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Studying the Influence of Cognitive Biases on the Investment Decision-Making of Retail Investors in India

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ABSTRACT
Behavioural biases haven't gotten much attention they merit, especially in the Indian context. This research aims to close this gap in the extant literature. The goal of the current research is to understand the behavioural biases that influence the investment decisions of individual investors. This study looks at how retail investors in India's rapidly evolving financial markets make decisions about their investments based on psychological factors. The research employs a mixed-methods design that incorporates statistical modelling and quantitative surveys, concentrating on four well-known cognitive biases: overconfidence, anchoring, availability, and confirmation. The data was collected from 169 active retail investors who represented a variety of demographic groups, particularly the young tech-savvy investor base in India (83% of whom were between the ages of 18 and 30). Using multiple regression and factor analysis techniques, the study presents significant findings. The two most powerful factors that account for 17.1% of the variance in investment choice are anchoring bias (β=0.289) and overconfidence bias (β=0.250). The effects of confirmation and availability biases are not statistically significant, but operate as separate psychological processes, influencing judgment through distinct mechanisms. These results challenge traditional rational-choice models of investor behaviour by providing empirical evidence in favour of behavioural finance concepts in emerging markets. The findings have important ramifications for lawmakers, financial educators, and fintech entrepreneurs who want to prevent bias-driven errors in retail investing. The study emphasises the need for targeted behavioural interventions for India's growing number of youthful investors who control online trading.

Keywords: Overconfidence Bias; Availability Bias; Anchoring Bias; Confirmation Bias; Investment Decision Making.

INTRODUCTION

In recent years, the remarkable rise of retail investors has changed the investment landscape in India. Millions of people are now able to actively participate in stock markets thanks to the democratisation of equity markets, which government-led digital initiatives, zero-brokerage platforms, financial influencers, and mobile trading apps have fuelled (Bhatnagar et al., 2022). This tendency gained especially much traction during and after the COVID-19 pandemic, which altered saving habits, made digital adoption easier, and encouraged the use of stock trading and other alternative revenue streams. According to SEBI, there were over 150 million Demat accounts in India (Byagari & Srinivas, 2024). This number demonstrates expanding financial inclusion and shifting household attitudes towards riskier products. Although this increase in participation is a sign of financial inclusion and economic maturity, it also raises questions about the calibre of investment choices being made, particularly by novice and relatively inexperienced investors (Punyatoya et al., 2018).

Traditional financial theories such as the Modern Portfolio Theory (Markowitz, 2009) and the Efficient Market Hypothesis (Fama, 1970) assert that individuals are self-interested, logical agents who make decisions based on complete information in order to maximise expected utility. These models make the following assumptions: prices reflect all available information, markets are efficient and investors logically adjust their portfolios in response to new information. However, real investors occasionally act contrary to these presumptions.

Severe market crashes, IPO speculative bubbles, overly persistent news reactions, and investment herding appear to suggest that investor decisions are typically influenced by feelings, instincts, crowd dynamics, and mental shortcuts rather than facts (Chatziantoniou et al., 2022). A field that integrates psychology and economics to comprehend why and how people make irrational financial decisions, behavioural finance was created as a result of this gap between theory and practice. The concept of cognitive biases—mental shortcuts that consistently skew perception, judgment, and reasoning—is a crucial topic of research in this field (Mohanty, 2023). Although much research has been done on cognitive biases in Western markets, little is known about how they affect Indian retail investors, especially in this faster-paced post-pandemic world. Information asymmetry, linguistic diversity, and India's distinct sociocultural setting make it a rich environment for behavioural research. Furthermore, demographic characteristics such as age, gender, income, and education distinguish Indian retail investors from one another. However, these important moderator variables are not taken into account by the majority of current models.

By investigating the impacts of four major cognitive biases that are known to have a significant impact on investment decisions, this study attempts to close that gap. Overestimation of one's expertise, ability, or control over financial outcomes is known as overconfidence bias (OCB) (Bailey et al., 2024). Anchoring Bias (ANB) is related to employing arbitrary anchors, e.g., when making decisions such as a stock's high or purchase price (Chuah & Devlin, 2011; Kang & Park, 2019). The propensity to base decisions more on information that is current, vivid, or emotionally charged than on impartial facts is known as availability bias (AVB) (Mashatan et al., 2022). Confirmation bias (CNB) is the selective search for or interpretation of data that supports pre-existing beliefs while avoiding data that contradicts them (Yüce, 2024).

The increasing use of retail participation in Indian capital markets necessitates understanding these psychological aspects not only theoretically but also practically for risk management, investor education, and policymaking. Understanding how and why investors become irrational, as well as how deviations from rationality vary by demographic characteristics, is beneficial for planners, regulators, and educators.

The present research aims to understand the Indian perspective on the bias. The next section discusses the extant literature on behavioural finance, referring to biases, followed by research objectives and hypotheses for the study. The sections after that discuss research methodology, data analysis, and findings. In the end, the conclusion and future research directions are discussed.

LITERATURE REVIEW

Foundations of Behavioural Finance

Traditional financial theories such as Modern Portfolio Theory (MPT) (Markowitz, 2009) and Efficient Market Hypothesis (EMH) (Fama, 1970) have influenced the understanding of investor behaviour for many years. According to these theories, investors use all available information to make logical decisions, and markets are efficient. According to the EMH, prices at any given moment accurately reflect the securities' worth, and stock selection or market timing cannot be used to regularly outperform the market. MPT also emphasises the importance of diversification, claiming that having a portfolio of assets lowers risk. Real market behaviour, however, defies these assumptions. Speculative bubbles, excessive volatility, and investor overreaction are just a few of the anomalies that run counter to the notion that markets are always efficient and that investors make logical choices. In response to these discrepancies, behavioural finance was created, which questions the rationality assumption and takes into account the psychological factors influencing financial judgment.

The field of behavioural finance got its start at the close of the 20th century when scholars developed Prospect Theory, which provided a more thorough explanation of how to make decisions in risky and uncertain circumstances (Ogunlusi & Obademi, 2021). Prospect theory demonstrated that people do not perceive gains and losses symmetrically; rather, losses frequently outweigh gains, leading to risk-averse behaviour in the case of gains and risk-seeking behaviour in the case of losses (Roger, 2011). The classical theory of utility, which holds that people rationally weigh risk and reward, was called into question (Peteros & Maleyeff, 2015). The foundation of behavioural finance, which emphasises the systematic errors in human judgment that lead to irrational decision-making, is cognitive bias, which includes overconfidence, the availability heuristic, and anchoring (Linsi & Schaffner, 2019). By acknowledging the impact of psychological factors on investment choices, behavioural finance offered a more positive explanation of investor behaviour and market irregularities.

The rise of retail investing in India has highlighted the relevance of behavioural finance, particularly in the post-COVID world (Burke et al., 2022). The growing number of people accessing stock markets online means that many of these investors lack formal financial education and rely on peer pressure, social media trends, and emotional reactions. The shifting demographics of investors make them extremely susceptible to cognitive biases (Saini & Singh, 2024). Retail investors are especially prone to overconfidence, availability anchoring, and confirmation biases in India, where the problem of financial literacy is still unresolved. A study on Indian Retail Investors observed the impact of these biases, revealing the significant influence of psychological factors on their market decisions. Along with other articles, this one highlights the need for a more thorough analysis of these biases in the Indian context, shedding light on how they affect market and investment outcomes (Chavan et al., 2024).

Key Cognitive Biases Influencing Indian Retail Investors

Overconfidence Bias (OCB)

In both scholarly research and actual investing, overconfidence bias is arguably the most well-documented cognitive bias. Overconfident investors exaggerate their expertise, their capacity to predict market movements, and their ability to make decisions. This is the reason why overconfident investors typically trade more, take on more risk, and diversify less than they ought to. Also noted that overconfidence leads to increased trading, which raises transaction costs and typically results in lower returns because market uncertainty is not anticipated. (Barber & Odean, 2001). Younger Indian investors are particularly prone to overconfidence, especially when using fintech platforms like Groww and Zerodha. By democratising access to financial markets, these platforms have facilitated entry for youthful tech-savvy investors. Due to the market's general optimism and recent success stories, many of these investors tend to overestimate their capacity to forecast future stock performance.

Studies show that despite lacking formal financial education, nearly 68% of Indian retail investors believed they could outperform the market (Samal & Mohapatra, 2021). Male investors exhibited greater overconfidence than female investors, which increased the likelihood of making poor decisions. Studies claim that overconfidence leads to careless trading and an underestimation of market volatility (Sowmya & Muralidhar, 2024). The bias causes investors to overestimate their financial powers and may discourage them from seeking professional advice or diversifying their holdings, which could result in significant long-term risks.

Availability Bias (AVB)

When people make decisions based on readily available information, typically from the media or personal experience, instead of conducting in-depth research, this is known as availability bias. Because investors tend to rely on emotionally charged or recently viewed information rather than more thorough and accurate data, this bias can lead to poor investment decisions. Due in large part to the widespread use of social media websites and online forums, availability bias is particularly prevalent in India. Indian retail investors turn to WhatsApp groups or social networks for investment advice, where they frequently encounter inaccurate or biased information (Pandey & Jessica, 2019).

Sensationalised or emotive terms like "multibagger," "safe bet," and "FOMO" dramatically impacted investor sentiment, as verified by an analysis of posts from over 1000 investment forums (Razzaqe & Basak, 2022). Several market trends, such as the 2020 Adani stock rally, have been linked to this reliance on sensationalised or emotive information. The majority of retail investors joined the trend despite warnings from regulatory agencies like SEBI purely because the stock was well-known in the media and on social media (Chauhan, 2024). Availability bias exposes investors to market volatility and turbulence by encouraging short-term speculative investing and disregarding basis analysis.

Anchoring Bias (ANB)

Anchoring bias occurs when investors rely on reference points that are no longer accurate in reflecting the stock's value, such as the first time they purchased the stock or its peak price, to guide their subsequent decisions. Investors may decide to hold onto losing stocks in the hopes that their value will rise or purchase stocks at alleged discounts that are not backed by the state of the market. In India, older investors who have long-term stock holdings and are reluctant to sell them at a loss are especially prone to anchoring bias. Further, out of all the biases, anchoring had the highest predictive value, indicating the significant impact anchoring bias can have on the behaviour of retail investors (Chauhan et al.,2024).

Additionally, it was found that even in cases where the stock's financial health has deteriorated, the purchase price is frequently used as a benchmark for future investment decisions. Due to this bias, investors continue to evaluate possible opportunities using out-of-date information, which prevents them from making rational decisions and leads to less-than-ideal trading behaviour (Ezenwobodo & Samuel, 2022).

Confirmation Bias (CNB)

The tendency to seek out or interpret information in a way that supports one's preconceptions and disregard evidence to the contrary is known as confirmation bias. When it comes to investing, this bias typically manifests as avoiding bad news or warning signs and selectively exposing oneself to positive news or success stories. Online investment groups are a prime example of confirmation bias in India, where individual investors establish echo chambers to support their prejudices. These investors are frequently exposed to optimistic projections and success stories at the expense of risk or regulatory prudence.

According to Mohanty (2023), members of investment groups on social media platforms like YouTube, Reddit, and Telegram typically only talk about profitable investment experiences and encourage skewed decision-making (Mohanty, 2023). Baker et al. (2019) found that over 60% of Indian millennials ignored SEBI's cautions against speculative shares because they didn't align with the upbeat narratives that were common in their social circles (Baker et al., 2019). Chavan et al. (2024) also pointed out that extremely self-assured investors often ignore criticism and stick to their previous plans even when losses are mounting. This selective filtering of information encourages poor investment strategies and reduces the likelihood of making diversified decisions (Chavan et al., 2024).

Research Objectives and Hypotheses

- Based on the literature review, the present research aims at the following objectives.
- To investigate the presence of selected cognitive biases among Indian retail investors.
- To identify which bias has the strongest influence on investment decision-making.

Extant literature on behavioural finance has highlighted the recent worldwide impact of cognitive biases on investment decision-making (Agudelo Aguirre & Agudelo Aguirre, 2024; El Ghmari et al., 2024; Kaur Maan & Shiva, 2024). Several psychological factors, such as cognitive dissonance, regret aversion, loss aversion, overconfidence, hindsight, illusion of control, herd instinct, self-attribution, and representativeness, have been found to have a significant impact on financial decision-making (Yasmin & Ferdaous, 2023). The influence of personality traits (Gupta, 2022), emotional biases (Khilar & Singh, 2020), and other behavioural biases (Bouteska & Regaieg, 2020) has also been found statistically significant on financial decision-making. Further, extant literature has also emphasised the risk-taking abilities for portfolio optimisation (Fooeik et al., 2024; Saxena et al., 2024). Behavioural finance has also shown great influence of decision heuristics in investment choices (Puaschunder, 2022). The present study, therefore, proposes the following hypothesis:

H1: Cognitive biases influence investment decision-making.

Some studies, however, emphasised the influence of knowledge over other personality-driven traits such as financial literacy, competency, and attitude (Gupta, 2022). Although cognitive biases hold a major influence on financial decision-making, their types have not been tested so far (Yasmin & Ferdaous, 2023). Further, in the Indian context, certain emotional biases such as overconfidence and loss aversion have been theoretically discussed (Khilar & Singh, 2020). The present research, therefore, hypothesised that the influence of cognitive biases, such as overconfidence, availability, anchoring, and confirmation biases, differently influences financial decision-making.

H2: Cognitive biases differently influence investment decision-making.

RESEARCH METHODOLOGY

Research Design

This study follows a quantitative, cross-sectional research design, aiming to identify relationships between cognitive biases and investment behaviour among retail investors. The study employed regression to test the influence of independent variables (IDV), Overconfidence Bias (OCB), Anchoring Bias (ANB), Availability Bias (AVB), and Confirmation Bias (CNB) on the dependent variable (DV), Investment Decision-Making (IDM).

Data Collection

A structured questionnaire was administered using 5-point Likert scale items (1 = Strongly Disagree to 5 = Strongly Agree), adapted from previously validated behavioural finance studies (e.g., Baker et al., 2019; Prosad et al., 2015). The sampling unit is taken as Retail investors in India aged 18 and above, actively involved in stock market activities.

A convenience sampling (via digital distribution through WhatsApp and investment forums) was used for data collection. A target sample size of n = 125 was calculated using a 95% confidence level and a 3% margin of error. A total of n = 169 valid responses were collected for analysis. The demographic profile of the respondents is given the Table 1.

The participants were informed about the purpose, scope, and voluntary nature of the study prior to participation. Consent was provided through a statement incorporated in the survey form. The research maintained total anonymity by not gathering any personally identifiable information. The responses were stored securely and used only for academic purposes. Voluntary participation with no financial or non-financial incentives was ensured, with the guarantee that the responses would not be coerced or subject to undue influence.

Table 1: Demographics

	Frequency	Percentage
Gender		
Female	56	33.1
Male	113	66.9
Age		
18 to <30	141	83.4
30 to 40	8	4.7
40 to 50	13	7.7
50 and above	7	4.1

(Source: Extracted from SPSS – Authors' work)

Data Analysis

Reliability

Cronbach's Alpha calculates a measure of the internal consistency between a set of items to see if they are measuring the same construct reliably (George & Mallery, 2018). Items CB1, AVB1, and ANB1 were excluded since including them lowered overall alpha values below acceptable levels. A substantial Cronbach's Alpha of 0.737 validates the reliability and non-duplicity of the variables used in the questionnaire (Sun et al., 2018).

Descriptive Statistics
Table 2 gives the descriptive statistics of all the variables used for analysis. It can be seen that the mean for all the questions measuring the biases is greater than 3, which indicates the presence of bias, except for the third question used to measure confirmation bias.

Table 2: dESCRIPTIVE sTATISTICS

	Mean	Std. Deviation
OCB1	3.71	0.954
OCB2	3.20	1.003
OCB3	3.05	1.151
AVB2	3.64	1.061
AVB3	3.85	0.814
CNB2	3.58	1.078
CNB3	2.56	1.023
ANB2	3.64	0.805
ANB3	3.30	1.027
ANB4	3.66	0.740

(Source: Extracted from SPSS – Authors' work)

AVB3, used to measure availability bias, has recorded the highest mean of 3.85, representing a relatively high level of bias among investors when it comes to being influenced by easily available information. The standard deviation ranges between 0.74 to 1.151, showing the highest consensus for ANB4 and the least for OCB3.

Factor Analysis
The Kaiser-Meyer-Olkin (KMO) value of 0.714 indicates the suitability of factor analysis. A significant Bartlett's Test of Sphericity shows that the data is good for factor analysis. Principal component extracted four factors with a variance of 64.271% which is considered sufficient as the research deals with social sciences (Hair et al., 2018).

The Varimax rotated matrix, as shown in Table 3, reveals four distinct cognitive bias factors, each with clear item loadings greater than 0.5. High loadings of OCB1, OCB2, and OCB3 show that these reliably capture investors' overconfidence and constitute one of the variables for regression. There is a loading of ANB2 with AVB2 and AVB3, which makes the three of them the second combined variable for regression. ANB4 and ANB3 load cleanly on factor 3, confirming that they both effectively measure the anchoring bias. CNB3 is highly loaded in the fourth factor with CNB2, both of which measure the confirmation bias.

Table 3: rOTATED cOMPONENT mATRIX

	OCB	AVB	ANB	CNB
OCB3	0.767			
OCB2	0.761			
OCB1	0.732			
AVB2		0.729		
AVB3		0.682		
ANB2		0.646		
ANB4			0.790	
ANB3			0.761	
CNB3				0.889
CNB2				0.566

(Source: Extracted from SPSS – Authors' work)

Regression
After extracting the independent variables from factor analysis, a regression is run for the influence of OCB, AVB, ANB, and CNB on the dependent variable investment decision making (IDM). The model gave an R-squared value of 0.171, showing the independent variables are explaining decision-making by 17.1%.

Though the value of 17.1% might seem low initially but when considering the fact that the influence of only four biases out of countless other biases and market factors has been taken into account, the value starts to seem reasonable. The F value of 8.470 and the significance value of less than 0.001% suggest that the model is statistically very significant and valid. Further, Table 4 gives the regression coefficients, which show that overconfidence (OCB) and anchoring bias (ANB) have a significant impact on investment decisions. The data, however, could not find any significant influence of availability (AVB) and confirmation (CNB) bias.

Table 4: CoefficIents

Variables	B	Std. Error	Beta	t	Sig
(Constant)	3.379	0.046		74.107	<0.001
OCB	0.161	0.046	0.250	3.514	<0.001
AVB	0.066	0.046	0.103	1.452	0.149
ANB	0.186	0.046	0.289	4.062	<0.001
CNB	0.078	0.046	0.122	1.710	0.089

(Source: Extracted from SPSS – Authors' work)

Anchoring bias (ANB) has the most influence on investment decision-making (IDM), with a coefficient of 0.186, followed by Overconfidence bias (OCB) with a coefficient of 0.161, both with relatively high beta values and significance. Therefore, the regression equation is:

IDM= 3.379 + 0.161*OCB + 0.186*ANB

DISCUSSION AND IMPLICATIONS

In line with the objectives of the study, the findings establish the influence of cognitive biases on investment decision-making. Further, it was also found that anchoring and overconfidence are the clearest predictors of retail investor decision-making in the sampled population, while availability and confirmation biases influence choices in more indirect ways, supporting H1. The regression results indicate that anchoring produced the largest standardised effect, which supports H2. The overall model explains a modest but meaningful share of variance in decision outcomes.

This pattern aligns with foundational and applied behavioural finance work. Prospect theory provides a conceptual account for why investors overweight salient outcomes and use reference points when evaluating gains and losses, and subsequent empirical work links overconfidence to excessive trading and suboptimal net returns in household accounts. Together, these literatures show how reference points and inflated self-assessment can systematically bias choices in financial contexts (Barber & Odean, 2001; Geweke et al., 2018). The influence of anchoring bias and overconfidence bias matches a study conducted in New Zealand and Australia (Lam et al., 2024), Brazil (Souza et al., 2024), China (Shahzad et al., 2024), and India (R et al., 2025; Raghu et al., 2025). Its importance is also crucial to budgeting decisions (Zhang et al., 2025), stock markets (Bushra et al., 2023; Marjerison et al., 2023), and insurance (Shapira & Venezia, 2008).

Platforms and brokers should present multiple, contextually relevant benchmarks and concise risk summaries alongside price history so that users evaluate performance against several comparators rather than a single reference point. Small design frictions that encourage brief reflection before high-risk trades, for example, a required confirmation step coupled with a one-line downside reminder, can reduce impulsive choices without materially restricting user autonomy. Regulators can support these changes by promoting standardised disclosures for risk metrics and by encouraging pilot tests of nudges on major trading platforms.

The study is bounded by its scope and design. Focusing on four biases means that other important tendencies such as loss aversion, disposition effects, and herding were not modelled, so the reported explained variance represents a lower-bound estimate of the total behavioural contribution to investor choice. The convenience sample recruited via digital channels skews younger and more digitally engaged, which reduces the extent to which findings can be generalised to older or less connected retail segments.

CONCLUSION

The study has successfully been able to met its objective by establishing the impact of cognitive biases on retail investments. The findings of the present study not only add to the body of knowledge but also open up the discussions on the role of psychological factors in several financial decisions, such as stock markets, insurance, and other fintech products. The managerial implications of the study guide the platforms and firms to use anchors, however, with caution, as it may be misleading with the changing market conditions. The investors must be provided with the detailed information regarding risks to mitigate overconfidence bias.

Future researchers may use a longitudinal research design to understand changes in investment patterns due to the cognitive influences. Other psychological factors, such as loss aversion, disposition tendencies, and real-time emotional measures, can also be included to increase the explainability of the model. Future studies may also explore how these biases interact with demographic factors, specifically gender and age, that have been demonstrated in previous studies to be powerful behaviour moderators. For example, younger investors are more likely to be impulsive and tech-savvy, influenced by peer recommendations and online media (Glaubitt et al., 2009), exposing them to availability and overconfidence biases. Contrarily, older investors may make decisions based on prior experiences or be resistant to changing their beliefs, which can lead to more ingrained anchoring or confirmation biases. Similar to this, gender-based differences in financial decision-making, such as risk appetite, confidence, and reliance on information sources, have been extensively studied but have received less attention in the Indian context (Baker et al., 2019).

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