

How Emotional Bias Effect The Investment Decision Making Of Retail Investors In India: Using Pls-Sem, Ann And Fsqca

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ABSTRACT

According to the expected utility theory, investors are assumed to be logical decision-makers in conventional finance theory. On the other hand, behavioural finance strongly challenges this rational viewpoint, claiming that investors frequently stray from reason when making financial decisions. Investing decisions these days are frequently made irrationally by investors. Their judgement, which is very different from logical assumption, is frequently the basis for the decision. Investors' decision-making is typically influenced by a variety of objectivities, emotions, and psychological elements when they are faced with risky situations. The objective of the this study is to identify the impact of emotional biases (Herding, Loss aversion, Regret aversion and status quo) on investment decision making and identify the most influential behavioural bias. Data are gathered from 379 Indian retail investors, who represent the majority of Indian states and union territories (UTs), using a multi-stage stratified random sampling technique. The study utilised the PLS-SEM approach in conjunction with artificial neural network (ANN) analysis and fuzzy set qualitative comparative analysis (fsQCA) to examine the proposed associations, verify the validity of the results, and extract significant practical knowledge. The findings of the research indicates that herding bias, loss aversion bias, regret aversion bias and status quo have a significant positive relation with investment decision making (IDM). And as per the outcome of ANN sensitivity analysis and fsQCA, loss aversion bias (LAB) is the most crucial determinant of investment decision making. It is followed by regret aversion bias (RAB), status quo bias (SQB), herding bias (HB). This study holds significance as it offers crucial implications for researchers, market participants, policymakers, and regulators involved in the development of Indian stock market.

Keywords: Emotional bias, herding bias, loss aversion bias, regret aversion bias, status quo bias, investment decision making.

1 | INTRODUCTION

The exciting topic of behavioural finance combines finance and psychology to study how people make financial decisions. Behavioural finance acknowledges that human behaviour is frequently impacted by emotions, biases, and cognitive errors, in contrast to classic finance theories which presume investors are rational and always act in their best interest. The investigation of cognitive biases is one of the main focuses of behavioural finance. These prejudices have the potential to cause investors to act irrationally and deviate from accepted financial ideas. Confirmation bias, for instance, leads investors to ignore contradicting evidence in favour of information that supports their preconceived notions. In a similar vein, investors may overestimate their skills due to overconfidence bias, which encourages excessive risk-taking. Another main focus of behavioural finance is the importance of emotions in financial decision-making. Investors may act impulsively due to fear or greed, for example, selling assets during a market collapse or investing in a speculative boom. The sculpture of wealth management has been an economic system's lifeline for decades. In light of this, practically all corporations in a capitalistic setting aspire to maximise wealth. This raises the value of enterprise and investments. Selecting the appropriate possibilities for persuasion and exploitation is crucial in defining the characteristics of investments and entrepreneurship (Shane and Venkataraman 2000). Conventional and behavioural finance assist institutional and individual investors in making the best decisions possible in this way. Previous research demonstrates that while trading equities, investors assess risk and associated projected returns using several traditional finance theories and models (Arora and Kumari 2015). Renowned academics have employed a number of traditional finance theories and presumptions to explain the financial models. According to traditional or classical economics and finance theories, investors make logical choices in order to maximise their returns (Çilingiroğlu et al., 2011). Contrary to popular belief,

investors exhibit irrational behaviour while trading on financial markets. For example, individuals may purchase stocks without considering their underlying value just because their close friends are doing so (Benjamin, Virani, et al. 2018). According to experts, this irrational component is closely related to investors' emotional and cognitive behavioural biases, which can only be investigated via the lens of behavioural finance theories. According to Alrabadi, Al-Abdallah, et al. (2018), behavioural finance differs from traditional finance in that it views investors as exhibiting irrational and psychologically biased behaviour, which in turn affects the frequency of trading by individual investors. Although the human mind is skilled at making complicated decisions, it may also be biased and prone to mistakes, which can result in poor decisions and financial losses. Emotions play a big role in decision-making, and they can occasionally result in poor investing choices. This emphasises how crucial it is to carefully research the emotional biases that influence investors' decision-making. Therefore, the purpose of this study is to look into how different emotional biases affect retail investors' decisions to buy and sell in the Indian stock market. The paper explores how emotional biases impact investor behaviour through the analysis of primary data, offering important insights for comprehending and mitigating these biases in the context of Indian investing.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 | HERDING BIAS

Herding bias is the term used to describe people's propensity to act in unison with the group or throng, frequently without independent thought or reason. Fear of missing out on chances and a need for social conformity are the root causes of this behavioural bias. When investors collectively base their decisions on the actions of others rather than basic analysis, herding bias can cause market bubbles or collapses in the financial markets. According to Hirschleifer and Teoh (2003), herding is a behavioural bias that happens when a number of people copy a certain behaviour, which causes the behaviour to converge. In the context of the financial markets, investors may choose to accept the decisions of the majority even if they disagree with them personally. The Bitcoin Bubble is one such example. As cryptocurrencies gained traction, more and more people many of whom had no prior experience or knowledge in the field began investing in them because they saw other people doing so. Analyst recommendations typically have an impact on investors, and these recommendations are affected by other analysts as well. People who embrace other people's judgements and choices because it is simpler for them to do so than to consider the specifics of those choices are said to be herding. Most investors follow other investors in order to obtain reliable market information when fear and uncertainty are present, or when making a decision could result in significant losses (Javed et al., 2017). Herding is a situation when logical people mimic the decisions and actions of others, leading to irrational behaviour. Numerous variables can contribute to herd behaviour amongst investors. Because they follow the lead of a large trading community, commonly referred to as noise traders, individual investors are subject to crowd action (Kumar & Goyal, 2015). Herding in the US market showed notable movements and tenacity in both bullish and bearish markets, as demonstrated by Hwang, S., & Salmon, M. (2004). Herding behaviour in the Pacific Basin financial markets was studied by (Thomas C. Chiang et al., 2012), who discovered a positive correlation between herding and stock returns and a negative correlation with market volatility. The existence of herding in both bullish and bearish phases was revealed by (Moatemri Ouarda et al., 2013) who also found that increased herding tendencies were associated with higher trading volume and greater volatility, primarily as a result of increased activity from short-term speculative traders. They also examined the effects of herding behaviour on returns, volatility, and transaction volume. Herding bias has been found by Ghalandari and Ghahremanpour (2013) to have a beneficial impact on investing decisions made in the Tehran Stock Market. They discovered that the Tehran Stock Market does not give investors adequate information and that the stock is still in its infancy. As a result, Iranian investors frequently follow the lead of those who have access to trustworthy sources of information. This study revealed that investors who are susceptible to herding bias think that taking the majority's decision lowers risks and improves return prospects.

Hypothesis 1: Herding Bias has significant and positive effects on the investment decision making.

2.2 | LOSS AVERSION BIAS

A psychological condition known as loss aversion bias occurs when people experience the anguish of losses more keenly than the joy of comparable gains. Put another way, even when the possible result is the same, people typically prefer to avoid losses over corresponding gains. Decision-making can be greatly impacted by this bias, especially when it comes to money. People may take unwarranted risks in an attempt to prevent losses or hang onto lost assets for longer than is prudent. An important idea in behavioural finance is loss aversion bias, which clarifies how feelings affect our risk tolerance and financial decisions. Two psychologists, Daniel Kahneman and Amos Tversky, initially discussed the concept of loss aversion in 1979. They assessed that humans feel double ache from loss as they feel satisfaction from gain (prospect theory). Investors with loss aversion prioritise protecting their shrinking capital and fear of losing money over increasing their investment value (profit). According to prospect theory, those who are more sensitive to a decrease in their capital than an increase in it are said to exhibit loss aversion. A study on the impact of loss aversion bias on investment decisions at the Rwandan stock market was carried out by Jacob Niyoyita Mahina et al. (2017). According to their research, there is a notable loss aversion bias among Rwandan investors, which has a big impact on how individual investors make decisions in the market. Experimental research on investor decision making under risk was conducted by Eyalert and

Idoerev (2013). The findings indicate that people are influenced by loss aversion bias when presented with options that have both gain and loss; on the other hand, investors are not impacted by loss aversion bias when the outcome is merely gain. Additionally, people could overanalyze gains and losses since they don't realise how rapidly they will adjust to these changes (Koszegi & Rabin 2006).

Hypothesis 2: Loss Aversion Bias has significant and positive effects on the investment decision making.

2.3 | REGRET AVERSION BIAS

In the field of behavioural finance, regret aversion bias refers to a cognitive bias in which people prioritise avoiding future regret over maximising potential rewards. This bias stems from a dread of making choices that one day one will come to regret. As a result, people might decide to make safer decisions or decide not to act at all in order to prevent having regrets. Regret aversion bias in investing can affect portfolio performance overall by causing investors to miss out on possibilities for larger returns or to be reluctant to sell failing investments. In behavioural finance, it's critical to comprehend and deal with regret aversion bias in order to make more logical and wise investing choices. An emotional bias that typically develops later in life in any investor is regret aversion. Sometimes, individual investors argue that if they had chosen a different course of action when trading, a bad outcome could have been averted (Ady 2019). Numerous investigations have examined this notion. For example, Deuskar, Pan, et al. (2020) examined the influence of emotional bias related to regret aversion on the frequency of trading behaviour of investors in China and found that the effect is greater when action is done as opposed to inaction. The role of regret in human decision-making is further supported by neuroscience, and the psychological concept of regret in all forms of decision-making has been thoroughly studied with empirical data in previous studies (Camille, Coricelli, et al. 2004, Bourgeois-Gironde 2010). (Awais and Estes 2019) carried out an extensive investigation into the causes of regret aversion bias in PSX. After conducting a thorough analysis, they concluded that conservatism, regret aversion, errors of commission, and a lack of analytical skills are the main causes of emotional bias development in Pakistan. In a similar vein, a recent study by Shah and Malik (2021) showed that individual investors who are registered with the PSX yet have regret aversion have lower trading frequency.

Hypothesis 3: Regret Aversion Bias has significant and positive effects on the investment decision making.

2.4 | STATUS QUO BIAS

One of the main features of behavioural finance is status quo bias, which has a significant impact on stock market decision-making. This bias is the propensity of investors to stick with their existing investing positions or strategies, even in situations where there are signs that veering off course could provide greater results. Investors' unwillingness to sell failing assets is a common manifestation of status quo bias in the stock market. Due to a psychological aversion to suffering losses, investors are reluctant to part with these assets in the hopes of a future gain. Additionally, even when newer options appear to offer higher returns, investors may display status quo bias by sticking with tried-and-true investment strategies or assets. Portfolios of investments may be greatly impacted by this prejudice. Investors risk missing out on opportunities to reallocate capital to more promising investments by holding onto poor assets, which could impede portfolio growth. In a similar vein, adhering to antiquated or conventional investment methods could result in lost chances for optimal returns and diversification. The status quo is when someone has different options but chooses the status quo out of pure preference (Weathers et al., 2005; Masatlioglu and Ok, 2005; Ortoreva, 2010; Gal and Rucker, 2018). Investors who are susceptible to status quo bias tend to conform to the status quo or make identical decisions on a regular basis. This prejudice is seen in investors who fail to improve their financial situation even when there is a chance they could profit from it. Investors stick onto their positions, for example, buying more stocks than selling them, or they act in ways that are not optimal (Baker & Ricciardi, 2014). The results show that investors are very likely to accept the status quo when faced with difficult choices, which results in more errors. This bad decision-making behaviour implies that investors would make decisions against their preferences due to status quo bias (Fleming & Thomas, 2010).

Hypothesis 4: Status Quo Bias has significant and positive effects on the investment decision making.

3 | METHODOLOGY OF THE STUDY

3.1 | DATA COLLECTION & DEMOGRAPHIC PROFILE OF THE RESPONDENT

The study distributed a questionnaire to retail investors engaged in the Indian stock market, aligning with its research objectives. Employing a quantitative research approach, the study utilized primary data collected and analyzed for its investigation. Dash and Paul (2021) advocate for variance-based PLS-SEM due to its flexibility, improved model fit, and capacity to handle non-normal data compared to covariance-based CB-SEM. Similarly, Mishra et al. (2023) suggest integrating PLS-SEM with ANN to capture non-linear relationships effectively. However, Kumar et al. (2022) highlight concerns regarding the effectiveness of symmetric modeling techniques like PLS-SEM and ANN when dealing with numerous predictors towards an outcome variable. In line with these insights, this study adopts PLS-SEM, ANN, and fsQCA as symmetric modeling techniques. Moreover, the study calculated the minimum sample size using power analysis and G*Power, determining N = 184 as the minimal requirement based on effect size, error types, and power considerations. With a sample size of 379, this study meets the necessary adequacy criteria for robust analysis.

The **appendix 1** gives a thorough demographic profile of the study participants, including information on their age ranges, gender distribution, levels of education, and yearly income. A wealth of information regarding the makeup of the sample population is provided by each category. To begin with, the gender distribution of the sample is displayed in the table. Of the 379 respondents, 197 were male, or roughly 51.97% of the sample, and 182 were female, or roughly 48.02%. This suggests that the study's gender representation is fairly balanced. Regarding age groupings, 246 respondents, or roughly 64.90% of the sample as a whole, were in the 18 to <30 age range. This was the biggest proportion of respondents. 58 respondents, or 15.30% of the sample, were in the 30 to 40 age group. 48 respondents, or 12.67%, were in the 40 to 50 age group. Finally, 27 respondents, or 7.12%, were in the 50 and above age group. This distribution points to a preponderance of younger participants in the research. 197 respondents, or roughly 51.97% of the sample, had post-graduate degrees, which accounted for the bulk of respondents' educational backgrounds. Graduates made up 144 respondents (37.99%), followed by those with doctorates (26; 6.86%) and those with other undefined qualifications (12; 3.16%). This indicates that the responders have a high degree of education, especially in graduate school. In terms of yearly income, the largest income group consisted of 201 respondents, or roughly 53.03% of the sample, who fell into the 240000–420000 lakh range. There were 104 respondents (27.44%) whose income was less than 240000 lakh, 38 respondents (10.02%) whose income was between 420000 and 600000 lakh, 23 respondents (6.06%) whose income was between 600000 and 1200000 lakh, and 13 respondents (3.43%) whose income was above 1200000 lakh. This distribution demonstrates the respondents' wide variety of income levels, with a sizeable share falling into the middle class. The demographic profile table, which highlights important demographic attributes like gender, age, education, and income levels, offers an all-around detailed overview of the study's sample population. These insights are essential for comprehending the makeup of the respondents and correctly interpreting the study's findings in light of these demographic considerations. The questionnaire, which consisted of 15 items, was recommended as the survey instrument (**Appendix 2**). There were two primary components to the questionnaire. Responses pertaining to the elements in the conceptual model were intended to be gathered in the second piece of art; the first portion contained the guidelines, the primary objectives of the study, and the demographic characteristics of the respondents. The degree to which investors agreed or disagreed with the influence of behavioural factors on their investment decision and the return on investment were measured using 5-point Likert scales. The scale has five points that range from 1 to 5, which are strongly disagree, disagree, agree, and strongly agree.

3.2 | COMMON METHOD BIAS

Harman's single-factor analysis was used to demonstrate that the data was free of common method bias (CMB) (Podsakoff et al., 2003). A single factor was expressed based on the 15 items. The greatest variance was clarified (44.882%), which is less than the 50% threshold value, indicating the proper hypothesis testing procedure was chosen after multivariate assumptions were tested.

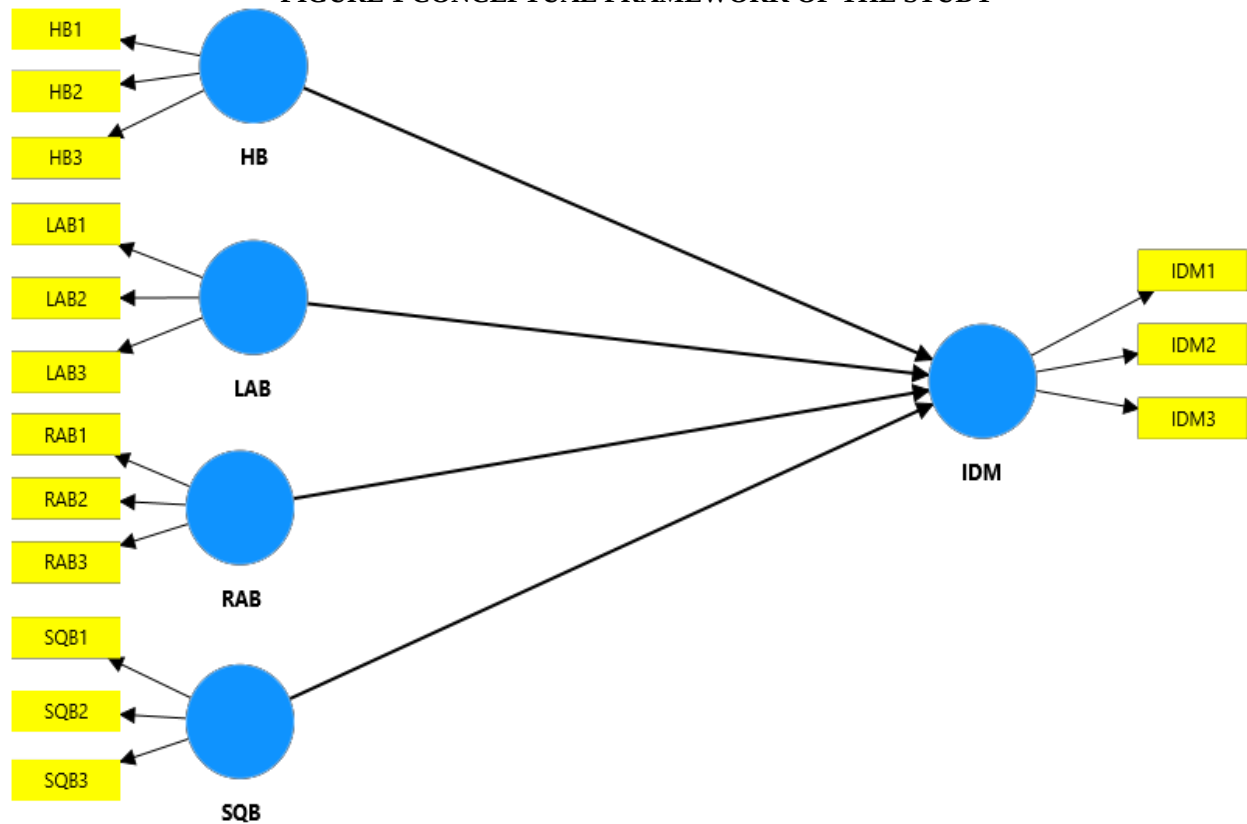
3.3 | MULTICOLLINEARITY

TABLE 1 VIF VALUE

Path	VIF
HB -> IDM	1.571
LAB -> IDM	2.794
RAB -> IDM	2.998
SQB -> IDM	2.771

Multicollinearity refers to a statistical phenomenon where independent variables in a model are highly correlated, leading to conflicting or redundant information in the analysis. The researcher conducted a multicollinearity test to assess the degree of correlation among the independent variables. The results of this test are presented in **Table 1**. The Variance Inflation Factor (VIF) was employed to detect multicollinearity, as recommended by Ahmad, Shafique, and Jamal (2020) and Shafique and Ahmad (2022). According to Cooper (2018), multicollinearity is typically considered problematic when the VIF exceeds 5. However, in **Table 1**, the highest VIF value recorded is 2.998, which is below the threshold of 5 for multicollinearity. Thus, the analysis found no significant multicollinearity issues in the dataset, as indicated by the VIF values aligning with the standard benchmark of 5.0 for both the inner and outer models.

FIGURE 1 CONCEPTUAL FRAMEWORK OF THE STUDY



Note. HB, Herding bias; LAB, Loss aversion bias; RAB, Regret aversion bias; SQB, Status quo bias; IDM, Investment decision making.

4 | RESULTS DISCUSSION

TABLE 2 RELIABILITY AND CONVERGENT VALIDITY

Construct	Items	Outer VIF	Factor Loading	Inner VIF	Cronbach's Alpha	Composite (Rho_C)	Reliability	AVE
IDM	IDM1	1.757	0.875		0.770	0.867		0.685
	IDM2	1.605	0.824					
	IDM3							
		1.467	0.782					
HB	HB1	1.892	0.876	1.571	0.762	0.863		0.678
	HB2	1.853	0.824					
	HB3	1.312	0.766					
LAB	LAB1	1.602	0.866	2.794	0.735	0.849		0.653
	LAB2	1.534	0.808					
	LAB3	1.334	0.747					
RAB	RAB1	1.825	0.880	2.998	0.759	0.862		0.675
	RAB2	1.638	0.815					
	RAB3	1.379	0.767					
SQB	SQB1	1.695	0.870	2.771	0.760	0.862		0.675
	SQB2	1.561	0.823					
	SQB3	1.438	0.770					

The confirmatory factor analysis (CFA) outcomes presented in **Table 2** indicate that all item factor loadings surpass the 0.60 threshold. Moreover, both composite reliability (CR) and Cronbach's alpha (α) values given in the table above, exceeding the 0.70 standard, which confirm the model's internal consistency and reliability. Additionally, the average variance extracted (AVE) values for all constructs, exceeding 0.50 as per J. Hair et al. (2017), demonstrate convergent validity (see above **Table 2**).

TABLE 3 DISCRIMINANT VALIDITY (Fornell-Larcker's criterion)

	HB	IDM	LAB	RAB	SQB
HB	0.812				
IDM	0.75	0.769			
LAB	0.719	0.685	0.826		
RAB	0.728	0.715	0.767	0.829	
SQB	0.595	0.58	0.477	0.509	0.826

One of the most effective methods for assessing validity is to determine discriminant validity, which demonstrates that each construct is empirically different and captures a notion that is not defined by other constructs in the statistical model. **Fornell and Larcker (1981)** established the discriminant validity technique. According to them, discriminant validity is supported if the correlation value of all other constructs is less than the square root of the AVE of each variable (**Table 3**) (**Franke & Sarstedt, 2019**).

TABLE 4 CROSS LOADING

	HB	IDM	LAB	RAB	SQB
HB1	0.876	0.53	0.562	0.465	0.435
HB2	0.824	0.38	0.401	0.292	0.251
HB3	0.766	0.46	0.477	0.475	0.437
IDM1	0.527	0.875	0.698	0.649	0.639
IDM2	0.423	0.824	0.568	0.623	0.567
IDM3	0.441	0.782	0.59	0.461	0.456
LAB1	0.572	0.707	0.866	0.681	0.654
LAB2	0.427	0.561	0.808	0.538	0.535
LAB3	0.419	0.532	0.747	0.545	0.523
RAB1	0.463	0.65	0.701	0.88	0.713
RAB2	0.358	0.537	0.538	0.815	0.629
RAB3	0.43	0.538	0.555	0.767	0.544
SQB1	0.441	0.627	0.655	0.704	0.87
SQB2	0.383	0.549	0.572	0.616	0.823
SQB3	0.314	0.477	0.516	0.567	0.77

The above **table 4** presents factor loadings from a factor analysis involving variables HB, IDM, LAB, RAB, and SQB across different factors denoted by numbers (e.g., HB1, HB2, etc.). Factor loadings represent the strength and direction of the relationship between variables and factors. Looking at the values, we can observe that certain variables have higher loadings on specific factors. For example, HB1 has a high loading (0.876) on factor HB1, indicating a strong association between this variable and the first factor under HB. Similarly, IDM1 shows a substantial loading (0.875) on IDM1, suggesting a strong relationship between IDM1 and the first factor under IDM. Conversely, some variables exhibit lower loadings or cross-loadings on multiple factors. These factor loadings provide insights into how variables contribute to defining specific factors. Variables with high loadings on a single factor are more distinct and contribute strongly to defining that factor. In contrast, variables with lower or cross-loadings may require further examination to understand their relationship with the underlying factors accurately. Overall, the table aids in understanding the structure of the factor analysis and identifying variables that significantly contribute to each factor while also highlighting potential issues such as cross-loadings that may warrant closer examination and refinement of the factor model.

TABLE 5 STRUCTURAL MODEL

Model Strength	IDM
R ²	.637
R ² Adj.	.633
Q ² predict	.624

We first assessed the measurement model and then used a variety of metrics, including R², Q² (based on blindfolding cross-validated redundancy), and Q² predict (using PLS-predict) (**J. F. Hair et al., 2018; Shmueli et al., 2016**), to test the relevance of the structural model. The model strength and predictive accuracy metrics for the structural equation model created with Smart PLS are shown in the above **table 5**. The percentage of variance in the dependent variable (in this case, IDM) that can be accounted for by the independent variables in the model is expressed as the R-squared (R²) value. The R² value in this table is 0.637, meaning that the variables in the model can account for about 63.7% of the variance in IDM. To avoid overestimating the model's explanatory power, the adjusted R-squared (R² Adj.) is a modified version of

R^2 that takes the number of predictors into consideration. Although it is marginally less than R^2 , the R^2 Adj. value in this case is 0.633, indicating a significant explanatory power of the model (J. Hair et al., 2017). The model's predictive accuracy, or more particularly, its capacity to forecast results for fresh data, is reflected in the Q^2 predict number. Based on the factors provided, the model does a good job of predicting IDM, as indicated by the Q^2 predict value of 0.624. The table presents the overall results of the structural equation model developed with Smart PLS. It shows that the model is robust and reliable for understanding and predicting the relationships between the variables included in the analysis. It also shows (Table 5) a good level of explanatory power (R^2 and R^2 Adj.) and predictive accuracy (Q^2 predict) for IDM.

TABLE 6 RESULTS OF HYPOTHESIS TESTING

Hypothesis	Path	Beta coefficient	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Support
H1	HB -> IDM	0.146	0.046	3.192	0.001	Yes
H2	LAB -> IDM	0.386	0.063	6.105	0.000	Yes
H3	RAB -> IDM	0.22	0.068	3.247	0.001	Yes
H3	SQB -> IDM	0.163	0.063	2.597	0.009	Yes

The results of hypothesis testing conducted inside a structural equation model (SEM) are shown in this table, which sheds light on the statistical significance and correlations between the variables. Within the model, each of the four hypotheses (H1, H2, H3 and H4) relates to a certain path or relationship. The table shows pertinent statistical metrics for each hypothesis, including beta coefficients, standard deviations (STDEV), T statistics, P values, and support. A route from HB (the hypothetical variable) to IDM (the dependent variable) is suggested by H1. The correlation between HB and IDM is positive, as indicated by the beta coefficient of 0.146. The statistical significance of this association is indicated by the T statistic of 3.192 and the matching P value of 0.001. The answer to the question "Yes" is in favor of H1. It is because of Herding bias causes people to make illogical decisions in the stock market on a regular basis. This bias results from a propensity to follow the herd, which is fueled by a fear of losing out and the conviction that the behaviours of others are informed by better knowledge. As a result, decisions are made that are not supported by logical reasoning. The outcome is consistent with prior studies that indicate a positive relationship between herding bias and investment decision making (Caparrelli et al. 2004; Kengatharan and Kengatharan, 2014; Lee et al. 2004)

H2 offers a similar route from LAB to IDM. With a low P value of 0.000 and a high T statistic of 6.105 (It is also match with the results of ANN and fsQCA), which both indicate statistical significance, the beta coefficient of 0.386 indicates a significant positive connection. The "Yes" in the support column indicates that H2 has a lot of support in the stock market, persons who are prone to loss aversion bias tend to make irrational decisions since they would rather minimise losses than maximise profits. The fear of losing money frequently leads to hanging onto lost investments for longer than necessary or selling winning investments too soon, which negatively affects the performance of investments as a whole. The outcome is consist with the prior studies (Kengatharan and Kengatharan, 2014; Khan, 2017).

The beta coefficient for H3, which examines the route from RAB to IDM, is 0.22, demonstrating a positive correlation once more. The statistical significance of the association is indicated by the T statistic of 3.247 and P value of 0.001, which results in a "Yes" in the support column. People tend to avoid acts that they may later regret, which causes illogical decisions in the stock market due to regret aversion bias. This may cause them to hang onto lost assets even when selling would be financially advantageous because they fear they will regret their choice. Similar to this study (Kengatharan and Kengatharan, 2014; Khan, 2017).

H4 finally looks at the route that leads from SQB to IDM. Positive correlation is indicated by the beta coefficient of 0.163, however it is comparatively smaller than for the other theories. "Yes" is given for support because the T statistic of 2.597 and P value of 0.009 still indicate statistical significance. All of the hypotheses (H1 through H4) are, in summary, supported by statistically significant correlations between the corresponding independent and dependent variables in the structural equation model, according to the data in the table. These results provide important new information on how variables interact and affect the setting of the research.

5 | ARTIFICIAL NEURAL NETWORK ANALYSIS

ANN was conducted using SPSS 26.0, employing a multi-layer perceptron feed-forward backward propagation (MLP-FFBP) training method with a sigmoid activation function (Figure 2). To prevent overfitting, a 10-fold cross-validation approach was adopted, with 70% of the data allocated for training and the remaining 30% for testing. As indicated in Table 7, both the training and testing models exhibited a mean RMSE value of 0.095, indicating robust explanatory capability (M. Sharma et al., 2022). Following the validation of the ANN model's predictive performance, a sensitivity analysis was conducted to determine the normalized importance of predictors in investment decision-making. This analysis utilized the mean relative importance values obtained from a 10-fold iteration of ANN (Table 8). The findings revealed that loss aversion bias held the highest importance, followed by regret aversion bias, status quo bias, and finally, herding bias, highlighting their varying degrees of influence on investment decisions.

FIGURE 2 ANN Model

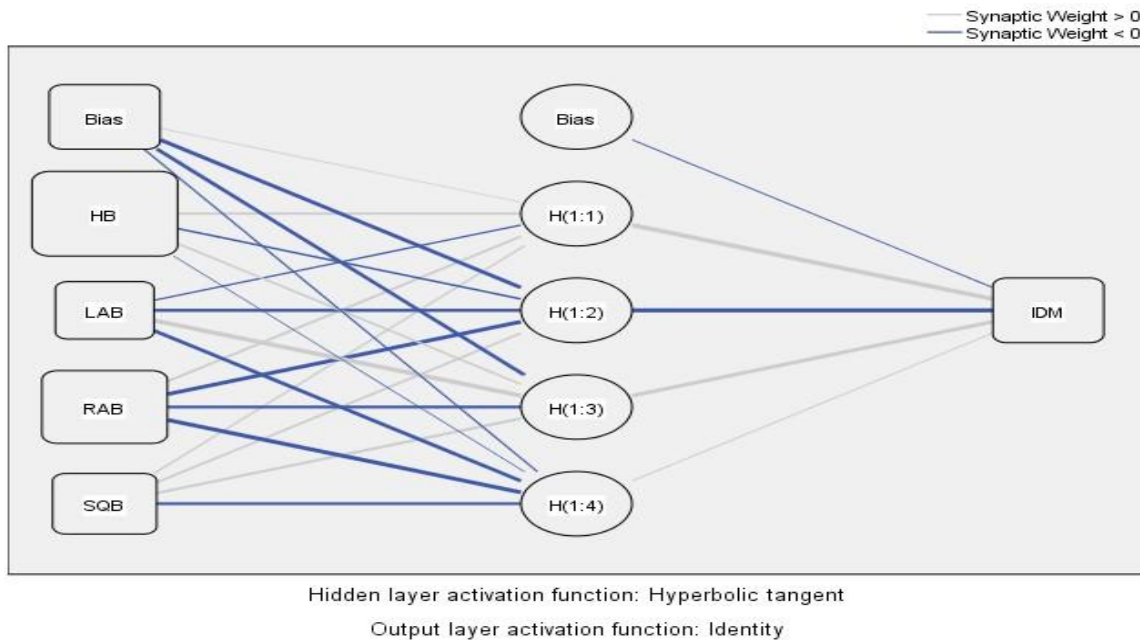


TABLE 7 RMSE-ANN

RMSSE-ANN Table						
	Traning			Testing		
CASE	N	SSE	RMSE	N	SSE	RMSE
ANN1	257	2.429	0.097	122	.929	0.087
ANN2	274	2.155	0.089	105	1.162	0.105
ANN3	257	2.492	0.098	122	1.007	0.091
ANN4	257	2.333	0.095	122	1.153	0.097
ANN5	258	2.277	0.094	121	1.13	0.097
ANN6	275	2.36	0.093	104	1.01	0.099
ANN7	260	2.795	0.104	119	1.131	0.097
ANN8	267	2.33	0.093	112	0.991	0.094
ANN9	267	2.313	0.093	112	0.927	0.091
ANN10	276	2.433	0.94	103	0.861	0.091
Mean			0.095			0.095
SD			0.0040			0.0051

TABLE 8 ANN SENSITIVITY ANALYSIS

Normalize Importance				
Case	HB	LAB	RAB	SQB
ANN1	51.6%	100.0%	61.1%	26.4%
ANN2	42.9%	100.0%	44.1%	39.5%
ANN3	51.9%	100.0%	69.4%	67.2%
ANN4	43.7%	100.0%	59.1%	14.3%
ANN5	41.1%	100.0%	32.1%	58.4%
ANN6	45.3%	100.0%	45.6%	50.2%
ANN7	30.6%	100.0%	57.3%	47.5%
ANN8	30.7%	100.0%	55.4%	37.8%
ANN9	39.6%	100.0%	46.4%	51.9%
ANN10	33.4%	100.0%	37.1%	44.7%
Ave Imp	41.1%	100%	51%	44%
Normal Imp	41%	100%	51% %	44%

In the current work, the authors performed fsQCA using an asymmetric technique using fsQCA 4.0 software. Initially, the 5-point Likert scale data was calibrated using commonly used criteria, such as "4" for full-set membership, "3" for the crossover point, and "2" for full-set non-membership. Following that, distinct truth tables were produced for each model in which IDM was a manifest variable. In order to minimise the number of rows in truth tables, a raw consistency threshold of 0.80 was applied. Subsequently, both models underwent standard analysis and necessary condition analysis. There are always sophisticated, economical, and intermediate solutions offered by the fsQCA process. When assessing configurations that best fit the unique context of a study, researchers frequently use their discretion. Dragan et al. (2023), for example, examined both sophisticated and frugal solutions in their study of the entrepreneurial phenomena. On the other hand, Pappas and Woodside (2021) assert that intermediate solutions are more consistent than their parsimonious and complex counterparts since they cover both core and peripheral circumstances. B. Lin and Su (2022) examined issuers' justifications for issuing green bonds as opposed to conventional bonds, with a particular emphasis on examining intermediate solutions. Similar to this, Mishra, Bansal, and Maurya (2023) used an approach that focused on middle solutions when examining the attitudes of investors towards socially conscious investing. In the current study, we have opted to examine intermediate solutions in accordance with the body of previous literature. **Table 9** summarizes the intermediate solutions offered by fsQCA and provides various combinations of predictors that explain the manifest variables, with respective coverage and consistency. The best solution in terms of coverage suggests that loss aversion bias can drive investment decision making sufficiently, path LAB, has a consistency coverage of 0.810534 and a raw coverage of 0.95513. This suggests that while the LAB condition alone explains a sizable amount of the outcome. The second-best solution suggests that in the absence of herding bias, both regret aversion bias and status quo bias should be present to drive investment decision making, a consistency coverage of 0.905589 and a raw coverage of 0.376301 are shown for the third path, RAB*SQB~HB. This pathway suggests that the absence of HB and the presence of RAB and SQB account for a reasonable amount of the result and are highly consistent in their explanation. And the third solution path, denoted by ~SQB*HB, has a consistency coverage of 0.941428 and a raw coverage of 0.269677. This implies that the result can be explained with high consistency even though the absence of the SQB condition in conjunction with HB has a low raw coverage. The above findings resonate with the higher importance of loss aversion bias identified through ANN analysis. Overall, the identified solutions from Model had coverage and consistency of 95.76% and 80.68% respectively, suggesting strong explanatory power and moderate predictive power. The fsQCA solutions provide robustness to the findings of PLS-SEM and ANN.

MODEL: IDM = f (HB, LAB, RAB, SQB,)

TABLE 9 fsQCA SOLUTION

Path	HB	LAB	RAB	SQB	Raw Coverage	Consistency Coverage
LAB		●			0.95513	0.810534
~SQB*HB	●			~	0.269677	0.941428
RAB*SQB*~HB	~		●	●	0.376301	0.905589
Solution coverage	0.95765					
Solution consistency	0.806808					

7 | DISCUSSIONS AND CONCLUSIONS

First off, there are noteworthy correlations between the independent variables (HB, LAB, RAB, and SQB) and the dependent variable (IDM) according to the hypothesis testing results in Table 6. All hypotheses are supported by low p-values and high T-statistics; the beta coefficients show the direction and intensity of these interactions. This implies that investors' judgements are significantly influenced by behavioural biases such status quo bias (SQB), regret aversion bias (RAB), herding bias (HB), and loss aversion bias (LAB). And the conclusion derived from the ANN Normalise Importance table 8 illustrates how each variable compares in terms of its ability to affect investors' decisions. In every scenario, LAB seems to be the most significant, followed by RAB, HB, and SQB. This demonstrates the greater influence of loss aversion and regret aversion biases than other biases, which emphasises their primacy in influencing investment behaviour. And from the fsQCA analysis the best solution in terms of coverage suggests that loss aversion bias can drive investment decision making sufficiently, path LAB, has a consistency coverage of 0.810534 and a raw coverage of 0.95513. This suggests that while the LAB condition alone explains a sizable amount of the outcome. The findings of the fsQCA resemble the PLS-SEM and ANN outcomes and provide robustness to the result. The objective of this paper is to identify which behavioral biases have the greatest impact on investment decision making. Hence we used these three tools (PLS-SEM, ANN and fsQCA) together to identify. And based on the analysis, we have seen that loss aversion bias influence investment decision making the most.

To sum up, these results highlight how behavioural biases have a big impact on stock market investment decision-making. Investors, financial analysts, and regulators must be aware of these biases in order to create solutions that lessen the negative consequences of making irrational decisions.

8 | IMPLICATION OF THE STUDY

8.1 | Theoretical Implication

The study offers a comprehensive comprehension of the noteworthy influence of behavioural biases, including but not limited to loss aversion, regret aversion, herding, and status quo biases, on the process of making investment decisions. These results advance our understanding of how psychological variables affect financial decisions and add to the body of knowledge regarding behavioural finance theories.

8.2 | Managerial Implication

By taking into account and reducing the adverse consequences of behavioural biases, financial professionals can use these insights to create more successful investment strategies. They can also create regulatory frameworks and risk-management procedures that safeguard investors and encourage logical stock market decision-making. This information is essential for developing solutions that reduce the negative effects of illogical decisions and promote an environment for investing that is better informed and more effective.

9 | FUTURE DIRECTION RECOMMENDATIONS

Subsequent investigations may explore the dynamic characteristics of behavioural biases in various market settings and across time. To further understand these biases and how they affect investment decisions, it would be helpful to look into how they change and interact with one another as the economy changes. Furthermore, it could be beneficial to investigate the efficacy of therapies or techniques meant to lessen the impact of behavioural biases on investment behaviour. Enhancing financial market decision-making procedures would be greatly aided by examining the long-term impacts of such changes and putting them into practice in actual investing environments.

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APPENDIX 1 DEMOGRAPHIC PROFILE

RESPONDENT DEMOGRAPHIC PROFILE			
	FREQUENCY	PERCENTAGE (%)	
GENDER	MALE	197	51.97%
	FEMALE	182	48.02%
AGE GROUP	18 TO <30	246	64.90%
	30 TO 40	58	15.30%
	40 TO 50	48	12.67%
	50 AND ABOVE	27	7.12%
EDUCATIONAL QUALIFICATION	GRADUATION	144	37.99%
	POST-GRADUATION	197	51.97%
	DOCTORATE	26	6.86%
	OTHER	12	3.16%
ANNUAL INCOME	BELOW 240000	104	27.44%
	240000-420000	201	53.03%
	420000-600000	38	10.02%
	600000-1200000	23	6.06%
	ABOVE 1200000	13	3.43%

APPENDIX 2 SUMMARY OF THE SURVEY ITEMS AND SOURCES

Code	Item	Source
IDM1	When I am making my investment decisions, I trust my inner feelings and emotions.	Khan et al. (2017)
IDM2	I generally make investment decisions that feel right to me.	Khan et al. (2017)
IDM3	When making investment decisions, I do what seems natural at the moment.	Prosad et al. (2015)
HB1	I prefer to invest in the assets that other investors are buying	Shusha and Touny (2016)
HB2	I follow others in all my investment decisions	Baker et al. (2019)
HB3	I change my opinion regarding investment in a security after hearing conflicting views from analysts	Jain et al. (2019)
LAB1	I never sell an investment at a loss with an expectation that it will eventually improve.	Chandra et al. (2017)
LAB2	Loss of Rs 1,000 is more painful than happiness of Rs 1,000 profit	Chandra et al. (2017)
LAB3	do not avoid an investment when I fear the loss	Baker et al. (2019)
RAB1	I regret when I miss an opportunity of getting good returns	Baker et al. (2019)
RAB2	I became risk-averse because I have incurred losses in the past	Khan et al. (2017)
RAB3	I became risk-seeking because I have made profits in the past	Prosad et al. (2015)
SQB1	I keep holding the investments because they are familiar to me	Kaustia and Perttula (2012)
SQB2	I think about changing my portfolio, but many times I do not change it	Menkhoff et al. (2006)
SQB3	I invest in that stock which is familiar to me	Kaustia and Perttula (2012)