An Empirical Investigation of the Impact of Retail Investors' Sentiment on their Investment Decisions

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Abstract

The current study aims to investigate the impact of retail investors' sentiment by taking overconfidence, self-attribution, overreaction, and underreaction as antecedents of investor sentiment on their investment decisions. The study uses a cross-sectional research design, and a structured questionnaire was designed to obtain responses using a snowball sampling technique. A total of 125 usable responses were collected via an online survey for data analysis. The study applied a two-staged "Partial Least Square-Structural Equation Modeling (PLS-SEM)" and "Artificial Neural Network (ANN) approach" for data analysis and hypothesis testing. The study outcomes demonstrate that overconfidence, self-attribution, overreaction, and under-reaction significantly impact investors' decisions. Further, the study found that overreaction is the most influencing and overconfidence is the least influencing behavioral bias that affects investors' investment decisions. The insights of the study are relevant for retail investors and financial advisors. The study results provide evidence that retail investors are predisposed to different behavioral biases. So, understanding the influence of these biases will help them make profitable investment decisions. Similarly, financial advisors can take the study's insight and guide their clients regarding financial matters by considering the potential impact of different behavioral biases.

Keywords: overconfidence, under-reaction, self-attribution, overreaction, sentiment

JEL: G10, G11, G12, G14

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1. Introduction

The increasing debate on the limitations of the traditional finance paradigm has attracted the attention of psychologists and economists to give a rational explanation for different stock market phenomena that traditional finance theories could not describe. Traditional finance theories are the base of modern portfolio management, and two such foundational pillars are the "Mean-Variance Portfolio Theory" and the "Efficient Market Hypothesis" (Park & Sohn, 2013; Zahera & Bansal, 2018). The "Capital Asset Pricing Model," "Intertemporal Capital Asset Pricing Model," and "Arbitrage Pricing Theory" have also significantly contributed to the development of traditional finance theories. These models/theories are based on certain fundamental axioms like the rationality of investors, unlimited computational capabilities of investors, and the efficiency of the financial market (Copur, 2015). But in an actual financial setting, such assumptions might not fit.

However, investors do not behave rationally as their decisions encounter different anomalies and biases when making investment decisions (Zahera & Bansal, 2018). Scholars question the validity of the assumptions of traditional finance theories, particularly from the domain of finance and psychology, from time to time. This is because traditional finance theories could not describe stock market phenomena like anomalies, bubbles, crashes, etc. (Prosad et al., 2015a; Hong & Stein, 1999). In the stock market, the challenge before the investor is to correctly predict the value of a security because the value of securities often deviates from its intrinsic value. Hence, investors make irrational investment decisions. The deviation of asset prices from the intrinsic value of securities is because of investors' erroneous beliefs (De Long et al., 1990). An erroneous belief formed by investors from past experiences is called sentiment. And investors' investment decisions are influenced by their sentiments (Prosad et al., 2015b; Peterson, 2016). De Long et al. (1990) defined "investors' sentiment" as "a belief that is formed by an investor about the future cash flows and also with the risk associated with the investment that is not properly being justified from the facts." The sentiment is a mistake by the investor and reflects the judgmental errors made by investors (Shleifer, 2002), and investor sentiment occurs because of investors' cognitive biases (Baker & Wurgler, 2006). De Long et al. (1990), in the "DSSW Model" (based on the initial name of De Long J. B., Shleifer A., Summers L.H., and Waldmann R. J.), describe that noise investors' investment decision is driven by their sentiment. Thus, investors often make irrational decisions dictated by their gut feelings, imitating behavior, and behavioral biases (Dasgupta & Singh, 2019). Therefore, it becomes imperative to find the key behavioral and psychological factors that drive investor sentiment, which eventually impact investors' investment decisions in the stock market.

Therefore, this research focuses on the following key research questions:

RQ1. What are the key antecedents of investor sentiment?

RQ2. What is the influence of retail investors' sentiment on their investment decisions?

Prior research on investor sentiment concentrated more on formulating an investor sentiment index by using different proxies and investigating the potential influence of sentiment on the stock market return. But it is challenging to capture the sentiment of investors considering only proxies. Hence, the direct measure is the best to capture the investors' sentiment. However, previous research mainly focuses on measuring investor sentiment and partly considers cognitive biases, although cognitive biases are the significant antecedent of investor sentiment. Existing research also focuses on the market sentiment ignoring the individual investors' sentiment. Further, in the Indian context, limited studies investigated the influence of investor sentiment on their investment decisions.

In emerging markets like India, investors rely on their sentiment for investment decisions. The influence of investors' sentiment on investment decisions is primarily given less attention in emerging markets. In India, limited studies have focused on investigating the effect of investors' sentiments on their investment decisions. North-East Region is an integral part of India, and 1.77 percent of the total registered individual investors are from this region (as per the BSE website). Despite this, the region was given less attention by researchers. Hence, the present study focuses on the influence of investors' sentiment on their investment decisions in the North-East Region of India. Analyzing the impact of investors' sentiment in investment decision-making will help financial regulators formulate policies for this region and help financial advisors and individual investors. Financial advisors can suggest that retail investors construct a profitable portfolio, and individual investors can also evaluate and regulate their sentiments to make better investment decisions.

2. Literature review and hypotheses development

2.1 Theoretical Review

The financial market is the most volatile. Such volatility compels a market player to make risky investment decisions. Deciding on a risky situation often makes an investor rely on their beliefs, called sentiment. Investor sentiment is a well-documented phenomenon in the finance literature (Park & Sohn, 2013). It has become an important way to explain market movements (Manuel et al., 2020). Researchers currently identified the importance of investors' sentiment in asset prices. They argued that asset prices could often be affected by investors' sentiment; hence, with low or high sentiment, investors tend to make pessimistic or optimistic decisions (Huang et al., 2015).

Direct, indirect, and meta-measures are three classifications that measure the investors' sentiment (IS) in the financial market (Pandey & Sehgal, 2019; Brown & Cliff, 2005). The direct measure is also a survey-based measure of investors' sentiment. For example, the "Investor's Intelligence Survey (II Survey)" and the "American Association of Individual Investors Survey (AAII Survey)" are popular direct measures of investor sentiment (Pandey & Sehgal, 2019). These measurement techniques measure investors' sentiment by labeling the responses as bullish, bearish, or neutral (Baker & Wurgler, 2006). According to market lore, the best time to include a stock in the portfolio by the investor is when the market is bearish, and the best time to discard a stock from the portfolio by the investor is when the market is bullish (Robert & Wheatley, 1998). Indirect IS measures include the development of the investor sentiment index and, subsequently, investigating its influence on stock returns (Pandey & Sehgal, 2019). Researchers used various proxies for constructing investor sentiment indexes like closed-end funds, IPOs, and liquidity. According to DSSW theory, noise traders are considered irrational investors, and their unexpected expectations about asset returns influence their sentiment. The reason is that individual investors who trust and trade based on noise can affect the prices of securities. The theory by Hong & Stein (1999) in under-reaction and overreaction considered two types of agents: 'momentum traders' and 'news-watchers,' and both agents are not entirely rational. The irrational behavior of momentum traders and news-watchers is because of under-reaction and overreaction. Barberis et al. (1998) argued that under-reaction and overreaction are two important phenomena that act as drivers to form investors' erroneous beliefs about the stock market reflected in the security prices.

Research in investor sentiment focuses on constructing an investors' sentiment index and finding the nature of the financial market, whether bullish or bearish. Prior research also focuses on the developed financial market and depends on the notion that it drifts away from the security prices from its fundamental value because of retail investors (Kumar and Lee, 2006; Pandey & Sehgal, 2019). The sentiment wave among retail investors is more prevalent

(Pandey & Sehgal, 2019). Therefore, it is imperative to understand the influence of retail investors' sentiments on their investment decisions in the financial market (Aggarwal, 2018; Davidson et al., 2000). Measuring sentiment is very difficult, and in the previous literature, numerous antecedents for investor sentiment and proxies of sentiment were used (Qiu & Welch, 2004). In this study, we have adopted key antecedents of investor sentiment from the models of Baker et al. (2012), Baker and Wurgler (2006), and Huang et al. (2014) to analyze the influence of investor sentiment on retail investors' investment decisions. So, the present study aims to investigate the impact of retail investors' sentiments on their investment decisions.

2.2 Hypotheses development

2.2.1 Overconfidence

"Overconfidence" is conceptualized as the tendency of the investor to give more weight to their abilities to predict future trends. Daniel et al. (1998) defined "overconfidence" as "the tendency of the investor to overestimate their abilities and perceive themselves more favorably than others view them." Theoretically, overconfidence bias is well known (Jaiyeoba et al., 2020) and the most dominant behavioral bias in the finance literature (C. Galariotis, 2014). Prior literature documented a positive and significant association between overconfidence and investment decisions (Prosad et al., 2015a; Metawa et al., 2018; Maqsood & Shah, 2019; Kasoga, 2021; Jain et al., 2021; Bhatia et al., 2021; Adil, Singh & Ansari, 2021). The existing empirical studies confirmed that overconfidence strongly affects investor investment decisions. In the Indian context also, it is one of the significant biases (Prosad et al., 2015a). Based on the evidence on overconfidence and investment decisions, the present study proposes the following hypothesis:

> H_1: Overconfidence significantly and positively impacts retail investors' investment decisions.

2.2.2 Under-reaction

"Under-reaction" is conceptualized as investors' belief about the financial market that positive earnings surprises won't last for a longer period. Barberis et al. (1998), in their model of Investor Sentiment, used under-reaction to explain how investors form a belief. They defined under-reaction as "the average return on the company's stock in the period following an announcement of good news is higher than the average return following bad news." Prior studies document that under-reaction significantly and positively impacts investor investment decision-making (Musnadi et al., 2018; Metawa et al., 2019; Janssen et al., 2020). Bouteska & Regaieg (2020) investigated the under-reaction behavior of financial analysts and found that under-reaction changes the financial analysts' forecasts. In their study with the secondary data, Bulkley & Herrerias (2005) found that investors under-react when the sources of profit-earning information are not precise. So, under-reaction influences the future earning potential of investors. In the present study, under-reaction is used as an antecedent of investor sentiment to aid existing literature. So, the proposed hypothesis is:

> H_2: Under-reaction significantly and positively influences retail investors' investment decisions.

2.2.3 Overreaction

"Overreaction" in this study is operationalized as investors overreacting after the declaration of good news. Barberis et al. (1998) incorporated 'overreaction' in the Investor Sentiment model. They defined overreaction as "the average return after the announcement of good news is lower than the average return after the bad news." The main reason is that after the good news, investors become optimistic about the future, and hence they overreact, and as a result, the stock price reaches high levels. But in the future, information announcements will likely to contradict their optimistic behavior and lower the return on investment. Empirically, prior research studies documented the existence of overreaction phenomena in the financial market (Boubaker et al., 2015; Piccoli et al., 2017; Musnadi et al., 2018; Metawa et al., 2019; Janssen et al., 2020). Further, Han et al. (2016) investigated overreaction in the "Foreign Currency Options Market" and found that overreaction exists in the options market. So, the present study uses overreaction as an antecedent of investor sentiment to aid the existing research, and hence the proposed hypothesis is:

> H_3: Overreaction significantly and positively impacts investors' investment decisions.

2.2.4 Self-attribution

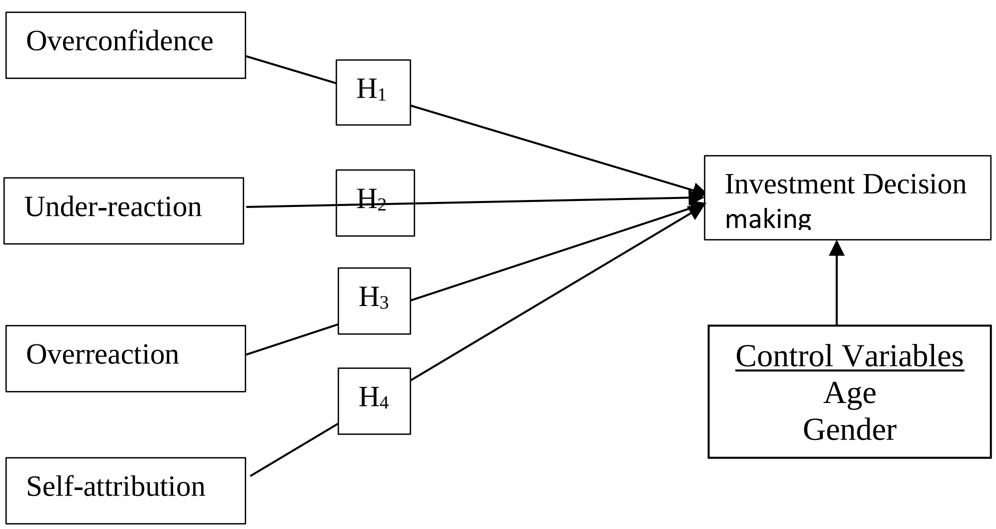
Daniel et al. (1998) incorporated another psychological factor in the Investor Sentiment model: self-attribution. People attribute themselves to their success stories and blame others for their failures. Mishra & Metilda (2015) state, "Self-attribution is a cognitive phenomenon by which people tend to attribute success to innate aspects such as talent and foresight, and attribute failures to situational factors." In this study, self-attribution is operationalized as taking credit for a successful investment and blaming others for an unsuccessful investment by an investor. Prior literature provided evidence that self-attribution significantly impacts investment decisions (Mushinada & Veluri, 2018; Hoffmann & Post, 2014). To a large extent, this self-attribution phenomenon influences investors' investment decision-making. Hence, self-attribution is used as an antecedent of investor sentiment. In this case, the proposed hypothesis is:

> H_4: Self-attribution significantly and positively influences retail investors' investment decisions.

2.3 Research Framework

In the present research paper, we proposed four dimensions of behavioral biases as antecedents of retail investors' sentiment, which will impact retail investors' investment decision-making, as shown in Fig. 1.

Fig. 1. Research Framework



3. Research methodology

3.1 Research Participants and data collection process

The present study's objective is to examine the influence of retail investors' sentiments on their investment decisions. This study's geographical area is India's North-Eastern Region (NER). For data collection purposes, Assam is considered because Assam represents approximately 74 percent (www.bseindia.com/) of the retail investors in this region. So, the sample applied in the study well represents the population, i.e., retail investors of NER of India.

Further, the "cross-sectional research design" was used in the study, and data were collected using the online survey method, i.e., google forms using the "snowball sampling technique." The study's respondents have prior investing experience of at least six months. The time frame for data collection was from February 2023 to May 2023. As a result, we received 125 usable responses from retail investors for data analysis.

3.2 Variable measurement

The research framework formulated above is based on the association among decision variables. A questionnaire was designed by adopting items from prior literature (Daniel et al., 1998; Barberis et al., 1998; Metawa et al., 2019; Prosad et al., 2015a; Aggarwal, 2018; Maqsood & Shah, 2019). Collectively, fifteen items were used in the study consisting of twelve items (three items for overconfidence, self-attribution, under-reaction, and overreaction) to measure the predictors and three items to measure investor decision-making (dependent variable). All the items in the questionnaire were in the English language only. And apart from demographic variables, a "five-point Likert Scale" was used to measure the intended variables representing 1 = "Strongly Disagree", 2 = "Disagree", 3 = "Neutral", 4 = "Agree" and 5 = "Strongly Agree".

3.3 Survey instrument

A survey was designed with a structured questionnaire to obtain retail investors' responses to examine the proposed hypotheses. The questionnaire used in the study has two sections. Section I contains information on key demographic variables relevant to the study shown in Table 2. Section II consists of information about the key drivers of investor sentiment that influence investors' decisions in a statement formulated to understand the effects of retail investors' sentiment in their investment decisions. Moreover, the survey was pretested with twenty-six retail investors, including one stockbroking agent, twenty-four retail investors' and one faculty member with expertise in finance. The questionnaire was modified as per the suggestions obtained in the pilot study.

3.4 Control Variables

To account for the possible impact of other variables on the dependent variable, we have included control variables in our study. So, in this study, we considered two control variables, namely the age and gender of the investors. Both control variables may impact investment decisions (Kumar & Goyal, 2016; Bailey et al., 2011).

4. Results

4.1 Demographics

In the present study, 125 usable responses were received and examined to achieve the research objective. The respondents' demographic profiles are reported in Table 1. The table shows that 53.60% are male and 46.40% are female. This ensures the absence of gender bias. Additionally, most respondents (45.60%) were from the age group 26-35 years, followed by 36.80% from the age group below 25 years and 17.60% from the age group above 36 years.

Table 1: Demographic profile

Division		Frequency	Percentage (%)
Gender	Male	67	53.60
	Female	58	46.40
Age group	Below 25 years	46	36.80
	26-35 years	57	45.60
	Above 36 years	22	17.60
Annual Income	Up to ₹ 2,50,000	43	34.40
	₹ 2,50,001-₹ 5,00,000	49	39.20
	₹ 5,00,001-₹ 7,50,000	17	13.60
	₹ 7,50,001-₹ 10,00,000	10	8.00
	Above ₹ 10,00,000	6	4.80

4.2 Common Method Bias (CMB) result

As in the study, we used a single instrument to obtain the data relating to the endogenous and exogenous variables, “Harman’s single-factor test” was used to evaluate the existence of the “Common Method Bias (CMB)” (Podsakoff et al., 2003). As per “Harman’s single-factor test,” a single factor should not explain most variance. The statistical analysis indicates that only one factor explains 31.330% of the total variance, below the higher threshold limit of 50% (Podsakoff et al., 2003). Based on this evidence, the inference can be drawn that CMB is not a concern in the present study.

4.3 Assumptions for multivariate statistical analysis

Before applying multivariate analysis, the assumptions of multivariate analysis need to be satisfied (Ooi et al., 2018). First, the linear and non-linear relationships were assessed, as shown in Table 2. Second, the multicollinearity problem was assessed by examining the “Variance Inflation Factors (VIFs)” and “Tolerance Level” (Wang et al., 2022). The outcome of the analysis indicates that the VIFs value falls between 1.174 – 1.572, which is not greater than the recommended value of 3 (Hair et al., 2018). And the tolerance level should be higher than 0.10 (Hew and Kadir, 2016). In the analysis, the tolerance level falls between 0.636 – 0.852, higher than the recommended value indicating that the multicollinearity issue is absent.

Third, the data normality was checked by applying the “one-sample Kolmogorov-Smirnov (K-S) Test.” For data normality, the p-value should be higher than 0.05; if not, the distribution is not normal (Leong et al., 2019). The K-S test results indicate that the data distribution is not normal, as the p-values are less than 0.05. As the data are not normally distributed and hence “Variance-Based Structural Equation Modeling (VB-SEM)” of the “Partial Least Square (PLS)” was adopted than the “Covariance-Based Structural Equation Modeling (CB-SEM).” Leong et al. (2019) opined that “PLS-SEM” is more robust than “CB-SEM” when the data distribution is not normal. Because of this reason, we have used SmartPLS 3 in our study to validate the proposed hypotheses.

Table 2: Linearity relationships

		Sum of squares	df	Mean Square	F	Sig.
OC*IDM	(Combined)	20.458	9	2.273	7.029	.000
	Linearity	11.936	1	11.936	36.911	.000
	Deviation from Linearity	8.522	8	1.065	3.294	.002
SA*IDM	(Combined)	15.896	6	2.649	7.487	.000
	Linearity	11.385	1	11.385	32.176	.000
	Deviation from Linearity	4.511	5	.902	2.550	.031
OR*IDM	(Combined)	27.983	9	3.109	12.053	.000
	Linearity	19.206	1	19.206	74.457	.000
	Deviation from Linearity	8.777	8	1.097	4.253	.000
UR*IDM	(Combined)	23.595	8	2.949	10.047	.000
	Linearity	17.146	1	17.146	58.407	.000
	Deviation from Linearity	6.449	7	.921	3.138	.005

Note: OC=Overconfidence, SA=Self-Attribution, OR=Overreaction, UR=Underreaction, IDM=Investment Decision Making.

Moreover, the "Artificial Neural Network (ANN)" is the best tool when the association between the endogenous and exogenous variables is not-normal (Leong et al., 2019). Hence, the ANN approach was used to find the best predictors based on SmartPLS analysis. Applying this "two-staged PLS-SEM-ANN" would provide the best result as "PLS-SEM" is best for hypotheses testing for linear associations but cannot detect the non-linear associations. ANN can detect the non-linear relationship, and ANN is not suitable for hypothesis testing. Further, the ANN model is appropriate for finding the best predictor variable (Sharma et al., 2017).

4.4 Structural equation model (SEM)

As discussed in the previous section, the "PLS-SEM" technique was used to test the proposed hypotheses. Additionally, "PLS-SEM" is best in case of small sample size and the data are not normal (Hair et al., 2019). Considering this, "PLS-SEM" was suitable for the current study.

4.4.1 Measurement model assessment

In the measurement model, "construct reliability" and "construct validity" were evaluated (Sharma et al., 2017). The results are reported in Table 3. From the table, it is observed that the values of "Composite Reliability (CR)" for all the constructs were higher than the lower limit of 0.70, which establishes the "construct reliability" (Hair et al., 2010). Further, to evaluate "construct validity," we assessed both "convergent validity" and "discriminant validity." First, to confirm "convergent validity," the "Average Variance Extracted (AVE)" should be higher than 0.5 (Hair et al., 2019; Leong et al., 2018). Table 3 shows that the AVE of all the constructs was greater than 0.50, establishing the "convergent validity."

Table 3: Reliability and validity analysis

Construct	Composite Reliability	Average Variance Extracted
Overconfidence	0.758	0.521
Self-Attribution	0.770	0.529
Overreaction	0.779	0.543
Underreaction	0.841	0.639
Investment decisions	0.809	0.586

To establish the discriminant validity, we followed multiple criteria. First, based on the Fornell-Larcker Criterion, the square root of AVEs (diagonal values) should be greater than the inter-correlation coefficients (Hair et al., 2019). Table 4 shows that all the diagonal values were higher than the inter-correlation coefficients satisfying the Fornell-Larcker Criteria. Second, the “discriminant validity” was also evaluated based on the “Heterotrait-Monotrait Ratio of Correlations (HTMT)” criteria (Hair et al., 2019). To assess the “discriminant validity,” the HTMT values should not exceed 0.90 (PLS-SEM, 2015). The result is reported in Table 5. From the table, it is observed that all the HTMT values were not greater than 0.90. So, the “discriminant validity” was confirmed.

Table 4: Fornell-Larcker Criteria

	1	2	3	4	5
1. Investment Decisions	**0.766**				
2. Overconfidence	0.496	**0.722**			
3. Overreaction	0.575	0.571	**0.737**		
4. Self-Attribution	0.455	0.289	0.285	**0.727**	
5. Underreaction	0.568	0.363	0.468	0.341	**0.799**

Table 5: HTMT Criteria of discriminant validity

	1	2	3	4	5
1. Investment Decisions					
2. Overconfidence	0.683				
3. Overreaction	0.884	0.788			
4. Self-Attribution	0.737	0.518	0.500		
5. Underreaction	0.831	0.523	0.683	0.537	

4.4.2 Structural model assessment

To check the significance of the model's path coefficients and estimate the magnitude of the path coefficients, a “PLS Bootstrapping with 5000 subsamples” was carried out (Hair et al., 2019). The results of the hypothesis testing are reported in Table 6, and empirical findings are in Figure 2. Firstly, we assessed the impact of gender and age as control variables on investment decisions. The outcome of the analysis reveals that the age of the investor (β=0.164, t=3.137) as a control variable is statistically insignificant at $p<0.05$. At the same time, the gender of the investor (β=0.053, t=0.928) is statistically significant at $p<0.05$. So, the impact of gender as a control variable in the present study is present.

Table 6 shows that self-attribution (β=0.247, t=3.579) significantly and positively impacts investment decisions. So, H4 is supported at $p<0.001$, and under-reaction (β=0.303, t=2.338) has a significant and positive influence on investment decisions. So, H_2 is supported at $p<0.01$. However, overconfidence (β=0.192, t=2.315) and overreaction (β=0.249, t=3.039) have a significant and positive influence on investment decisions, and so both H_1 and H_3 are supported at $p<0.05$.

Table 6: Path analysis

Hypotheses	Path	Path coefficients	t-statistics	p-value	Remarks
H_1	OC->ID	0.192	2.315	0.019	Yes*
H_2	UR->ID	0.303	2.338	0.002	Yes**
H_3	OR->ID	0.249	3.039	0.020	Yes*
H_4	SA->ID	0.247	3.579	0.000	Yes***

Note: OC=overconfidence, OR=overreaction, UR=Underreaction, SA=Self-Attribution, ID=investment decision, $^{***}p<0.001$, $^{**}p<0.01$, $^{*}p<0.05$.

Lastly, the explanatory power of the model was assessed by determining the endogenous construct's R^2, and the model's predictive relevance was assessed by determining "Stone-Geisser's Q^2" values respectively (Hair et al., 2019). From Table 7, it is clear that the R^2 value provides good explanatory power of the model as the value of R^2 for investment decisions is 0.543. The predictors employed in the model explained 54.3% of the variance in investment decisions. Moreover, for the high predictive relevance of any model, the Q^2 value should be greater than 0 (Hair et al., 2019). In the present study (see Table 7), the Q^2 value was higher than 0. It can be opined that the proposed research model has high predictive relevance.

Table 7: Predictive validity and predictive relevance

	R^2	R^2 Adjusted	Q^2
Investment Decisions	0.543	0.520	0.276

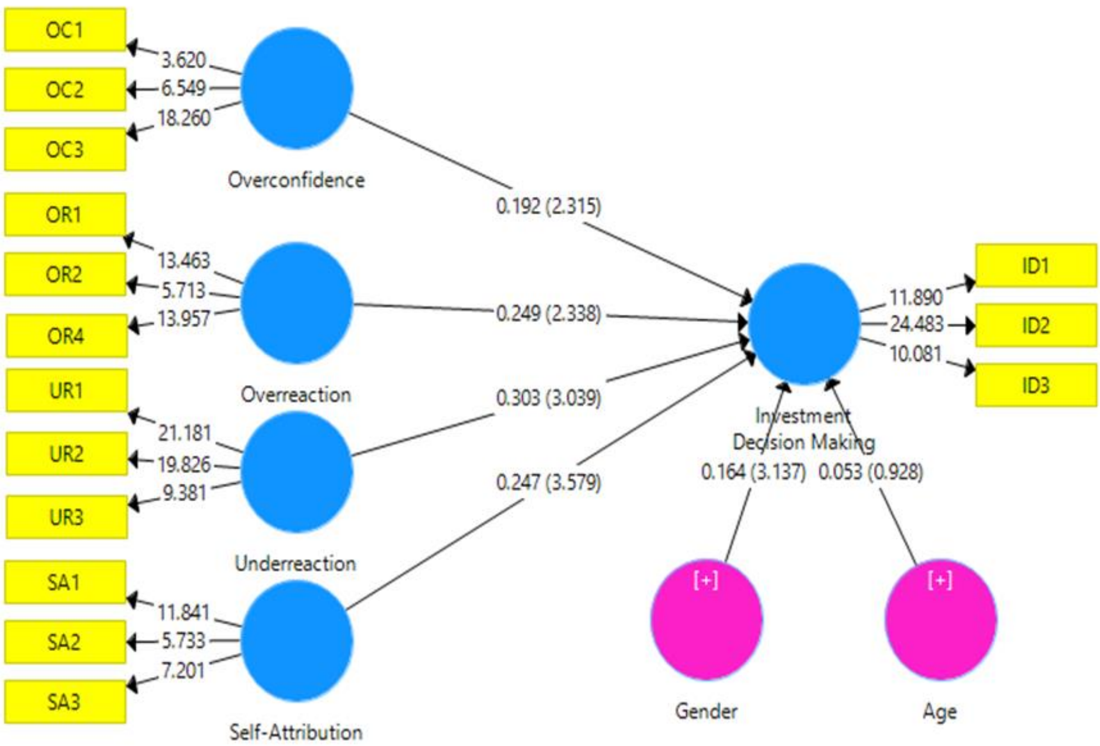


Fig. 2: Structural model

4.5 Artificial Neural Network (ANN) Analysis

Statistical techniques like "regression analysis" and "structural equation modeling (SEM)" are not sufficient enough to capture complex human decision-making processes. The reason is that these techniques decrease the complexity involved in the decision-making process, and also, these techniques are based on linear relationships (Chan and Chong, 2012). This issue can be overcome by using the "Artificial Neural Network (ANN)" as this technique can identify not only linear but also non-linear relationships (Leong et al., 2019), and this technique does not depend on any multivariate assumptions (Leong et al., 2015; Chong et al., 2013). The ANN has the highest predictive capability than the conventional linear model as it is highly robust and acceptable and usually outperforms conventional statistical techniques (Chong et al., 2013). The ANN is also robust when noise, a small sample size, and outliers exist (Leong et al., 2017).

In this study, we have conducted an ANN analysis adopting the similar technique of Liébana-Gabanillas et al. (2017), and IBM's SPSS was used for the ANN analysis. A neural network has "multiple hierarchical layers," i.e., "input layer," "output layer," and "hidden layer" (Liébana-Cabanillas et al., 2017). For the input and output layers, the "multilayer perceptrons" and "sigmoid activation functions" were used (Sharma & Sharma, 2019). However, EL Idrissi et al. (2019) asserted that the errors could be minimized, and several rounds of the learning process can improve the best predictor. The samples were allocated 90% and 10% for the training and testing procedures, respectively, similar to Leong et al. (2018). A "ten-fold cross-validation procedure" was carried out to avoid overfitting the model, and the "Root Mean Square of Errors (RMSE)" was obtained (Ooi & Tan, 2016). RMSE can predict the model's accuracy (Chong, 2013). Table 10 provides the average RMSE value for training and testing procedures. From the table, it is clear that the mean values of RMSE for both the training (RMSE = 0.171) and testing (RMSE = 0.107) are very small (Sharma et al., 2015). Hence, the conclusion can be drawn that the model fits very well.

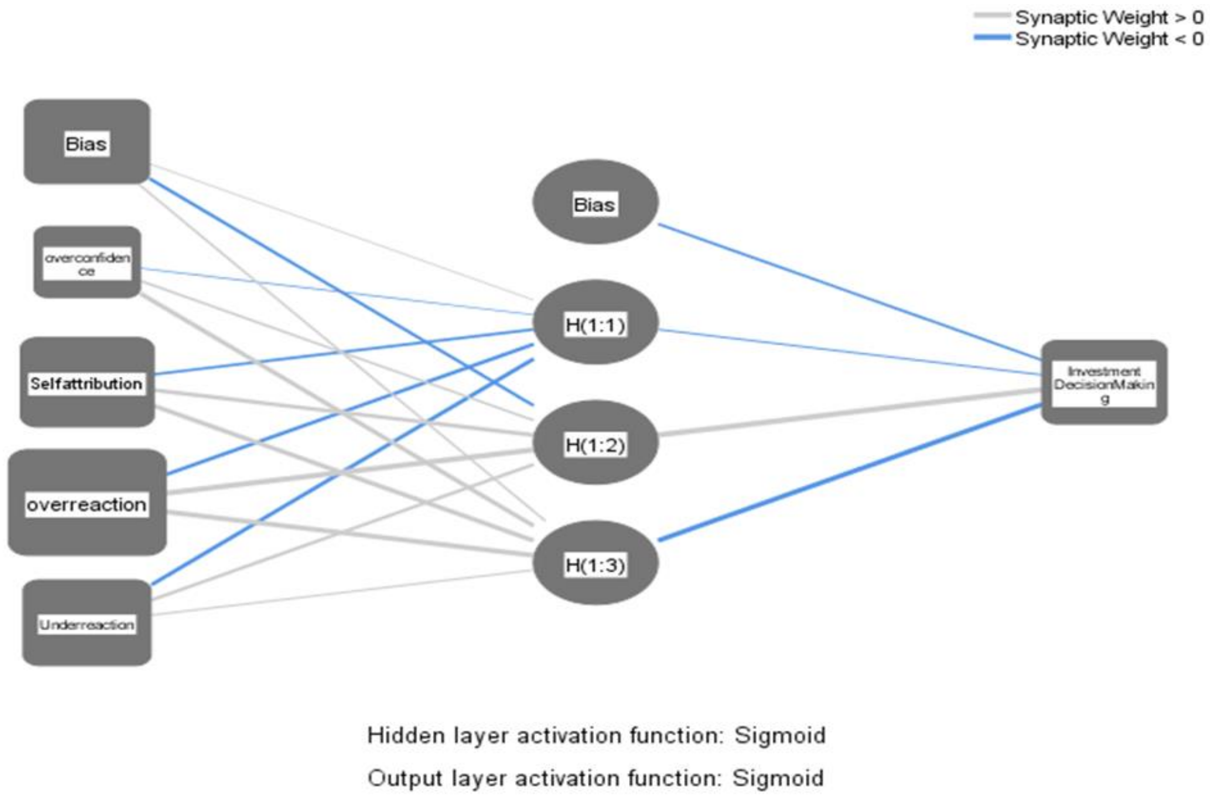


Fig. 3: ANN model

Table 8: ANN results (Root Mean Square of Errors values)

Artificial Neural Network (ANN)	Training			Testing			Total Samples
	Sample size	Sum Square of Errors	Root Mean Square of Errors	Sample size	Sum Square of Errors	Root Mean Square of Errors	
1	112	1.789	0.164	13	0.126	0.112	125
2	111	1.856	0.120	14	0.129	0.093	125
3	112	1.824	0.090	13	0.128	0.083	125
4	111	2.691	0.436	14	0.157	0.177	125
5	112	1.731	0.250	13	0.124	0.139	125
6	110	1.821	0.101	15	0.129	0.082	125
7	112	1.742	0.071	13	0.125	0.074	125
8	111	1.888	0.118	14	0.130	0.092	125
9	105	1.849	0.182	20	0.133	0.095	125
10	114	2.034	0.178	11	0.134	0.127	125
	Mean	1.923	0.171	Mean	0.131	0.107	
	Standard deviation	0.269	0.102	Standard deviation	0.009	0.030	

4.6 Sensitivity analysis

The sensitivity analysis was conducted to discover the strength of each independent variable in predicting the dependent variable (Leong et al., 2019). In the present study, the sensitivity analysis was conducted using Chong's (2013) approach. The normalized importance of each independent variable was obtained by dividing the relative importance by the maximum importance and presented in the form of a percentage (Karaca et al., 2019). The outcome of the sensitivity analysis is reported in Table 9. From the table, it is observed that overreaction is the most influencing independent variable that influences the dependent variable, i.e., investment decisions, followed by under-reaction (89.76%), self-attribution (88.02%), and overconfidence (49.53%).

Table 9: Sensitivity analysis

Constructs	Importance	Normalized importance
Overconfidence	0.4304	49.53%
Self-attribution	0.7648	88.02%
Overreaction	0.8689	100.00%
Underreaction	0.7799	89.76%

5. Discussion

The research objective is to examine the influence of retail investors' sentiment on their investment decisions in the North-East Region of India. The qualitative validation of the proposed model confirms that all the independent variables (overconfidence, self-attribution, under-reaction, and overreaction) significantly and positively impact investment decisions. The results of the study are discussed below in more detail.

First, age and gender are control variables in this research that may impact investment decision-making. However, from the analysis, it is clear that an investor's age does not significantly impact investment decisions. In comparison, investors' gender is likely to influence investment decisions significantly. It means that there is a difference in information processing for both genders.

Second, the present research confirms that overconfidence is having a positive impact on investment decisions. Retail investors who depend more on their abilities and capabilities to select the best stock for their portfolio will likely influence their investment decision-making. Though it is not the strongest predictor of investment decisions, it still affects retail investors' decisions. The results are like the prior research studies carried out by Metawa et al. (2018); Prosad et al. (2015a); Maqsood & Shah (2020); Quaicoe & Eleke-Aboagye, (2021); Adil, Singh, & Ansari, (2021).

Third, it also confirms the positive impact of overreaction on investment decisions. It is the most potent predictor variable in our research model. Investors who overreact to any news are more likely to impact their decisions. The results are consistent with the prior studies conducted by Metawa et al. (2019), Boubaker et al. (2015), and Mushinada & Veluri (2018).
Fourth, the current study confirms that under-reaction positively impacts investment decisions. It is the second strongest predictor variable of the research model. It means that investors who react lately to any positive news are likely to impact their investment decisions. The results are consistent with Metawa et al. (2019) and Musnadi et al. (2018).

Fifth, it was also found that self-attribution positively impacts investment decisions. Empirically, self-attribution is the third most potent predictor of investment decisions. So, it can be inferred that retail investors who blame others for disadvantageous decisions and credit themselves for the favorable decision are more likely to impact their decision-making. The findings are consistent with Mushinada & Veluri's (2018) study.

Furthermore, while investigating the model's explanatory power, the R^2 value for the endogenous variable, i.e., investment decisions, is 54.3%, greater than the suggested value of 40% (Straub et al., 2004). It indicates that the model's performance is satisfactory predictive power.

6 Research Implications

6.1 Theoretical implications

Based on the result, the present study has two theoretical implications for the behavioral finance literature. First, to the best of the authors' knowledge, this study is the first to investigate the association between investor sentiment and investment decision-making, taking behavioral biases like overconfidence, overreaction, under-reaction, and self-attribution as the antecedents of investor sentiment. However, Haritha & Uchil (2019; 2020) investigated the factors that affect investor sentiment considering herd behavior, social interaction, market-specific factors, etc. This study is unique because mere behavioral biases are considered the antecedents of investor sentiment in this study.

Second, unlike prior studies that used linear models to establish the association between the endogenous and exogenous variables, we applied a "two-staged PLS-SEM-ANN approach" comprising both linear and non-linear models. This new approach investigates the association between antecedents of investor sentiment and investment decisions. Moreover, by using the non-compensatory ANN model, we have successfully tested the model. The deficiency of the compensatory model is also addressed and thus offers a new theoretical contribution to the existing studies.

6.2 Practical implications

This research is handy for retail investors, financial advisors, and regulators about investors' sentiments. First, from the result of the study, it is perceptible that retail investors' investment decision is influenced by investors' sentiment (overconfidence, overreaction, under-reaction, and self-attribution). It means that retail investors depend on noise while making an investment decision, which affects their investment decision. Hence, the implication for financial advisors is that they should present decision-relevant information to retail investors so they can make better investment decisions.

Second, for retail investors, it is observed that their investment decisions are affected by their sentiments. Based on the present study, the key drivers of their sentiment are overconfidence, overreaction, under-reaction, and self-attribution. They should be careful when making investment decisions, as investor sentiment drivers can significantly impact retail investors' decisions. Instead of depending on noise information, investors should understand how the drivers of investor sentiment affect their investment decisions before making any investment decision. Understanding the key drivers of investor sentiment enable an investor to make efficient and effective investment decisions that will enable them to form a profitable portfolio.

Finally, the present study's findings are relevant for the regulators as, from the result of the study, it can be observed that the Indian financial market is inefficient. The inefficient financial market lacks financial literacy and awareness about the events in the financial market. So, regulators must observe and strengthen the guidelines of corporate governance and must make the activities of corporate houses transparent so that information asymmetry can be reduced, and thereby the behavioral biases can be minimized, and retail investors can make better investment decisions.

7 Limitations and future research agenda

The present research has threefold limitations. First, there is a geographical limitation as the study was carried out in the NERI to examine the influence of retail investors' sentiments on their investment decisions. Hence, results cannot be generalized to India as a whole. Second, the study was conducted with a smaller sample size. Third, the proposed research model in the study was formulated based on limited predictors. Hence, ample scope is there for future studies to test the model by adding other predictors. In the future, studies can be carried out (i) by incorporating a larger sample size in the study, (ii) by extending the geographical limitation, and (iii) by using the longitudinal approach instead of the cross-sectional approach to investigate the association between investors sentiment and investment decisions.

8 Conclusion

The study has successfully tested the proposed relationships using a "two-staged PLS-SEM-ANN approach." Overconfidence, self-attribution, overreaction, and under-reaction were key drivers of investor sentiment in the study. The result shows that all the predictors significantly and positively impact investment decisions. In terms of normalized importance, under-reaction is the most important factor, followed by overreaction, self-attribution, and overconfidence.

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