive Statistics

Table A.1 provides an explanation of the survey respondents' demographic traits. Male respondents made up a bigger percentage of the sample (73%) than female respondents (27%). A smaller percentage of respondents (26%) were investors over the age of 40, while the majority (74%) were under that age. The fundamental qualities of investors were also assessed in relation to the information acquisitions, and it was discovered that they were evenly distributed throughout the total model.

Table A.1: Descriptive Characteristics

Particulars	Overall Model	
	Frequency	Percentage
Age:		
Below 40yrs	276	73.5
Above 40yrs	100	26.5
Gender:		
Female	100	26.7
Male	276	73.3
Information Acquisition:		
Less Information	188	50
More Information	188	50

Source: Authors' Calculations

4.2 Measurement Model

All reflective constructs were subjected to first-order measurement model evaluations in accordance with the recommendations made by Hair et al. (2022) and Hair et al. (2019), which are listed in Table A.2. Henseler's rho_A with composite reliability and Average Variance Extracted (AVE) were used to address the convergent validity and reliability of the constructs. According to Hair et al. (2019), all AVE values for reflective constructs were found to be more than the required value of 0.50 to prove convergent validity. In order to establish the internal consistency of the responses, Hair et al. (2019, p. 15) observed that the composite reliability and Henseler's rho_A of reflective items were both above the minimum value of 0.60 and below the maximum value of 0.95.

Table 2: Construct Reliability and Validity

Constructs	Composite reliability (rho_a): (rho_c)	Average Variance Extracted (AVE)
Disposition Effect	0.842 - 0.900	0.751
Miscalibration	0.798 - 0.874	0.698
Overconfidence Bias	0.864 - 0.893	0.511
Trading behavior	0.875 - 0.902	0.654

Source: Author's Calculation

Table A.3 represents the HTMT values to evaluate the discriminate validity of all first-order constructs. All the HTMT values were under the threshold limit of 0.85 (Henseler *et al.*, 2015). Thus, the discriminant validities of all reflective constructs in the proposed conceptual model were established.

Table 3: Discriminant Validity using Heterotrait - Monotrait ratio of correlations

Constructs	Disposition Effect	Mis-calibration	Over-confidence Bias
Miscalibration	0.295		
Overconfidence Bias	0.684	0.568	
Trading behavior	0.595	0.448	0.718

Source: Author's Calculation

4.4 Assessment of Structural Model

The structural model was tested by bootstrapping 10,000 subsamples (Hair et al., 2022), which includes computing the variance inflation factor (VIF), hypothesis testing, and variable mediation analysis (Saari et al., 2021; Hair et al., 2019). A maximum value of 3.009 was recorded for the inner VIF, which is much less than the required value of 3.33. There is no multicollinearity as a result (Hair et al., 2022). Second, to test the hypothesis, 10,000 bootstrap subsamples were used (Figure 2). It was found that traders' trading behaviour had a positive influence on investors' overconfidence bias (β =0.369, ρ<0.001). The H1 thus establishes the link between overconfidence bias and trading activity. Overconfidence bias was also discovered to have an impact on miscalibration (β=0.479, ρ<0.001) to support H2, and that miscalibrated individuals display variations in their trading behaviour (β =0.181, ρ<0.001). Additionally, it was discovered that overconfidence had a significant impact on how investors behaved (β =0.585, ρ<0.001), and the disposition effect affected trading behaviours as a result. (β=0.255, ρ<0.001), supporting both H4 and H5. It was found that there was no relationship between the control variables and any of the constructs being measured, as can be observed in Table 5. The standardised root mean square residuals (SRMR) of estimated model was found to be 0.072 to justify model fit indices with threshold limit at 0.080 (Hair et al., 2022).

4.5 Mediation Analysis

Table 5 displays the findings of the parallel mediation. The findings show that miscalibration (effect = 0.128, p>0.01) significantly moderated the association between overconfidence bias and trading behaviour. The association between overconfidence bias and trading conduct was also significantly mediated by the disposition effect (effect=0.053, p>0.01). As a result, it

Table 4: Structural Model Assessment

Hypothesis	Predictors	Path relationships	β	CI	VIF	f²	Significance?
	Age	Age -> Trading behavior	0.002	[-0.145:0.201]	1.000	0.000	No
	Gender	Gender -> Trading behavior	-0.139	[-0.315:0.213]	1.000	0.004	No
	Information Acquisition	Information Acquisition -> Trading behavior	-0.079	[-0.281:0.223]	1.000	0.001	No
	Trading Experience	Trading Experience -> Trading behavior	-0.072	[-0.416:0.264]	1.000	0.001	No
H1	Overconfidence Bias	Overconfidence Bias -> Trading behavior	0.369	[0.207:0.518]	3.009	0.072	Yes
H2	Overconfidence Bias	Overconfidence Bias -> Miscalibration	0.479	[0.396:0.558]	1.000	0.298	Yes
H3	Miscalibration	Miscalibration -> Trading behavior	0.181	[0.065:0.296]	2.319	0.024	Yes
H4	Overconfidence Bias	Overconfidence Bias -> Disposition Effect	0.585	[0.514:0.655]	1.000	0.521	Yes
H5	Disposition Effect	Disposition Effect -> Trading behavior	0.255	[0.119:0.402]	2.428	0.048	Yes

Source: Author's Calculation

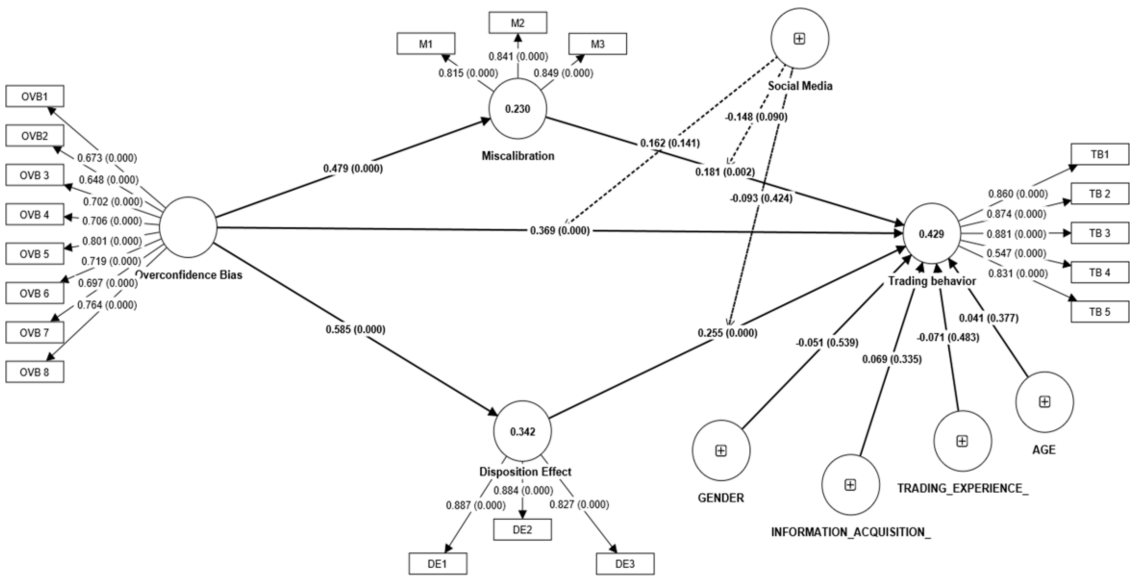

Figure 2: Structural Model Assessments

supported the hypothesis that the association between overconfidence bias and trading behaviour was mediated by both the miscalibration and disposition effects.

Table 5: Mediating Effects

Mediation Effects	Beta	Confidence Interval (CI)	Significance
Indirect Effect			
Overconfidence Bias -> Disposition Effect -> Trading behavior	0.128	[0.064:0.195]	Yes
Overconfidence Bias -> Miscalibration -> Trading behavior	0.053	[0.014:0.099]	Yes
Total Indirect Effect			
Overconfidence Bias -> Trading behavior	0.181	[0.105:0.257]	Yes

Source: Author's Calculation

Test of Moderated mediation: To find the unstandardized beta in the first stage of moderated mediation, 10,000 data were used to bootstrap the model. Testing the hierarchical regression analysis was the second stage of the analysis. The association between overconfidence bias and trading activity, which is mediated by miscalibration, was examined for the moderating effect of social media (Figure 3). The findings showed that a strong social media presence attenuates the connection between trading conduct and miscalibration. The results are in agreement with Lee et al. (2022), who noted that inaccurate results may not necessarily result in aggressive trading conduct.

Similar to Figure 3, Figure 4 shows that investors' cautious trading behaviour is influenced by reduced social media usage and lower disposition effects. According to this outcome, which is consistent with Jin et al. (2021) and Max and Liêu (2022), investors kept their riskier investment portfolios. The positive correlation between overconfidence bias and trading activity was also used to investigate the moderation effect of social media. According to the findings shown in Figure 5, there is a stronger association between overconfidence bias and investors' trading behaviour as social media influence increases (Abreu and Mendes, 2012; Dorn and Huberman, 2005; Barber and Odean, 2001).

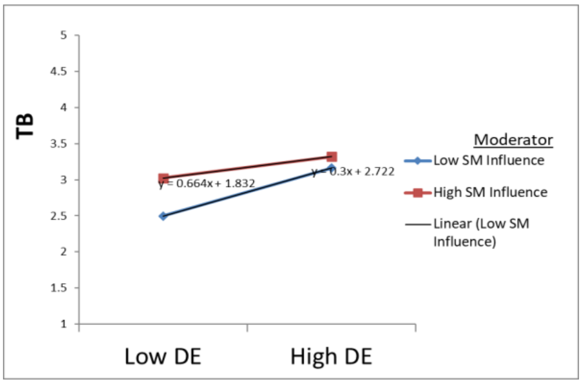

Figure 4: Moderating effects of social media on disposition effect-trading behaviour relationship

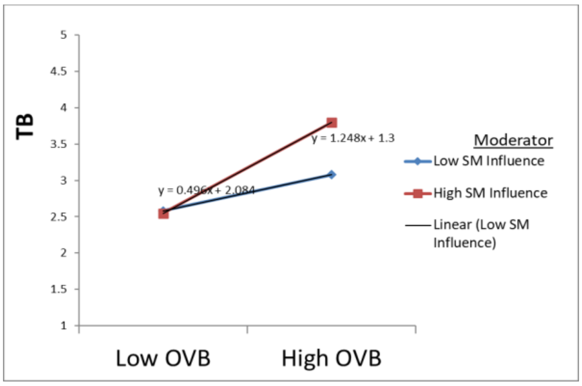

Figure 5: Moderating effects of social media on overconfidence bias -trading behaviour relationship

5. Discussion and Implications

The findings of this study suggest that while assessing the trading behaviours of retail investors, overconfidence bias and financial literacy should be taken into consideration. According to past research, overconfidence bias needs to be specifically considered when assessing trading behaviour (Rahman & Gan, 2020; Azam et al., 2022; Paisarn et al., 2021). The results of this study support the assertions made by Antonelli-Filho et al. (2021), Khan et al. (2019), and ul Abdin et al. (2022), according to which it is impossible for researchers to ignore miscalibration and the disposition impact while taking into account investors' overconfidence bias and trading behaviour. According to previous research (Abreu and Mendes, 2012; Dorn and Huberman, 2005; Yang et al., 2021), social media has a positive moderating effect on the link between overconfidence bias and investor trading behaviour. The findings were in line with research by Lee et al. (2022), Jin et al. (2021), and Max and Liêu (2022) on the impact of social media on the relationship between miscalibration and disposition effect and investor trading behaviour.

5.2 Theoretical Implications

The present article offers insight into how overconfidence bias affects how retail investors trade on Indian financial markets. First, we provide a contribution to Markowitz's (1952) portfolio theory, which assessed the impact of overconfidence bias on investors' decisions to maximise return and minimise risk by offering a plausible interpretation. The research also considered the illusion of control theory (Ellen Langer, 1975), which promoted the idea that an investor's objectivity is less likely to result in success than personal biases. The results of this study support these hypotheses, indicating that the overconfidence bias of retail investors influences their trading conduct.

5.3 Managerial Implications

According to the current study, overconfidence bias has an impact on how retail investors trade on the financial markets. The study's findings demonstrated a moderating effect of social media on the association between overconfidence bias and investor trading activity. The moderation effect of social media was also examined for the mediating constructs of disposition effect and miscalibration. According to the findings, social media has a positive influence on the relationship between overconfidence bias and trading behaviour, which implies that an investor with a strong social media following and a high overconfidence bias will engage in aggressive trading on the financial markets.The study confirmed that investors' miscalculation and disposition impact do not always result in aggressive trading conduct. Investors continue to hold riskier investment portfolios as a result. The plan may be determined by experts in the stock market, mutual funds, and the fintech sector once they have a greater understanding of how regular investors behave. These experts may concentrate on high-quality information under the impact of social media and develop investment proposals and approaches in order to increase returns on their investment decisions.

6. Conclusion

The current study took a novel strategy to determine how social media can moderate the association between overconfidence bias and investors' trading behaviour on the stock market. The results show that social media has a moderating effect on retail investors' investment decisions. The miscalibration and disposition impact was also found to be a mediator in the link between overconfidence bias and trading behaviour. Parallel mediation, which is taken into account in the current study, can be replaced in further investigations with serial mediation of miscalibration and disposition effect. The study only took into account overconfidence bias; however, in the future, other behavioural biases, such loss aversion and mental accountability, may also be taken into consideration to determine an investor's trading style. In addition to all of these other variables, financial literacy can be taken into account when analysing the moderating impact on the association between overconfidence bias and trading activity.

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