Effect of Behavioral Biases and Financial Literacy on Investors' Investment Decision-Making

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Abstract

The effect of behavioral biases and financial literacy on investment decision-making among individual investors in the Bombay Stock Exchange and National Stock Exchange were investigated in this research. The study explores the relationships between behavioral biases such as herding, overconfidence, and anchoring, and market anomalies, including fundamental and technical anomalies. Utilizing a structured questionnaire and employed structural equation modeling (SEM) using AMOS, to evaluate the hypotheses outlined in conceptual framework.The findings reveal significant associations between these biases and anomalies, highlighting their substantial influence on investment decisions. Notably, herding bias (HB) and anchoring bias (AB) positively influence both fundamental anomalies (FA) and technical anomalies (TA), while overconfidence bias (OB) negatively impacts fundamental anomalies (FA). Moreover, financial literacy is identified as a crucial moderator, affecting the decision-making process. While limitations exist, such as potential biases in data collection, the study underscores the importance of addressing behavioral biases and enhancing financial literacy to promote informed investment strategies and market stability. These findings contribute to enhancing financial knowledge and market efficiency.

Keywords: Behavioral biases, stock market anomalies, financial literacy, investment decision making.

1. Introduction

Behavioral finance examines how psychology affects investors and financial markets(Daxhammer et al., 2023). It seeks to understand and clarify the reasons behind inefficiencies and misjudgements in financial markets (Leković, 2020). The emergence of behavioral economics, particularly behavioral finance, as a unique discipline, can be attributed to the pioneering work of psychologists Daniel Kahneman and Amos Tversky (Truc, 2022). The importance of this research was recognized when Daniel Kahneman was awarded the Nobel Prize in Economics in 2002 (Altman, 2004). The Nobel Committee emphasized the crucial importance of biases, heuristics, and framing effects in the decision-making processes of actual individuals, which contrasts with the assumed flawless rationality of economic "agents" in conventional economics (Cervellati et al., 2024).

Before the rise of behavioral finance, it was widely believed that traditional finance theory accurately depicted investors as rational thinkers who carefully make decisions based on estimations or economic models (Pompian, 2012). The traditional finance theory assumes that individuals possess consistent, clearly defined preferences and that agents strive to maximize those preferences rationally (Hens, and Riege, 2016). The rational individual is assumed to be economical, rational, experienced, and can assess the potential outcomes for different options. They then select the most beneficial alternative that enhances their satisfaction while minimizing expenses (Kahneman, 2003). The concept of efficient stock markets originated in the late 1960s with the efficient market hypothesis (EMH) (Fama, 1970) and it is the base for traditional finance. According to this hypothesis, investors have access to market information and asset prices, and they are also perceived to be rational (Madaan, and Singh, 2019). Following several experimental studies, it became apparent that human decision-making frequently relies on their characteristics, intuitions, and habitual cognitive or emotional biases (Kahneman, 2003).

Behavioral biases have emerged as fundamental components of behavioral finance, serving as the foundation for the contrasts between traditional finance and behavioral finance. These biases are pivotal in challenging the notion of rationality, leading to the development of Behavioral Finance through various studies (Tversky, and Kahneman, 1971). Behavioral biases explain why there is a difference in the way people make decisions when it comes to gains versus losses. An individual who is risk-averse when it comes to decisions involving gains may become a risk seeker when making decisions to avoid losses (Tversky, and Kahneman, 1971). Overconfidence, anchoring, herding, cognitive dissonance, self-attribution, availability bias, framing,mental accounting, and representative bias, are among the biases considered fundamental elements of behavioral finance, exerting substantial influence on the decision-making processes of individual investors (Singh, 2016).

Over the last thirty years, there has been a notable discussion regarding the effectiveness of stock markets, drawing the interest of researchers investigating stock returns and their movements (Sharma, and Kumar, 2020). Since the financial market is comprised of investors, the collective actions of these investors in the market reflect the behavior of the entire financial market (Zeckhauser et al., 1991). When a significant portion of investors in the market exhibit biases in their investment decision-making processes, it can lead to the emergence of specific market anomalies. These anomalies are typically associated with particular types of financial securities, resulting in either overperformance or underperformance (Giles et al. 2014; Thaler 2005). These anomalies account for occurrences, such as specific fluctuations in stock prices, that cannot be clarified by the efficient market hypothesis (Silver, 2011). The presence of stock market anomalies can, in turn, impact investors' behaviors and the overall performance of the stock market (Brealey et al. 2012). For a long time, three categories of anomalies—namely fundamental, technical, and calendar anomalies—have been widely recognized to exist within the stock market (Lam et al. 2008).

This research investigates the impact of behavioral biases on investors' decision-making in the Indian stock market during 2023 and 2024. To achieve this, we developed and distributed a questionnaire among investors and collected responses for analysis. We explored the relationships between behavioral biases, anomalies, financial literacy, and investment decisions. Specifically, the study examines how three types of stock market anomalies (fundamental, technical, and calendar anomalies) mediate between behavioral biases and investment decisions, especially those biases that lead to irrational investment choices. Additionally, we explore the moderating role of financial literacy in the relationship between biases and stock market anomalies.

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The structure of the paper is outlined as follows: Section 2 reviews the current literature and formulates hypotheses; Section 3 describes the sample selection and research methodology; Section 4 presents the empirical findings and discussion of the empirical results; and Section 5 wraps up the paper with concluding remarks.

2. Literature review

In standard finance, decisions are made within a predetermined range of outcomes, considering all potential consequences and alternatives to achieve the best solution for maximizing wealth. However, actual individual behavior often deviates from theoretical expectations and classical financial models (Raiffa 1968; Kahneman and Tversky 1979). Individuals often neglect the fundamental principles of investment theory and instead rely on intuition and the advice of others, which goes against rational theory (De Bondt 1998). In such scenarios, the efficient market hypothesis and rational behavior theory fail to accurately predict market trends.

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Prospect theory serves as an evaluation or critique of expected utility theory, offering a thoughtful representation of indecision, with the value function assessing individual outcomes independently (Kahneman and Tversky 1979). The adaptive expectation theory (Tinbergen 1939), regret theory (Loomes and Sugden 1982), bounded rational theory (Simon 1955), and prospect theory (Kahneman and Tversky 1979) jointly explain the influence of diversity on investors' preferences and decision-making processes. However, prospect theory is better suited for addressing behavioral biases, anomalies, and investment in the stock market (Barberis 2013; Barberis et al. 2001; Shiller 1999). They make their decisions using bounded rationality, as outlined in decision theory (Barberis and Thaler 2003).Additionally, heuristic biases directly explain investment decisions in Pakistan (Mumtaz et al. 2018; Malik et al. 2022; Farooq and Sajid 2015).

The impacts of emotional and cognitive biases in investors' decision-making processes result in stock market anomalies (Thanki et al., 2022). These anomalies, in turn, influence the performance of the stock market and the decision-making of individual investors. These anomalies are typically linked to specific types of securities, leading them to either underperform or outperform (Thaler 2005). These anomalies refer to the occurrences or fluctuations in stock prices that cannot be explained by the efficient market hypothesis (Silver, 2011).

Inefficient markets exhibit three types of anomalies: fundamental anomalies, calendar anomalies, and technical anomalies. Fundamental anomalies are linked to aspects of fundamental analysis (Thushara and Perera, 2013). Technical anomalies are associated with technical analysis, which forecasts expected stock returns based on movements in stock prices and trading volume (Mizrach and Weerts, 2009; Bako and Sechel, 2013). In calendar anomalies, stock prices exhibit variations at different times, reflecting seasonal fluctuations in stock prices (Thushara and Perera 2013; Thaler 2005). All three categories of anomalies are relevant within the framework of prospect theory, aiding in the comprehension of market conditions that influence the behavior of individual investors (Abideen et al., 2023).The study's hypotheses, as outlined below, have been tested through analysis, and the results have been interpreted accordingly.

- H1a: The degree of Herding Bias has a significant positive association with fundamental anomalies.
- H1b: The degree of Herding Bias has a significant positive association with Technical Anomalies.
- H2a: The degree of overconfidence bias has a significant positive association with fundamental anomalies.
- H2b: The degree of overconfidence bias has a significant positive association with technical anomalies.
- H3a: The degree of Anchoring Bias has a significant positive association with fundamental anomalies.
- H3b: The degree of Anchoring Bias has a significant positive association with technical anomalies.

- H4: There is a significant positive association between fundamental anomalies and individual’s investment decisions
- H5: There is a significant positive association between technical anomalies and individual’s investment decisions
- 2.3. Behavioral Biases and Investment Decisions
- H6: There is a significant positive association between herding bias and individual’s investment decisions
- H7: There is a significant positive association between overconfidence bias and individual’s investment decisions
- H8: There is a significant positive association between anchoring bias and individual’s investment decisions
- H9a: Financial literacy positively affects herding bias and fundamental anomalies.
- H9b: Financial literacy positively affects herding bias and technical anomalies.
- H9c: Financial literacy positively affects overconfidence bias and fundamental anomalies.
- H9d: Financial literacy positively affects overconfidence bias and technical anomalies.
- H9e: Financial literacy positively affects anchoring bias and fundamental anomalies.
- H9f: Financial literacy positively affects anchoring bias and technical anomalies.

Comment [PT4]: Nothing is mentioned on financial literacy

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3. Methodology

The research aims to explore both the positive and negative influences of behavioral biases on investors' decisions regarding investments, examining how stock market anomalies and financial literacy may mediate and moderate these effects. The study focuses on individual investors active in the Bombay Stock Exchange and National Stock Exchange. To gather data, we employed a structured questionnaire using purposive and snowball sampling methods, resulting in 220 respondents from India's stock exchanges in 2024. The questionnaire was carefully crafted with concise questions to facilitate ease of response for participants. To begin, organize and optimize the data in SPSS. Once the data distribution is normalized, employed structural equation modeling (SEM) using AMOS, to evaluate the hypotheses outlined in our conceptual framework. This model allows us to quantify the statistical parameters of the structural relationships, including the explained variance of latent variables (Götz et al., 2009). This procedure facilitates the extraction of results from a structural equation model used in the conceptual framework of the study. In the empirical

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The questionnaire devised for this study comprises eight distinct sections. The initial section comprises twelve questions concerning the respondents' backgrounds. Subsequent sections address specific variables relevant to the study, drawing upon existing literature for guidance in formulating the questions. For example, the second section focuses on investment decisions (ID), with three questions derived from prior studies (Le Luong and Thi Thu Ha, 2011; Waweru et al., 2008). Following this, three sections each address behavioral biases as independent variables: herding bias (HB), overconfidence bias (OB), and anchoring bias (AB). Each of these sections contains three questions, referencing relevant literature sources (Kengatharan and Kengatharan, 2014; Pompian, 2011). Additionally, two sections are dedicated to exploring stock market anomalies: fundamental anomalies (FA) (Waweruetal.2008), and technical anomalies (TA) (Waweruetal.2008; Achelis2001). These anomalies serve as mediators in the study. Finally, the last section includes three questions related to financial literacy (FL), serving as the moderator (Alessie et al., 2011). Figure 1 describes the conceptual framework of the research.

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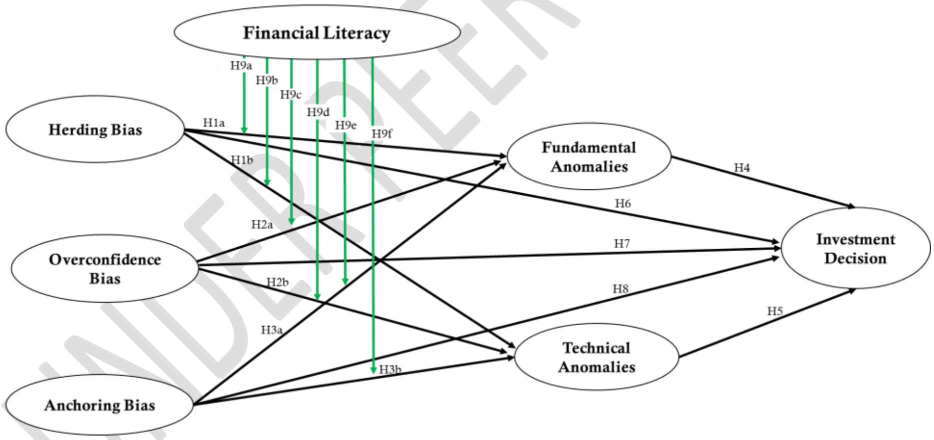

Figure 1. Conceptual framework

4. Results and discussions

This section presents findings from the empirical analysis, encompassing descriptive statistics, correlation analysis, Cronbach's alpha, simple regression, and multiple regression tests.

4.1. Descriptive statistics

Table1 presents an overview of respondent characteristics. The data reveals that our sample consists of 198 male (90.00%) and 22 female (10.00%) participants. Among them, 35.00% are married while 65.00% are unmarried. Notably, unmarried individuals exhibit greater involvement in stock trading compared to married individuals. Regarding educational qualifications, 9.09% have intermediate education, while the majority hold graduation (70.91%) followed by post-graduation degrees (20.00%). In terms of experience in the stock market, the largest proportion of respondents (56.36%) have 3 to 5 years of experience, followed by 1 to 2 years (21.36%), 6 to 10 years (12.73%), and 11 years or more (9.55%).

Table1. Descriptive statistics

	Frequency	Percentage
Gender		
Male	198	90.00
Female	22	10.00
Marital status		
Married	77	35.00
Unmarried	143	65.00
Qualification		
Intermediate	20	9.09
Graduation (UG)	156	70.91
Post-Graduation	44	20.00
Experience in Investment		
1 to 2 years	47	21.36
3 to 5 years	124	56.36
6 to 10 years	28	12.73
11 to onwards	21	9.55

Note: The above table presents descriptive statistics such as gender (male and female), marital status (married and unmarried), qualification (intermediate, graduation (UG) and post-graduation) and experience in investment were depicted in percentage.

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4.2. Reliability Statistics – Cronbach's Alpha

Table2 presents the psychometric properties of various constructs, including investment decision (ID), herding bias (HB), overconfidence bias (OB), anchoring bias (AB), fundamental anomalies (FA), technical anomalies (TA), and financial literacy (FL), measured through a questionnaire. Each construct consists of three items, with their respective Cronbach's Alpha values indicating high internal consistency. The mean scores across constructs range from 3.88 to 4.3, suggesting a generally positive perception or attitude towards the measured variables. Standard deviations, reflecting the dispersion of scores around the mean, vary from 0.758 to 1.038, indicating differing levels of variability within the constructs.

Table2. Reliability Statistics – Cronbach's Alpha

Constructs	No of items	Cronbach's Alpha value	Mean	Standard deviation
ID	3	0.892	3.98	0.956
HB	3	0.925	4.256	0.981
OB	3	0.91	4.07	0.872
AB	3	0.895	3.88	0.758
FA	3	0.975	4.3	0.972
TA	3	0.868	3.95	1.038
FL	3	0.937	4.05	0.835

Note: The above table presents the Cronbach alpha value to check the reliability of the variables such as investment decision (ID), herding bias (HB), overconfidence bias (OB), anchoring bias (AB), fundamental anomalies (FA), technical anomalies (TA), and financial literacy (FL). All the calculations were carried out in SPSS.

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For each component within a scale to demonstrate internal consistency and reliability, Cronbach's alpha value must exceed 0.70 (Hair *et al*., 2013). As the table shows, all variables exhibit Cronbach's alpha values surpassing the 0.70 threshold.

4.3. Factor Loadings, Composite Reliability, and Average Variance Extracted (Measurement Model)

In this study, Confirmatory Factor Analysis (CFA) is utilized to assess the strength of the relationship between observed variables and underlying latent constructs The analysisevaluates the validity of constructs, examining factors such as factor loading, composite reliability (CR), and average variance extracted (AVE) obtained from regression analysis.

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Two models are employed in CFA analysis: the measurement model and the structural model. The measurement model assesses convergent and divergent validity. Convergent validity is confirmed if factor loadings, CR, and AVE surpass the threshold value of 0.50 (Hinkin1998). Additionally, CR and AVE values should fall within an acceptable range. Intable3, the Investment Decision construct demonstrates robust convergent validity with factor loadings of 0.8 for ID1, 0.76 for ID2, and 0.91 for ID3, yielding CR and AVE values above the acceptable range. Similarly, other constructs such as Herding Bias, Overconfidence Bias, Anchoring Bias, and Financial Literacy exhibit strong convergent validity.

Table3. Factor Loadings

Constructs	Items	Factor Loading	CR	AVE
Investment Decision	ID1	0.8	0.87	0.68
	ID2	0.76		
	ID3	0.91		
Herding Bias	HB1	0.85	0.89	0.74
	HB2	0.82		
	HB3	0.92		
Overconfidence Bias	OB1	0.81	0.86	0.66
	OB2	0.79		
	OB3	0.85		
Anchoring Bias	AB1	0.91	0.87	0.68
	AB2	0.75		
	AB3	0.81		
FundamentalAnomalies	FA1	0.91	0.95	0.85
	FA2	0.95		
	FA3	0.92		
Technical Anomalies	TA1	0.76	0.83	0.61
	TA2	0.82		
	TA3	0.77		
Financial Literacy	FL1	0.79	0.9	0.74
	FL2	0.91		
	FL3	0.88		

Note: The above table presents the factor loading values of each observed variable, which allows the evaluation of constructs in terms of validity. The table provided comprises five columns. The initial two columns present the constructs and their corresponding items. The third column has the factor loading values. The fourth and fifth columns display the Composite Reliability and Average Variance Extracted values, respectively.

Divergent validity is assessed through discriminant validity tests. To evaluate discriminant validity, it's essential that the square root of Average Variance Extracted (AVE) for each construct, when placed on the diagonal of a correlation matrix, exceeds the correlations between constructs found off the diagonal (Barclay et al., 1995; Fornell and Larcker, 1981). The results in Table4 observed that the values on the diagonal for all constructs are higher than those off the diagonal, suggesting there are no issues with discriminant validity, or strong evidence supporting discriminant validity.

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Table4. Discriminant validity

Construct	FL	ID	TA	FA	AB	OB	HB
FL	0.793						
ID	0.612	0.817					
TA	0.470	0.419	0.783				
FA	0.709	0.609	0.442	0.761			
AB	0.713	0.629	0.727	0.617	0.779		
OB	0.769	0.665	0.532	0.825	0.827	0.829	
HB	0.659	0.559	0.549	0.196	0.418	0.789	0.838

Note: The above table presents the divergent validity assessment using correlation matrix. Investment decision (ID), herding bias (HB), overconfidence bias (OB), anchoring bias (AB), fundamental anomalies (FA), technical anomalies (TA), and financial literacy (FL).

The structural model, depicted in Figure 2, examines relationships between latent constructs. Model fit indices are also evaluated to assess the validity of the structural model.

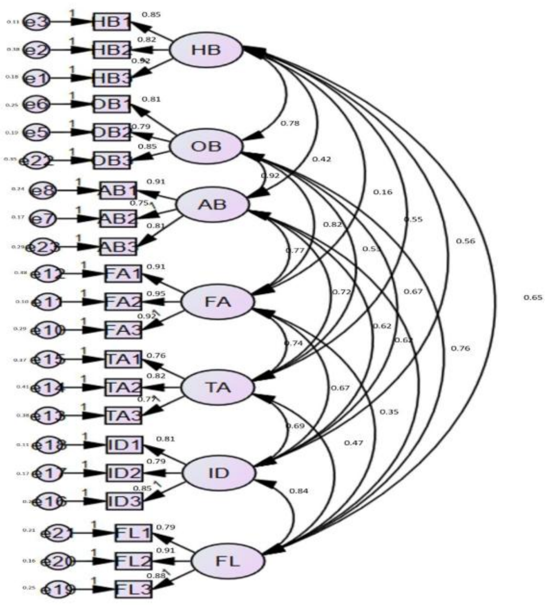

Figure 2. Structural equation model

4.4. Model Fit Indices

The study employed a confirmatory factor analysis to assess the reliability and validity of our measurement model. Our findings, presented in Table5, indicate that the model performs well within acceptable parameters, showcasing good validity and reliability of the variables. Theindices include the normed chi-square (X2/DF = 1.45), comparative fit index (CFI = 0.96), Tucker Lewis index (TLI = 0.97), goodness-of-fit index (GFI = 0.98), incremental fit index (IFI = 0.86), root mean square error of approximation (RMSEA = 0.04), and root mean square residual (RMR = 0.03). This indicates that our structural equation model is suitable for regression analysis, as each variable demonstrates acceptable values. Overall, our model fits the data well, as evidenced by the comprehensive range of model fit indices.

Table5. Competition model of confirmatory factor analysis.

Category	**Model Fit statistic**	**Obtained Index Value**	**Threshold value**	**Sources**	**Results**
Absolute Fit Measure	TFI	0.978	≥ 0.90	Bentler (1990)	**Accepted**
	RMSEA	0.049	≤ 0.08	Hu and Bentler (1998)	
Incremental fit indices	NFI	0.939	≥ 0.90		**Accepted**
	GFI	0.917	≥ 0.90	Hair *et al*., 2010	
	CFI	0.944	≥ 0.90	Bentler (1990)	
	RMR	0.05	≤ .080	Hu and Bentler (1998)	
Chi-square	x^2 / df	2.87	≤ 3.0		**Accepted**

Note: The above table presents the values of model fit indices with obtained index values compared to the threshold value of the different indices.

4.5. Direct effects

Simple regression analysis examined the direct relationships between variables outlined in hypotheses H1 to H8. The findings, including the confirmation or rejection of these hypotheses, are summarized in Table6, specifically in column (5). Significance levels were assessed using Critical Ratio (CR) and p-values. For a hypothesis to be deemed significant, its CR value should exceed 1.96, corresponding to a significance level of 0.05. The results from the regression analysis indicate that several hypotheses have been supported at a significance level of 0.05. Hypotheses H1a, H1b, H2b, H3a, H3b, H6, and H7 have all been accepted, implying significant relationships between various constructs. However, hypotheses H2a, H4, H5, and H8 were not supported, suggesting no significant relationships. These findings provide valuable insights into the relationship between various psychological biases and financial decision-making processes.

Table6. Hypothesis confirmation: Direct effect.

Hypotheses	Path	Beta Coefficient	CR	Result
H1a	HB -> FA	0.693	9.557	**Accepted**
H1b	HB -> TA	0.177	3.662	**Accepted**
H2a	OB -> FA	0.055	0.871	**Rejected**
H2b	OB -> TA	0.083	1.978	**Accepted**
H3a	AB ->FA	0.212	4.48	**Accepted**
H3b	AB ->TA	0.178	2.505	**Accepted**
H4	FA -> ID	-0.112	-1.894	**Rejected**
H5	TA -> ID	0.065	0.73	**Rejected**
H6	HB -> ID	0.337	4.364	**Accepted**
H7	OB -> ID	0.269	4.796	**Accepted**
H8	AB -> ID	0.088	1.337	**Rejected**

Note: The above table presents the relationship between all the variables in the study. The provided table consists of five columns. The first two columns outline the hypotheses and the paths of relationship between variables. The third column displays the coefficients of correlation, while the fourth and fifth columns show the Critical Ratio (CR) values and the hypotheses were accepted or rejected respectively and the p-value reached a level of significance at 5%.

4.6. Indirect effect of behavioralbiases on investment decisions through the mediators

Whether market anomalies could act as a mediator in the link between behavioral biases and investors' decision-making processes. Conducting this test is crucial for understanding the true nature of the relationship between behavioral biases and investment decisions. To accomplish this, we utilize the bootstrap method within the AMOS software and perform a "path analysis" to examine the relationship among the mediators. The findings of this analysis are presented in Table7.

To determine whether the stock market's mediation effect exists, a common approach is to check if the value 0 falls between the lower and upper bounds. If it does, then the mediation role is not supported. The findings from the initial two rows of the table confirm that fundamental anomalies (FA) and technical anomalies (TA) play a mediating role between herding bias (HB) and investment decisions (ID).

Table7. Hypothesis confirmation: Mediating effect.

Path	Beta Coefficient	Lower Bound	Upper Bound	Results
HB ->FA -> ID	0.135	-7.951	6.057	**Rejected**
HB ->AB -> ID	0.479	-0.455	...	**Rejected**
OB ->FA -> ID	0.005	-0.506	0.218	**Rejected**
OB -> TA ->ID	0.111	0.035	0.863	**Accepted**
AB -> FA -> ID	0.006	0.536	7.65	**Accepted**
AB -> TA -> ID	0.541	-0.286	...	**Rejected**

Note: The above table presents the indirect relationship between behavioral biases and investment decisions through the mediating variable stock market anomalies. In the table provided, there are five columns. The first two columns display the path and beta coefficients.The third and fourth columns show the lower and upper bound values, while the fifth column indicates whether the hypothesis has been accepted or rejected.

The table presents the beta coefficients along with lower and upper bounds for various paths of the constricts. Inferences drawn from the results indicate that the paths from HB to FA to ID and OB to TA to ID are rejected, suggesting no significant mediation effect. Conversely, the paths from HB to AB to ID, AB to FA to ID and AB to TA to ID are accepted, indicating a significant mediation effect in these relationships. These findings imply that overconfidence bias and anchoring bias indirectly influence investment decisions through technical anomalies and fundamental anomalies, respectively, herding bias and anchoring bias do not exhibit significant mediation effects

4.7. Moderating role of financial literacy betweenbehavioral biases and market anomalies

As mentioned in Section 2, the research aims to investigate if financial literacy influences the relationship between behavioral biases and market anomalies. The research employed a multi-regression model to analyze the impact of financial literacy on the relationship between behavioral biases and market anomalies. The findings of this analysis are detailed in Table8.

Table8. Hypothesis confirmation: Moderating effect of financial literacy on behavioral biases

Path	Coefficients	CR	P- value	Results
HB x FL -> FA	-0.843	-3.017	0.003	**Rejected**
HB x FL -> TA	0.352	1.962	0.033	**Accepted**
OB x FL -> FA	-1.274	-4.936	***	**Rejected**
0B x FL -> TA	-0.164	-1.042	0.298	**Rejected**

AB x FL -> FA	-0.792	-2.882	0.004	**Rejected**
AB x FL -> TA	-0.17	-1.051	0.293	**Rejected**

Note: The above table presents the moderating effect of financial literacy on behavioral biases inferred using the critical values and the hypothesis is tested and the p-value reaches a level of significance at 5%.

The table8presented the results of the study examined the relationships between various factors in investment decision-making. The coefficients indicate the strength and direction of these relationships. Notably, the relationship between herding bias (HB) and fundamental anomalies (FA) is found to be negative and significant, leading to the rejection of hypothesis H9a. Conversely, the relationship between herding bias (HB) and technical anomalies (TA) is positive and significant supporting the acceptance of hypothesis H9b. The path coefficients reveal significant negative impacts of overconfidence bias interacting with financial literacy on fundamental anomalies leading to the rejection of hypothesis H9c. Similarly, the interaction between overconfidence bias and financial literacy on technical anomalies (OB x FL → TA) also exhibits a negative coefficient (-0.164),consequently rejecting H9d as well.The hypothesis H9e and H9f are rejected based on the following significant values: for the path AB x FL → FA, with a CR of -2.882 indicating rejection. Similarly, for the path AB x FL → TA, with a CR of -1.051, also leading to rejection. These results suggest a significant relationship between behavioral bias and both fundamental and technical anomalies, thereby implying the influence of psychological biases on investment decisions.

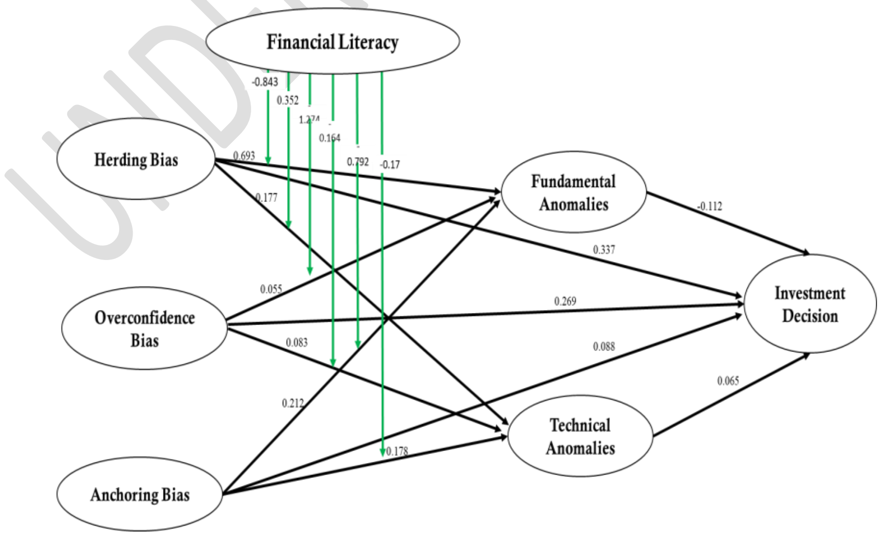

Figure 3. Structural model

5. Conclusion

Comment [PT13]: How about the implication of the study?

The study aims to identify the effects of behavioral biases on investors' investment decision-making, as well as the roles played by stock market anomalies and financial literacy during this process. Through a structured questionnaire distributed to investors in the Bombay Stock Exchange and National Stock Exchange, we collected responses from 220 participants in 2024. The empirical analysis reveals significant associations between behavioral biases and market anomalies, underscoring their substantial influence on investment decisions. Specifically, we found that herding bias (HB) positively impacts technical anomalies (TA), while overconfidence bias (OB) negatively influences fundamental anomalies (FA). Additionally, anchoring bias (AB) demonstrates significant relationships with both fundamental and technical anomalies. Financial literacy (FL) moderates these associations, affecting the investors' decision-making process. The study highlights the critical role of financial literacy in mitigating biases and promoting optimal investment strategies. However, limitations exist, including potential biases in data collection and the inability to fully address endogeneity concerns. Future research should encompass broader investor demographics and employ more comprehensive methodologies to enhance the understanding of behavioral finance theories and improve investment decision-making practices (Hair et al., 2013; Hinkin, 1998; Barclay et al., 1995). The findings underscore the importance of addressing behavioral biases and enhancing financial literacy to foster stability in the stock market and facilitate informed investment decisions, thereby contributing to financial knowledge and market efficiency.

6. Reference

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