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Examining the Impact of Cognitive Biases on Investment Decision-Making of Individual Investors in India: An Integrated Sem-Ann Method

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ABSTRACT

Aim- The study aims to examine the impact of cognitive biases (Overconfidence, Representativeness, Availability, Confirmation and Anchoring) on investment decision-making.

Methodology– Using multi-stage stratified random sampling, data are collected from 402 Indian retail investors-representing most Indian states and union territories (UTs). The study utilized the PLS-SEM technique in conjunction with artificial neural network (ANN) research to examine the proposed hypothesis, verify the stability of the results, and extract significant practical knowledge.

Findings – The findings of the research indicate that Overconfidence (OC), Representativeness (RB), Availability (AVB), Confirmation (CB) and Anchoring (ANB) biases have a significant positive relation with investment decision-making (IDM). According to the results of the ANN sensitivity analysis, anchoring bias (ANB) emerged as the primary influencer of investment decision-making, followed by Confirmation (CB), Availability (AVB), Overconfidence (OC), and Representativeness (RB) bias, in descending order of significance.

Research implications – Based on this present research finding, the study is more productive for retail investors at the time of making investment decisions. The study offers insights for financial advisors regarding cognitive biases' impact on investors' choices, enriching financial literature and aiding future research in behavioral finance. It serves as a foundation for scholars, guiding deeper understanding of stock market behavior and behavioral finance's applicability.

Originality/Value- This pioneering study explores the link between cognitive bias and individual investors' decision-making, contributing to a deeper understanding of behavioral influences in investment management, especially in emerging markets. It also expands the literature on behavioral finance, particularly regarding cognitive bias in investment strategies, an area still nascent even in developed economies, and largely unexplored in developing nations.

Keywords: Cognitive biases, overconfidence bias, representativeness bias, availability bias, confirmation bias, anchoring bias, investment decision-making.

1 | INTRODUCTION

For a long time, the prevailing belief was in the accuracy of traditional finance theory, which posits that investors act rationally and make decisions based on informed estimations or economic models. These theories also assert that investors aim to maximize returns while minimizing risks. Financial theories, including the efficient market hypothesis (Malkiel and

Fama, 1970), modern portfolio theory (Markowitz, 1952), and the arbitrage principle by Modigliani and Miller (1958), further support the notion of rational decision-making and efficient capital markets. In contrast to these theories, the prospect theory (Kahneman and Tversky, 1979) contends that investors make irrational decisions because they don't utilise all of the information at their disposal and instead base their decisions on their assessments of their utility (Wang, 2017). Economists in the financial and other sectors are interested in stock market anomalies. These abnormalities lead to erroneous investing decisions and are caused by cognitive and behavioural biases. Investors in the stock market are significantly impacted by behavioural biases (Kumar and Goyal, 2016). According to the prospect theory, investors' choices are influenced by possible profits and losses (Scalco et al., 2015), and they favour profit over loss when given the choice (Emami et al., 2020). Put differently, rather than considering perceived losses, investors base their decisions on perceived benefits (Kahneman and Tversky, 1979; Baker et al., 2019). According to the prospect hypothesis, investors make limited and illogical decisions because of cognitive, environmental, and personal variables. Irrational investors argue that market equilibrium is unattainable due to barriers to entry and exit, casting doubt on the efficiency of securities market arbitrage (Baker et al., 2007). Research rooted in prospect theory suggests that various factors, such as human instincts, emotions, reasoning, and social interactions, contribute to stock price fluctuations (Bannier and Neubert, 2016). According to Shefrin (2011), behavioral finance explores how psychology shapes financial markets and decision-making. Given psychology's focus on human behavior and judgment, it provides valuable insights into deviations from traditional economic theories in real-world behavior. According to Budhiraja et al (2018) research, behavioural finance theory is crucial for investors because behaviour and psychology play a significant role in the decision-making process when making investments. The conclusions echo the results of Kandpal & Mehrotra's (2018) investigation, affirming that behavior is pivotal in guiding individuals towards prudent investment choices. Likewise, research by Mudzingiri et al. (2018) underscores how financial behavior significantly impacts investment decisions. The origin of cognitive biases as delineated by Kahneman and Tversky (1972) delineates them as judgment errors, spanning from memory-related to problem-related issues. Investors in the financial industry frequently make reasonable or irrational judgements based on their knowledge, a topic that is extensively debated in both conventional and behavioural finance. According to conventional wisdom, investors are logical beings who choose wisely to optimise their profits by choosing the optimal course of action, particularly during challenging times (Kumar and Goyal, 2015). In the end, the idea of behavioural finance evolved to speed up the process of making investment decisions that consider social, political, economic, and geographic factors. Using a multidisciplinary approach that addresses psychology, economics, finance, and other subjects, behavioural finance is being developed in an interactive manner (Andriamahery and Qamruzzaman, 2022; Ritika and Kishor, 2022). Behavioral finance delves into how behavioral factors shape an individual's decision-making process. Through a questionnaire and empirical data collection on business students' self-perceived biases, researchers explored the cognitive biases and heuristics affecting them. This study highlighted the impact of bias on decision-making, offering fresh insights into investor irrationality and broadening our understanding of rationality (Chira, Adams & Thornton, 2008). I chose this subject because behavioural biases influence investment decisions significantly, and it's critical to comprehend these biases to make wise and prudent financial judgements. My objective is to get a more profound understanding of how five distinct biases in behavioural finance affect investor behaviour and investment results. This subject gives me the chance to investigate the nexus between psychology and finance, providing insightful knowledge about how people make decisions in the financial markets. This study is structured into eight key sections: 1. Introduction: Provides an overview of the research issue, highlighting the critical examination of behavioral biases in financial decision-making. It outlines the study's goals, parameters, and background context. 2. Review of Literature: Summarizes existing research on behavioral biases, investing decision-making, and related topics. It identifies gaps in knowledge, synthesizes prior findings, and forms the basis for the study's hypotheses. 3. Demographic Profile: Presents the demographic profile of the research participants, including age, gender, occupation, education, and other relevant factors. 4. Research Methodology and Discussion: Details the study's design, sample strategies, data collection methods, and analytical tools. It ensures study validity, reliability, and interpretation of results. 5. Conclusion: Summarizes the study's main conclusions, discusses implications for theory and practice, and suggests areas for further research. It emphasizes contributions to the field. 6. Study Importance: Highlights the study's relevance to behavioral finance and investment decision-making. It discusses advancements in understanding and potential impacts on financial practices.7. Future Direction: Proposes potential avenues for further investigation based on study findings. It addresses open-ended issues and discusses areas for insightful research. The study aims to deepen our understanding of behavioral biases in financial decision-making, provide guidance for professionals in investing and finance, and contribute to ongoing discussions in behavioral finance.

2 | REVIEW OF LITERATURE AND HYPOTHESIS DEVELOPMENT:

2.1 | ANCHORING BIAS

Anchoring bias is the emotional condition of affairs that arises when investors place an excessive amount of weight on emotionally and statistically determined anchors, leading them to make illogical judgements. This emotional state is known as "anchoring" (Tseng, 2011; Liang and Qamruzzaman, 2022). An alternate definition of anchoring bias would be investors' tendency to anchor their thinking, i.e., basing their investment decisions on something irrationally unrelated to the matter at hand. The propensity of investors to trade with little risk is known as "anchoring bias" (Ofir and Wiener, 2012). People tend to "anchor" on a specific piece of information or feature while making decisions. Predicting the probability of an uncertain event is the original application of the term "anchoring". Anchoring is a process that happens when previous data is used to determine an important cutoff (Tversky & Kahneman, 1974; Farooq & Sajid, 2015). When someone allows a piece of knowledge to influence his ability to reason and make decisions, this is known as anchoring. Relying solely on the initial information presented, like the stock's opening price, reduces the likelihood that decision-makers will update their assessments in light of new information (Baker & Ricciardi, 2014). When investors make a financial decision based just on a single piece of information from the abundance of information at their disposal, this is known as Anchoring (Dickason& Ferreira, 2018). When people base their future assessments on past values, a process known as "anchoring" takes place (Kahneman & Tversky, 1979).

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

2.2 | CONFIRMATION BIAS:

Confirmation bias plays a significant role in investment decision-making by influencing an individual's reluctance to change pre-existing beliefs (Cheng, 2018). This bias particularly impacts investors in the stock market, where decisions are influenced by considerations related to short-term and long-term welfare. Investors often seek out models that align with their beliefs and reinforce their decisions, leading to confirmation bias behaviour. This bias manifests when investors join virtual communities to validate their opinions, disregarding information that contradicts their beliefs (Trehan & Sinha, 2021). It's a natural tendency for people to favour ideas that confirm their beliefs while ignoring opposing viewpoints. Despite its importance, there are relatively few studies in behavioral finance literature focused on confirmation bias (Costa et al., 2017). This bias can create a false sense of knowledge and overconfidence, ultimately negatively impacting investment performance (Barber and Odean, 2001; Jonas et al., 2001).

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

2.3 | OVER CONFIDENCE BIAS

Overconfidence, a cognitive bias, leads investors to overrate their investment skills and often take undue risks. Parveen et al. (2020) highlight how overconfident investors perceive risks favorably and tend to make riskier financial decisions. This study underscores the significant impact of behavioral biases, including mental accounting, anchoring, herd bias, and overconfidence, on investment decisions. The emotional and psychological aspects that impact investors in the securities market are examined by Wattanasan et al. (2020), who focus on biases such as risk tolerance, availability, herding, conservatism, and overconfidence. Their findings reveal that psychological factors like appreciation, tax considerations, and income generation significantly impact investors. Gervais and Goldstein (2003) explored how overconfidence affects team performance, noting a positive correlation. Glaser and Weber (2007) examined how overconfidence impacts trading volume, finding a notable increase among individual investors. Ngoc (2013) studied behavioral biases' impact on investor decisions in Ho Chi Minh City, Vietnam, indicating a noticeable influence. Lewellen (2006) analyzed volatility and debt costs' effects on financial decisions, finding volatility to be a key factor. Hirshleifer and Luo (2001) investigated overconfident traders' survival in competitive markets, where overconfident traders outperformed rational ones. Jhandir and Elahi (2014) studied biases' impact on investment decisions, finding positive and significant effects of overconfidence, disposition, and herding behavior.

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

2.4 | REPRESENTATIVENESS BIAS.

It entails evaluating an event's or object's qualities and comparing them to those of other similar occurrences or items. This leads them to believe that the thing or event has a higher chance of occurring, even though it might not. It was presented in the early 1970s by Tversky and Kahneman. People have a tendency to categorise new information based on their prior experiences and classifications, a phenomenon known as representativeness bias or belief perseverance bias. They give their classifications too much weight because they think they are acceptable. According to research, this bias arises from people's tendency to categorise ideas and objects into unique groups to make sense of their experiences. Investing is prone to stereotypes. (June 2018, Kanan Budhiraja). Representativeness heuristics can have two distinct effects on investors' decisions. Firstly, they can cause similar information to be interpreted as a pattern, which causes people to overreact when estimating a company's future performance and give more weight to recent news about the company. Secondly, they can cause people to expect a reversion to mean when they encounter a series of similar information, even if the series is too short to apply that law (Kaestner 2006).

Hypothesis 4: Representativeness Bias has significant and positive effects on investment decision-making.

2.5 | AVAILABILITY BIAS:

Availability bias arises when individuals judge the likelihood of an event solely based on how easily it comes to mind (Tversky & Kahneman, 1974). Javed et al. (2017) note that events easily recalled are often deemed more probable. This bias can lead investors to favor stocks from heavily advertised companies, limiting their consideration of other investment options (Barber & Odean, 2000; Harris & Raviv, 2005). Decision-makers relying on readily available data also exhibit availability bias (Siraji, 2019). When people assess event probabilities based on recall speed, they are susceptible to availability bias (Ritika & Kishor, 2022). It indicates that to spare themselves the pain and suffering associated with making investment decisions, people frequently evaluate information according to how quickly it can be recalled. The ease with which information may be accessible, allowing investors to base their decisions on it without further research or data collection to confirm its accuracy, is known as availability bias (Siraji, 2019). Another tactic for making snap decisions is availability bias, however, it frequently results in errors (Dimara et al., 2016). Accessible information shapes investor preferences, therefore sometimes investment decisions are influenced by seemingly unconnected facts. Availability bias-prone investors usually select stocks that have been carefully examined by experts and invest in local stocks (Jain et al., 2020). According to Pandey & Jessica (2019), behavioural bias and investment decision-making are mediated by investment satisfaction. Irrational investor behaviour is a result of behavioural bias, which influences investment decision-making (Kumar & Goyal, 2015). The availability bias influences the equities that investors select for their portfolios and make investment decisions (Shantha Gowri & Ram, 2019).

Hypothesis 5: Availability Bias has significant and positive effects on the investment decision-making.

2.6 | INVESTMENT DECISION MAKING

No matter what investing strategy is used, an efficient market is one in which average returns are never higher than those that are justified given the risk involved (Barberis & Thaler, 2003). In the 1950s, Markowitz proposed the Portfolio Modern Theory. He investigated how the decision-maker locates substitute investment options and contrasts them to establish a connection between these options. The markets are meant to be rational, but not all investors are, according to the Efficient Market Hypothesis (EMH). Despite this idea, behavioural finance proposed that there are instances in which information markets are not efficient (Ritter, 2003). Making wise decisions and maximising profits is the primary goal of any investor, just as a business seeks to maximise profits. This has made investment selections extremely crucial. However, some investors base their decisions on information and data, while others depend on their own judgement.

3 | DATA COLLECTION & DEMOGRAPHIC PROFILE

The multi-stage stratified random sampling method was used for data collection. Furthermore, we computed the minimal necessary sample size using power analysis and G*Power, with f^2 (effect size) = 0.15, α (error type 1) = 0.05, and β (error type 2) = 0.20. N = 184 is the minimal sample size determined by the calculation. Consequently, the 402 sample size for

this study satisfies all adequacy requirements. The given **(Table 1)** provides a thorough understanding of the respondents' demographic profile by illuminating a number of variables, such as gender, age group, educational background, yearly income, and investment experience. Gender distribution of the participants in the poll, 62.43% of respondents were male, making up a slight majority of the respondents. In contrast, 37.56% of respondents were female. This discrepancy in gender distribution may be the less participation of female in stock market investment. Age distribution of the respondents, we find that 69.40% of them are between the ages of 18 and 30. This implies that the majority of respondents in the survey sample are younger which represents Demographics' Dividend. Moreover, the percentage of responders declines gradually as the age groups increase, with the exception of a small minority of people (1.49% of the total) who are 50 years of age or older. Educational qualification the sample, 56.47% of respondents have completed post-graduation education. This represents the majority of respondents in terms of educational qualifications. Those having an education up to the graduate level come next, making up 30.85% of the total. It is noteworthy that there are responders with doctorates, even though their percentage is lower at 8.95%. Furthermore, 3.73% of respondents had other qualifications, demonstrating that the population under survey has a varied educational background. Income Distribution of the respondents' annual income distribution reveals a range of financial situations. 41.79% of respondents report having an annual income of less than 240,000 Lakh, which suggests that a sizeable section of the population falls into lower income categories. Furthermore, a sizable portion of respondents—37.81% of the total-fall into the 240,000–420,000 income range. On the other hand, only 2.98 percent of respondents report being in a higher income category, with an annual income of more than 1,200,000 Lakh. And information about the respondents' investing experiences is also included in the table. The majority, 65.67%, report having fewer than three years of experience in the financial industry, which suggests that a sizeable section of the population may be comparatively new to the financial world. With 15.92% reporting 3 to 5 years, 15.42% reporting 5 to 10 years, and 2.98% reporting more than 10 years of investment experience, there is a noticeable representation of those with
Moderate to substantial experience. In conclusion, the table depicting the demographic profile of the respondents provides important information on the traits and backgrounds of the people surveyed. In addition to giving a quick overview of the demographics, this study helps to clarify the makeup of the questioned group, allowing for more insightful interpretations and possible ramifications for future research or decision-making projects. The survey utilized a questionnaire comprising 20 items (**see appendix 1**). This questionnaire consisted of two primary sections: the first part outlined instructions, research objectives, and respondent demographics, while the second part gathered responses regarding factors in the conceptual model. A 5-point Likert scale was employed to gauge investors' agreement levels regarding the influence of behavioral factors on investment decisions and returns. The scale ranged from 1 to 5, representing strongly disagree, disagree, neutral, agree, and strongly agree, respectively.

TABLE 1 DEMOGRAPHIC PROFILE

Respondent demographic Profile			
		Frequency	**Percentage (%)**
Gender	Male	251	62.43%
	Female	151	37.56%
Age group	18 to <30	279	69.40%
	30 to 40	60	14.92%
	40 to 50	57	14.17%
	50 and above	6	1.49%
Educational Qualification	Graduation	124	30.85%
	Post-graduation	227	56.47%
	Doctorate	36	8.95%
	Other	15	3.73%
Annual Income	Below 240000	168	41.79%
	240000-420000	152	37.81%
	420000-600000	52	12.93%
	600000-1200000	18	4.47%
	Above 1200000	12	2.98%
	Less than 3	264	65.67%

Investment Experience	3 to 5	64	15.92%
	5 to 10	62	15.42%
	10 above	12	2.98%

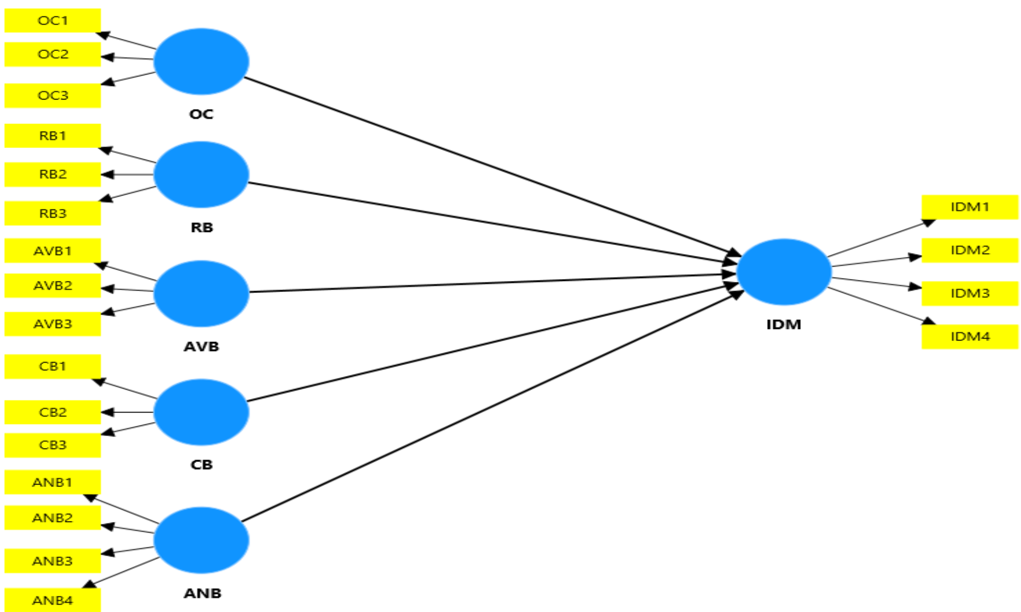
4 | METHODOLOGY OF THE STUDY

Individual stock market investors in India were the subject of this study. The questionnaire was distributed to retail investors who invest in the Indian stock market in accordance with the study's research goals. It was examined and revised before it was distributed to make sure that there were no unclear questions or controversial statements. To address the research challenges and objectives, the current study used a quantitative research approach. Primary data that was gathered and examined was used in the study. Dash and Paul (2021) propose the adoption of variance-based PLS-SEM over covariance-based CB-SEM, citing its advantages in flexibility, improved model fit, and handling of non-normal data. Additionally, Mishra, Bansal, Maurya, and Kar (2023) advocate for the integration of PLS-SEM with ANN to account for non-linear relationships. Despite the widespread use of symmetric modeling approaches like PLS-SEM and ANN in various social science research domains, their effectiveness is scrutinized when modeling a large number of predictors towards an outcome variable (Kumar et al., 2022). In alignment with these recommendations, the present study employs PLS-SEM and ANN as symmetric modeling techniques. Initially, the measurement model's reliability and validity were assessed through confirmatory factor analysis (CFA). Subsequently, the structural model's explanatory and predictive capabilities were evaluated using R^2 and Q^2-predict. Hypotheses were then tested using a bias-corrected and accelerated (BCA) bootstrapping procedure with 5,000 subsamples. In the subsequent stage, significant predictors were utilized as input neurons in the ANN model to determine their relative importance in explaining observable variables.

4.1 | COMMON METHOD BIAS (CMB)

Common method bias is a phenomena that arises when research participants are swayed by the questionnaire they are asked to complete for the study, leading to a common variation that influences the study's outcome. To determine whether common technique bias has an impact on the research's data. We evaluated common method bias by examining the Variance Inflation Factor (VIF) within the inner model. In this study, all VIF values were found to be below 3.3, indicating the absence of common method bias according to Kock (2015).

FIGURE 1: RESEARCH FRAMEWORK



Note: - OC, Over confidence; RB, Representativeness Bias; AVB, Availability Bias; CB, Confirmation Bias; ANB, Anchoring Bias; IDM, Investment Decision Making.

TABLE 2 RELIABILITY AND CONVERGENT VALIDITY

Construct	Items	Outer VIF	Factor Loading	Inner VIF	Cronbach's Alpha	Composite Reliability (Rho_C)	AVE
IDM	IDM1	1.789	0.846		0.767	0.851	0.592
	IDM2	1.673	0.807				
	IDM3	1.554	0.777				
	IDM4	1.246	0.629				
OC	OC1	1.615	0.870	2.323	0.715	0.840	0.638
	OC2	1.532	0.806				
	OC3	1.256	0.713				
RB	RB1	1.504	0.831	2.282	0.731	0.847	0.650
	RB2	1.557	0.843				
	RB3	1.339	0.741				
AVB	AVB1	1.426	0.831	2.216	0.816	0.825	0.612
	AVB2	1.316	0.774				
	AVB3	1.283	0.739				
CB	CB1	1.756	0.869	1.764	0.798	0.881	0.711
	CB2	1.826	0.864				
	CB3	1.585	0.795				
ANB	ANB1	2.322	0.855	1.515	0.816	0.878	0.647
	ANB2	2.309	0.860				
	ANB3	2.095	0.859				
	ANB4	1.497	0.615				

4.2 | MEASUREMENT MODEL ASSESSMENT

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 Table 2**). Subsequently, discriminant validity was assessed using the HTMT ratio and Fornell-Larcker's criterion. According to Fornell-Larcker's criterion, the HTMT ratio for each construct remains below 0.85 (Fornell & Larcker, 1981; Henseler et al., 2015), and the square root of AVE exceeds the inter-construct correlation values (**refer to Table 3**).

TABLE 3 DISCRIMINANT VALIDITY

	ANB	**AVB**	**CB**	**IDM**	**OC**	**RB**
ANB	**0.804**					
AVB	0.523	**0.782**				
CB	0.489	0.589	**0.843**			
IDM	0.603	0.629	0.607	**0.769**		

OC	0.457	0.639	0.536	0.591	**0.799**	
RB	0.457	0.627	0.538	0.579	0.702	**0.806**
HTMT RATIO						
ANB						
AVB	0.676					
CB	0.575	0.791				
IDM	0.731	0.857	0.765			
OC	0.563	0.803	0.681	0.777		
RB	0.562	0.885	0.694	0.762	0.758	

Note: The bold values in the data were higher than the values found in the respective row and column, thus confirming the assumptions of discriminant validity.

TABLE 4 CROSS LOADING

Cross loadings						
	ANB	**AVB**	**CB**	**IDM**	**OC**	**RB**
ANB1	**0.855**	0.527	0.486	0.587	0.500	0.494
ANB2	**0.860**	0.395	0.376	0.465	0.324	0.345
ANB3	**0.859**	0.457	0.432	0.521	0.391	0.367
ANB4	**0.615**	0.243	0.221	0.311	0.183	0.200
AVB1	0.506	**0.831**	0.519	0.539	0.562	0.530
AVB2	0.289	**0.774**	0.437	0.487	0.498	0.485
AVB3	0.428	**0.739**	0.421	0.444	0.430	0.453
CB1	0.530	0.571	**0.869**	0.570	0.577	0.539
CB2	0.366	0.458	**0.864**	0.524	0.420	0.419
CB3	0.319	0.454	**0.795**	0.428	0.329	0.387
IDM1	0.544	0.575	0.551	**0.846**	0.597	0.540
IDM2	0.526	0.487	0.465	**0.807**	0.422	0.411
IDM3	0.443	0.476	0.436	**0.777**	0.411	0.444
IDM4	0.305	0.370	0.401	**0.629**	0.354	0.366
OC1	0.464	0.574	0.529	0.556	**0.870**	0.635
OC2	0.253	0.528	0.399	0.440	**0.806**	0.538
OC3	0.360	0.417	0.331	0.405	**0.713**	0.496
RB1	0.432	0.564	0.479	0.496	0.636	**0.831**
RB2	0.374	0.486	0.432	0.499	0.578	**0.843**
RB3	0.286	0.465	0.385	0.395	0.471	**0.741**

According to **Table 4's** results, various variables' cross-loadings in the context of factor analysis or structural equation modelling are represented. Cross-loadings indicate the amount that each

Observed variable loads onto each latent factor. Variables: In the analysis, these stand for observed variables or manifest indicators (ANB, AVB, CB, IDM, OC, and RB). ANB1, ANB2, RB3: These represent different scenarios or locations within the analysis, where we compute the cross-loadings. Each value in the table indicates the strength of the correlation between a specific observed variable and a latent component. Greater values signify a more robust association or loading, implying a closer link between the latent factor and the observable variable.

The observable variable ANB1 and the latent factor ANB have a good correlation, as shown by **(Table 4)** ANB1's loading of 0.855 onto the ANB latent factor. ANB1's loading of 0.527 onto the AVB latent factor indicates a similar moderate link. The table's additional cases and variables carry the same interpretation. Understanding the model's structure and the contributions made by each observable variable to the underlying latent factors depends on these cross-loadings. They support the evaluation of the model's convergent and discriminant validity, as well as the detection of possible problems like multicollinearity.

TABLE 5 STRUCTURAL MODEL

Model Strength	IDM
R^2	.573
R^2 Adj.	.567
Q^2 predict	.555

4.3 | MODEL PREDICTIVE RELEVANCE

We first assessed the measurement model and then used a variety of metrics, including R^2, Q^2 (based on blindfolding cross-validated redundancy), and Q^2 predict (using PLS-predict) **(J. F. Hair et al., 2018; Shmueli et al., 2016)**, to test the relevance of the structural model. Table **5** lists several statistical metrics that evaluate the model's robustness and predictive accuracy in relation to investment decision-making (IDM). Let's examine each metric in detail and evaluate its importance: R-squared (R^2): The R^2 value of.573 means that the independent variables in the model can account for about 57.3% of the variance in investment decision-making. Put another way, the model explains more than half of the variation in sample population investment decisions. An increased R^2 value often denotes a more favourable model fit to the data, signifying that the independent variables effectively account for variations in the dependent variable (IDM). Q^2 Predict: The model's predicted accuracy is evaluated using the Q^2 predict value of.555. It shows how well the model can anticipate or forecast the results of investment decision-making for fresh or untested data. A Q^2 predict value of.555 indicates that the model can reasonably estimate IDM based on the independent variables employed in the model, indicating a moderate to strong predictive ability **(J. Hair et al., 2017; O. Al Muhaisen., 2020; O. Al Muhaisen., 2020)**. Overall, the interpretation of these metrics shows that, when applied to investment decision-making, the model has a respectably high explanatory power (as demonstrated by R^2 and R^2 Adj.) and an acceptable predictive capacity (as demonstrated by Q^2 prediction). After that, the BCa bootstrapping procedure approved 5 of the 5 hypotheses **(Table 6)**. In the sections that follow, the outcomes of the hypothesis testing procedure are covered in more detail.

TABLE 6 RESULTS OF HYPOTHESIS TESTING

Hypothesis	Path	Beta Coefficient	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Support
H1	**ANB -> IDM**	0.278	0.060	4.626	0.000	**Yes**
H2	**CB -> IDM**	0.222	0.057	3.915	0.000	**Yes**
H3	**OC -> IDM**	0.147	0.059	2.509	0.012	**Yes**
H4	**RB -> IDM**	0.111	0.055	2.010	0.044	**Yes**
H5	**AVB -> IDM**	0.189	0.054	3.503	0.000	**Yes**

We discovered all of the presented hypotheses are highly significant. The results showed that **H1** Anchoring Bias (ANB) has a significant influence on Investment Decision Making (IDM) ($\beta = 0.278$, T= 4.626, $P < 0.001$) Investment decision-making is impacted by anchoring bias, which makes people overly rely on firsthand information, regardless of its veracity or applicability. Because of this cognitive bias, people tend to base their later decisions on this initial point of reference, which frequently leads to inaccurate assessments and decisions that deviate from the rules of rational decision-making. As a result, anchoring bias has the potential to distort perceptions and assessments, producing less-than-ideal results and conclusions that are not consistent with reason. The studies supported by (Jinesh et al. 2019; Manazir et al. 2016).

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H2 Confirmation Bias (CB) has a significant influence on Investment Decision Making (IDM) ($\beta = 0.222$, T= 3.915 $P < 0.001$) Due to this prejudice, investors may ignore cautionary tales or discount opposing viewpoints, which may cause them to make poor investing decisions. Investors may avoid doing a full examination by selectively processing information to support preconceived conceptions. This could result in suboptimal portfolio management and even financial losses because their judgements are not grounded in an objective appraisal but rather in the reinforcement of preexisting prejudices (Megha, 2021)

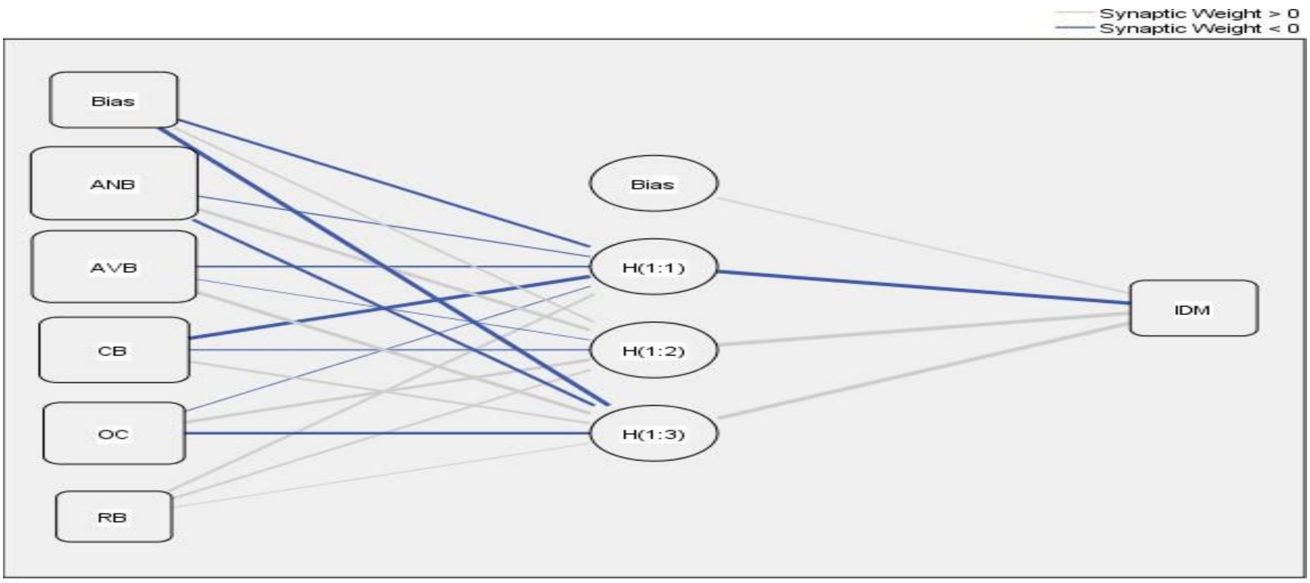
H3 Overconfidence Bias (CB) has a significant influence on Investment Decision Making ($\beta = 0.147$, T= 2.509 $P < 0.005$). Overconfidence in the financial market can be expressed in a variety of ways by investors, but it is a behavioural issue. An overconfident investor possesses a strong conviction in their own talents. Overconfidence is the main cause of trading, and as an investor completes a significant number of transactions, his experience and confidence increase with each one. But because his forecasting is greater than would be truly justified, this line of action has become an overconfidence bias. Decision-making in commercial and personal investing is influenced by the overconfidence bias. Overconfidence among investors results in an overestimation of knowledge, an underestimation of dangers, an inability to see opportunities, and a lack of control over events (Nofsinger, 2002). According to earlier studies (Malik et al. 2019; Manazir et al. 2016; Miller et al. 2015, Prosad et al. 2012; Barber & Odean 2001), the results are fairly similar.

H4 Representativeness Bias (RB) has a significant influence on Investment Decision Making ($\beta = 0.111$, T= 2.010 $P < 0.05$) Investors may overestimate or underestimate possible risks and rewards as a result of their mistaken assumption that historical patterns or trends will persist. Due to this bias, investors may make poor investing decisions by failing to take fresh information into account or modify their current methods, which could result in losses or missed opportunities. According to earlier studies (Sohani, 2012; Hirshlefer. 2021; Merkaset, et al. 2005) the results are fairly similar.

H5 Availability Bias has a significant influence on Investment Decision Making (AVB) ($\beta = 0.189$, T= 3.503 $P < 0.001$) This bias could cause investors to ignore more thorough data or historical trends in favour of focusing too much on current news stories or market happenings. Consequently, rather than doing a comprehensive study of all relevant elements, investors may make rash or poorly informed decisions as a result, which could result in worse than ideal investment outcomes. According to earlier studies (Sohani, 2012; Hirshlefer. 2021; Merkaset, et al. 2005) the results are fairly similar. Thus, we found that all the hypotheses are strongly supported. **Table 6** above summarize the hypotheses testing.

4.4 | ARTIFICIAL NEURAL NETWORK ANALYSIS

FIGURE 2 ANN Model



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Identity

TABLE 7 RMSE-ANN.

RMSE-ANN Table						
Dependent- Investment Decision Making						
Training				**Testing**		
Case	**N**	**SSE**	**RMSE**	**N**	**SSE**	**RMSE**
ANN1	272	2.581	0.097	130	1.290	0.100
ANN2	270	2.591	0.098	132	1.26	0.098
ANN3	276	2.743	0.100	126	1.072	0.092
ANN4	289	2.505	0.093	113	1.316	0.108
ANN5	277	2.846	0.101	125	1.689	0.116
ANN6	281	2.858	0.101	121	1.417	0.108
ANN7	281	3.467	0.111	121	0.807	0.082
ANN8	292	2.829	0.098	110	1.049	0.098
ANN9	278	2.45	0.094	124	1.425	0.107
ANN10	293	2.766	0.097	109	0.96	0.094
Mean			0.099			0.100
SD			0.0050			0.0099

TABLE 8 ANN Sensitivity Analysis.

Normalize Importance					
Case	**ANB**	**AVB**	**CB**	**OC**	**RB**
ANN1	88%	45.8%	100.0%	77.9%	33.9%
ANN2	100%	56.4%	73.4%	55.0%	31.6%
ANN3	94.5%	72.8%	100.0%	56.8%	60.4%
ANN4	80.7%	88.8%	100.0%	50.3%	67.8%
ANN5	93.7%	100.0%	84.0%	74.5%	56.1%
ANN6	98.5%	56.7%	68.2%	6.1%	100.0%
ANN7	30.1%	100.0%	83.7%	16.5%	50.1%
ANN8	100%	53.7%	53.4%	54.1%	28.2%
ANN9	89.2%	87.4%	100.0%	74.8%	34.6%
ANN10	100%	61.7%	76.7%	57.9%	52.6%
Ave Imp	87%	72%	72%	84%	52%
Normal Imp	100%	83%	96%	60%	59%

The use of artificial neural networks (ANNs) is recommended since different predictors and outcome variables exhibit non-normality and non-linearity (A. C. Teo et al., 2015). Against small samples, noise, and outliers. For the ANN analysis, we incorporated crucial factors identified from hypothesis testing as input neurons into the SPSS ANN module. The model used Taneja & Arora's (2019) well-known feed-forward-backward-propagation (FFBP) multilayer perceptron training technique with a sigmoid activation function. This technique involves error estimation flowing backwards while inputs are propagated forward.

To ensure model robustness and minimize prediction errors, we conducted a 10-fold cross-validation procedure and assessed the root mean square error (RMSE) as the primary accuracy metric. Following standard practice, we allocated 70% of the dataset for training and retained the remaining 30% for testing. Table 8 shows that each ANN operation's average RMSE values throughout training and testing were exceptionally low, at 0.099 and 0.100, respectively, suggesting a very good model fit. We calculated the normalised value of predictors using a sensitivity analysis method that involved dividing their relative relevance by the greatest importance shown in percentage form (Table 9). Among the predictors of investment decision-making, anchoring bias (ANB) obtained the first rank, followed by confirmation bias (CB). Availability bias (AVB) was the third-most important factor, overconfidence bias (OC) was fourth-most important factor and the least important factor is representativeness Bias (RB).

5 | CONCLUSION AND RECOMMENDATIONS

The results of the study highlight the significant influence that cognitive biases have on investing decision-making (IDM). The biases of overconfidence (OC), representativeness (RB), availability (AVB), confirmation (CB), and anchoring (ANB) were found to be important in influencing the decisions made by investors in the Indian stock market. The most important factor influencing IDM among these biases, according to the ANN sensitivity analysis, is Anchoring Bias (ANB), which is followed by Confirmation Bias (CB), Availability Bias (AVB), Overconfidence Bias (OC), and Representativeness Bias (RB). This realization has important ramifications for financial institutions as well as individual investors. To make well-informed and logical investing decisions, it is imperative to acknowledge and address these prejudices. Biases can be mitigated by employing techniques like diversification, in-depth study, and keeping an eye on the big picture. These results further highlight the significance of cognizance and education regarding cognitive biases in financial decision-making. Investors can become more adept at navigating the intricacies of the investment landscape by encouraging increased awareness and analytical thinking. The study's conclusion emphasizes the necessity of an all-encompassing approach to investment decision-making (IDM) that takes into account psychological variables that can have a big impact on investment outcomes in addition to market trends and economic data.

6 | IMPLICATION OF THE STUDY

6.1 | Theoretical Implication: The study's findings will provide researchers and academics with a fundamental resource that will direct their future research in behavioural finance. The study's identification of important topics that merit additional investigation will direct scholars and researchers in the future as they formulate their research questions. Thanks to the insights this study provides, future scholars will have a deeper theoretical and practical grasp of concepts related to behavioural finance and the stock market.

6.2 | Managerial Implication: By understanding the influence of behavioural biases on investors' investing decisions, financial advisors will benefit from the study's findings. This study will advance knowledge in the field and add insightful new information to the financial literature. Before making wise investment selections, investors can understand and assess stock investment behaviours with the help of this study. The purpose of this study is to assess behavioural finance's suitability for the financial markets.

7 | FUTURE DIRECTION

To validate the results of this study, more research is required, which calls for a larger sample size and a wider range of participant demographics. Additionally, more study is required to improve the measurement instruments employed in behavioural finance. More thorough research is also necessary to extend the use of behavioural finance to better understand the factors influencing the decisions made by individual investors in the Indian stock market. The report makes several useful research recommendations for the future. The impact of five behavioural characteristics on investment decision making is examined in this study, and further research is recommended to clarify the interrelationships between the variables. This study's primary data collection strategy can be compared to other strategies, such as secondary data sources, that other researchers might take into account for their own research.

AVAILABILITY STATEMENT OF DATA

The data supporting the study's conclusions will be made available upon request from the corresponding author. Due to ethical and privacy considerations, the data cannot be made publicly available.

STATEMENT OF DECLARATION OF INTERESTS
No conflicts of interest are disclosed by the writers.

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Appendix 1.

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**
IDM4	When I make investment decisions, it's more important for me to feel the decisions are right than to have a rational reasons for it.	**Baker et al. (2019)**
OC1	I always feel optimistic about the future returns of my investments	**Baker et al. (2019)**
OC2	I am confident of my ability to make investment decisions better than others	**Prosad et al. (2015)**
OC3	I have complete knowledge of various types of investments	**Jain et al. (2019**
RB1	All my investment decisions are based on trend analysis of some of my similar investments earlier.	**Jain et al. (2019)**
RB2	Before selecting an agent/broker, I do not analyze his/her track record	**Jain et al. (2019)**
RB3	I make investment decisions based upon my assessment of performance of previous investments of similar kind	**Baker et al. (2019)**
AVB1	The information from my close friends and relatives is a reliable reference for my investment decisions	**Menkhoffet al. (2006)**
AVB2	While considering the track record of an investment, I put more weight on its recent performance	**Shusha and Touny(2016)**
AVB3	I consider the recent records of a security before investing	**Jain et al. (2019)**
CB1	I value positive information more than negative information regarding my investment choices	**Menkhoffet al. (2006)**
CB2	When an investment is not going well, I seek information that confirms I made the right decision	**Menkhoffet al. (2006)**
CB3	I ignore the information that does not match my thoughts regarding the future of my investment decision	**Menkhoffet al. (2006)**
ANB1	I usually rely on past experience in the market for my next investment	**Jain et al. (2019)**
ANB2	Current price of the security helps me to forecast its future price	**Shusha and Touny (2016)**
ANB3	I usually buy stocks, which have fallen considerably from previous closing or all time high	**Shusha and Touny (2016)**
ANB4	I usually consider the purchase price of stocks as reference point for trading	**Shusha and Touny (2016)**