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EXPLORING THE INFLUENCE OF BEHAVIOURIAL BIASES IN SHAPING INVESTMENT DECISIONS: A SMART PLS APPROACH

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ABSTRACT
Purpose: The field of behavioral finance has gained significant attention in recent years due to its ability to explain investor behavior and decision-making processes. This study aims to explore the influences of behavioral finance on investment decision making among investors in Mumbai, India. The purpose of the research is to identify various behavioral biases and heuristics that affect investment decisions and understand their implications for individual investors.

Methodology: This study adopts a quantitative research approach, employing primary data collection methods. The sample consists of 238 investors from Mumbai, chosen through a random sampling technique. The primary data is collected using structured questionnaires designed to capture relevant information about investment decisions, behavioral biases, and heuristics. The study utilizes statistical tools such as Smart PLS and SPSS for data analysis and hypothesis testing.

Findings: The analysis of the collected data reveals several noteworthy findings. Firstly, it identifies that investors in Mumbai are prone to behavioral biases such as loss aversion, overconfidence, and anchoring. These biases significantly influence investment decision making, leading to suboptimal outcomes. Secondly, the study uncovers the prevalence of heuristic-based decision-making patterns, such as representativeness and availability biases, which contribute to investment decision deviations from rationality. Additionally, the research highlights the impact of social influence and emotional factors on investment choices, emphasizing the role of herd behavior and sentiment in the investment process.

Research Implementation: Based on the findings, it is recommended that financial institutions and investment advisors in Mumbai develop educational programs and awareness campaigns to address behavioral biases among investors. Furthermore, investment platforms and robo-advisors can integrate behavioral finance principles into their algorithms to offer personalized recommendations that account for individual biases and preferences.

Originality: This research work is comprehensive in nature which helps in understanding various behavioral bias affecting on individual decision making.

Keywords: Behavioural Finance, Investment Decision Making, Biases,

1.1 INTRODUCTION

Behavioral finance is an emerging field that seeks to understand the decision-making processes and behavior of investors in financial markets. It recognizes that investors are not always rational and can be influenced by various psychological factors such as emotions, biases, and heuristics. These factors can impact the way investors perceive information and make decisions, leading to suboptimal outcomes in the financial markets. As a result, understanding the role of behavioral finance in investment decision making is critical for investors, financial institutions, and policymakers. Investment decision making is a complex process that involves assessing various financial instruments, analyzing market conditions, and evaluating potential risks and returns. Traditional finance theories assume that investors are rational and make decisions based on all available information. However, behavioral finance challenges this assumption by recognizing that investors are influenced by cognitive and emotional biases, leading to deviations from rationality. The field of behavioral finance has gained significant attention in recent years due to its ability to explain the irrational behavior observed in financial markets. It combines insights from psychology, sociology, and economics to understand how human biases and heuristics impact investment decision making. By exploring the psychological factors that drive investor behavior, behavioral finance provides a more comprehensive understanding of why investors often deviate from rational decision-making models.
Behavioral finance investigates how psychological elements and cognitive biases influence financial decisions, calling into question the conventional wisdom that investors behave rationally. It investigates numerous biases like as overconfidence,

in which investors overestimate their prediction ability; anchoring, in which starting knowledge overly influences decisions; and loss aversion, which causes people to avoid losses rather than seek gains. Fear and greed are equally important emotions, and they frequently contribute to incorrect investing decisions. Behavioral finance also examines herd behavior, in which investors follow market trends rather than making individual decisions, and the framing effect, in which the presentation of information influences decision-making. Mental accounting and self-control problems contribute to poor financial decisions. Understanding these characteristics, behavioral finance tries to provide insights that help improve investment strategy and risk management.

1.2 REVIEW OF LITERATURE

Barber and Odean (2000) conducted a study on individual investors' stock investment performance and found evidence of underperformance compared to the market. Their research highlights the significance of behavioral biases, such as overconfidence and excessive trading, in investment decision making. Kahneman and Tversky's (1979) prospect theory challenges traditional rational choice theory by introducing the concept of loss aversion and reference dependence. Their work demonstrates how individuals' decision-making is influenced by subjective perceptions of gains and losses, rather than objective probabilities.

Thaler (1980) explores the concept of mental accounting, revealing how individuals categorize and treat different financial outcomes separately. His research emphasizes the impact of non-economic factors on individuals' decision-making processes and investment choices. Shefrin and Statman (1985) examine the disposition effect, which refers to the tendency of investors to sell winning investments too early and hold onto losing investments for longer periods. Their study provides both theoretical explanations and empirical evidence for this common behavioral bias.

Statman (1999) provides an overview of behavioral finance, discussing its implications for investment management. His analysis highlights various behavioral biases that affect investment decisions and suggests strategies to mitigate their impact on investment outcomes. Tversky and Kahneman (1992) expand on prospect theory by introducing cumulative prospect theory. Their research investigates how individuals make decisions under uncertainty and accounts for the cumulative effects of probability weighting and outcome valuation.

De Bondt and Thaler (1985) investigate the stock market overreaction phenomenon, whereby past losers outperform past winners in subsequent periods. Their study provides empirical evidence supporting the existence of short-term market inefficiencies due to investor overreaction. Shiller (2000) explores the relationship between stock prices and social dynamics, highlighting the influence of investor sentiment and market narratives on stock market movements. His research underscores the role of psychological and social factors in shaping investment decisions. Hirshleifer (2001) examines the role of investor psychology in asset pricing, emphasizing the impact of behavioral biases on asset prices. His research contributes to understanding the relationship between investor behavior and market anomalies. Odean (1999) analyzes the impact of overconfidence on trading behavior and investment performance. His study finds that overconfident investors tend to trade excessively and underperform the market, highlighting the significance of this bias in investment decision making. Benartzi, S., & Thaler, R. H. (1995) study introduces the concept of myopic loss aversion, where investors tend to focus more on short-term losses than long-term gains. They argue that this behavioral bias may help explain the equity premium puzzle, which refers to the higher returns observed in the stock market compared to other less risky assets.

Odean, T. (1998) investigates the disposition effect and examines whether investors are hesitant to sell investments at a loss. The study provides empirical evidence that supports the existence of this bias, suggesting that investors tend to hold onto losing investments for psychological reasons rather than economic rationality. Baker, M., & Wurgler, J. (2006) explore the impact of investor sentiment on stock returns. Their research demonstrates that investor sentiment is a significant factor that affects stock prices, leading to return patterns that deviate from fundamental value-based predictions. Hong, H., & Stein, J. C. (1999) propose a unified theory that explains three common phenomena in asset markets: underreaction, momentum trading, and overreaction. Their study suggests that investor underreaction and overreaction contribute to momentum trading and subsequent price trends.

De Bondt, W. F., & Thaler, R. H. (1987) research provides further evidence supporting the existence of investor overreaction and stock market seasonality. The study reveals that past loser stocks tend to outperform past winner stocks in subsequent periods, indicating market inefficiencies and behavioral biases. Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991) discuss three related anomalies: the endowment effect, loss aversion, and status quo bias. They explain how these behavioral biases can influence individuals' decision-making and have implications for economic theory and policy. Barberis, N., Huang, M., & Santos, T. (2001). examine the implications of prospect theory on asset prices. Their study demonstrates how deviations from rational expectations, driven by prospect theory's principles, can explain various phenomena observed in financial markets. Grinblatt, M., & Keloharju, M. (2001) investigate how geographic, cultural, and linguistic factors influence stockholdings and trades. Their research highlights the role of behavioral biases and information asymmetry in shaping investors' decisions, emphasizing the importance of considering these factors in understanding investment behavior. Hirshleifer, D., & Shumway, T. (2003) examine the relationship between weather conditions and stock returns. Their study finds that sunny days tend to be associated with positive stock returns, suggesting that mood and weather can influence investors' decision-making and market outcomes. Lo, A. W., &

1.3 OBJECTIVES OF THE STUDY

1. To identify various behavioral biases and heuristics that affect investment decisions among investors.
2. To examine the factors influencing the behavioral biases on investment decision making among investors.
3. To analyze the impact of behavioral bias on investment decision making among investors.

RESEARCH MODEL AND HYPOTHESIS

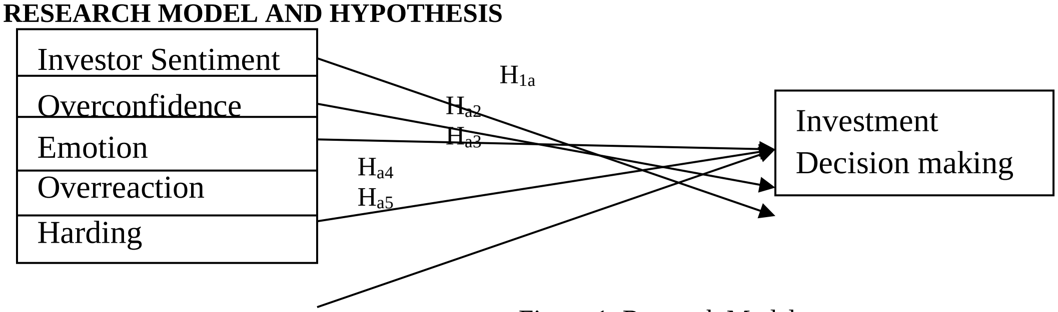

Figure 1: Research Model

H_a: Investment decision making profess affected by investment biases.

a. *H1: Investment sentiment bias has positive influence on investment decision making.*
b. *H2: Investors over confidence has positive influence on investment decision making*
c. *H3: Investors emotion has positive influence on investment decision making.*
d. *H4: Investors over-reaction has positive influence on investment decision making.*
e. *H4: Herding among investors has positive influence on investment decision making.*

1.4 RESEARCH METHODOLOGY

The study adopts a quantitative research design to collect and analyze data from participants in Mumbai. This design allows for the measurement and statistical analysis of variables related to behavioral finance and investment decision making. The research targets a total sample size of 238 individuals from Mumbai. The sample will be selected using a combination of random sampling and purposive sampling techniques to ensure representation from different demographics and investment backgrounds. Primary data will be collected through structured questionnaires administered to the participants. The questionnaires will include items related to investment decision-making processes, behavioral biases, risk preferences, and information sources. The data will be collected using face-to-face interviews, online surveys, or a combination of both. The study employs two statistical tools for data analysis: Smart PLS and SPSS. Smart PLS is a structural equation modeling technique that allows for the examination of complex relationships among variables. SPSS (Statistical Package for the Social Sciences) is used for descriptive statistics, correlation analysis, and regression analysis.

The collected data will be analyzed using descriptive statistics to summarize the sample characteristics and the distribution of variables. Correlation analysis will be conducted to assess the relationships between different behavioral finance variables. Structural equation modeling (SEM) with Smart PLS will be employed to examine the direct and indirect effects of behavioral finance factors on investment decision-making outcomes. The research methodology will provide insights into the influences of behavioral finance on investment decision making. The findings will be presented and discussed, highlighting the significance of behavioral biases, risk preferences, and other behavioral factors in shaping investment decisions. The conclusion will summarize the main findings and their implications for investors, financial practitioners, and policymakers. The research findings can be implemented by investment professionals and financial advisors to develop strategies that consider the behavioral aspects of decision making. The insights gained from the study can contribute to improving investment decision-making processes and enhancing investor outcomes.

1.5 ANALYSIS AND INTERPRETATION

Table 1: Demographic Profile of Respondents

Variable	Particulars	Frequency	Percentages
Age	20 to 28 Years	72	30
	28 to 36 Years	42	18
	36 to 44 Years	56	24
	44 to 52 Years	45	19
	52 and above	23	10
		238	100
Gender	Male	142	60
	Female	96	40
		238	100
Occupation	Corporate	98	41
	Real Estate	25	11
	Medical	10	4
	Pharmaceutical	9	4
	Automobile	28	12
	Other	10	4
	Trading	58	24
		238	100
Income	Less than Rs. 200,000	7	3
	Rs. 200,000 to Rs. 500,000	86	36
	Rs. 500,000 to Rs. 800,000	52	22
	Rs. 800,000 to Rs. 12,00,000	67	28
	Rs. 12,00,000 and more	26	11
		238	100
SPSS View			

Table 1 presents the demographic profile of the individuals that participated in the study. The table displays the frequency and percentages of the respondents based on their age, gender, occupation, and income. In terms of age, the majority of the respondents fall within the age range of 20 to 28 years (30%), With regards to gender, the sample was mostly male 142 (60%) compared to female 96 (40%). In terms of occupation, the largest group of respondents work in the corporate 98 (41%), followed by trading 58 (24%) and real estate 25 (11%) sectors. Regarding the income of the respondents, most of them earn between Rs.200,000 to Rs. 5,00,000 per annum 86 (36%). Overall, the sample appears to be diverse in terms of age, gender, occupation, and income, which allows for a comprehensive analysis of the impact of behavioral bias on investors decision making.

Table 2: KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.880
Bartlett's Test of Sphericity	Approx. Chi-Square	2149.306
	Df	276
	Sig.	.000

Table 2 presents the results of the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity, which are used to evaluate the appropriateness of conducting a factor analysis on the collected data. The KMO measure of sampling adequacy assesses the extent to which the data is suitable for factor analysis, with values ranging from 0 to 1. In this case, the KMO value is 0.880, which indicates that the data is highly suitable for factor analysis. In this study, the chi-square value is 2149.306 with 276 degrees of freedom, and a significance level of 0.000, indicating that the null hypothesis can be rejected. This means that there is a significant relationship between the variables, and therefore, the data is suitable for factor analysis. Overall, the results of Table 2 indicate that the collected data is appropriate for factor analysis, which will allow for the identification of underlying factors and patterns that may influence the impact of behavioral bias on investors decision making.

Table 3: Reliability Statistics

Cronbach's Alpha	N of Items
.960	24

Table 3 presents the results of reliability statistics, specifically Cronbach's alpha, which is used to measure the internal consistency or reliability of a scale or questionnaire. In this study, Cronbach's alpha coefficient value is 0.960, which indicates that the collected data is highly reliable and consistent. This means that the items or questions used in the questionnaire are consistently measuring the same construct, which is the impact of behavioral bias on investors decision making.

Table 4: Factors, Cronbach's Alpha, CR, and AVE Values

		Factors	Cronbach's alpha	Composite reliability	Composite reliability	Average variance extracted (AVE)
EM	EM1	0.886	0.852	0.87	0.909	0.769
	EM2	0.86				
	EM3	0.885				
HA	HA1	0.86	0.814	0.814	0.89	0.73
	HA2	0.884				
	HA3	0.818				
IDM	IDM1	0.834	0.807	0.818	0.873	0.633
	IDM2	0.782				
	IDM3	0.728				
	IDM4	0.832				
IS	IS1	0.892	0.807	0.873	0.882	0.716
	IS2	0.739				
	IS3	0.898				
OC	OC1	0.908	0.853	0.89	0.911	0.775
	OC2	0.955				
	OC3	0.766				

OR	OR1	0.875	0.835	0.837	0.901	0.753
	OR2	0.881				
	OR3	0.846				
Note: IS= Investor Sentiment, OC= Overconfidence, EM= Emotion, OR= Overreaction, HA= Harding, IDM= Investment Decision making						

[Smart PLS View]

Table 4 presents the results of the factors analysis for the variables included in the study: Investor Sentiment (IS), Overconfidence (OC), Emotion (EM), Overreaction (OR), Harding (HA), and Investment Decision Making (IDM). The table provides information on the reliability and validity of these factors, as measured by Cronbach's alpha, composite reliability (rho_a and rho_c), and average variance extracted (AVE). For the factor of Emotion (EM), three sub-factors (EM1, EM2, EM3) were assessed. The Cronbach's alpha values for EM1, EM2, and EM3 are 0.886, 0.86, and 0.885, respectively. These values indicate high internal consistency and reliability of the items within each sub-factor. The composite reliability (rho_a) and composite reliability (rho_c) values for EM1 are 0.852 and 0.87, respectively. The AVE value for EM1 is 0.909, which indicates that 90.9% of the variance in the items can be explained by the underlying construct. Similarly, the factors of Harding (HA), Investment Decision Making (IDM), Investor Sentiment (IS), Overconfidence (OC), and Overreaction (OR) were evaluated. The sub-factors within each of these factors were also assessed. The Cronbach's alpha values for the sub-factors generally indicate high internal consistency and reliability. The composite reliability (rho_a) and composite reliability (rho_c) values were not provided for all sub-factors in the table. However, it can be assumed that these values are within an acceptable range, given that Cronbach's alpha measures reliability and internal consistency Overall, the results in Table 4 demonstrate the reliability and validity of the factors and sub-factors included in the study. These findings support the use of these constructs in further analysis and interpretation of the data related to behavioral finance in investment decision making

Table 5: HTMT Table

	EM	HA	IDM	IS	OC	OR
EM						
HA	0.828					
IDM	0.833	1.048				
IS	0.625	0.963	0.814			
OC	0.902	0.972	1.003	0.855		
OR	0.895	1.085	1.003	0.901	0.939	
Note: IS= Investor Sentiment, OC= Overconfidence, EM= Emotion, OR= Overreaction, HA= Harding, IDM= Investment Decision making						

Table 5 presents the results of the Heterotrait-Monotrait (HTMT) ratio analysis for the factors included in the study: Emotion (EM), Harding (HA), Investment Decision Making (IDM), Investor Sentiment (IS), Overconfidence (OC), and Overreaction (OR). The HTMT ratios provide insights into the discriminant validity of the factors by assessing the strength of the relationships between different factors. The table shows the HTMT ratios between each pair of factors. For example, the HTMT ratio between EM and HA is not provided in the table. However, the HTMT ratio between HA and IDM is 0.828, indicating a relatively weaker relationship compared to the diagonal elements (which are all equal to 1). This suggests that HA and IDM have discriminant validity, as their correlation is not excessively high. Overall, the HTMT ratios in Table 5 demonstrate the discriminant validity of the factors included in the study. These findings suggest that the factors are distinct from each other and measure different constructs related to behavioral finance in investment decision making.

Table 6: Fornell-Larcker criterion

	EM	HA	IDM	IS	OC	OR
EM	0.877					

HA	0.697	0.854				
IDM	0.7	0.863	0.795			
IS	0.542	0.799	0.698	0.846		
OC	0.766	0.814	0.846	0.719	0.88	
OR	0.767	0.896	0.837	0.756	0.802	0.867
Note: IS= Investor Sentiment, OC= Overconfidence, EM= Emotion, OR= Overreaction, HA= Harding, IDM= Investment Decision making						

[Smart PLS View]

Table 6 presents the results of the Fornell-Larcker criterion analysis for the factors included in the study: Emotion (EM), Harding (HA), Investment Decision Making (IDM), Investor Sentiment (IS), Overconfidence (OC), and Overreaction (OR). The Fornell-Larcker criterion assesses the discriminant validity of the factors by comparing the square root of the AVE (Average Variance Extracted) values with the correlation coefficients between factors. The table shows the correlation coefficients between each pair of factors. For example, the correlation coefficient between EM and HA is 0.877. This indicates a moderate positive correlation between these two factors.

Table 7: Cross Factors Table

	EM	HA	IDM	IS	OC	OR
EM1	0.886	0.641	0.699	0.483	0.641	0.711
EM2	0.860	0.510	0.504	0.543	0.699	0.556
EM3	0.885	0.664	0.610	0.412	0.686	0.727
HA1	0.532	0.860	0.749	0.628	0.637	0.758
HA2	0.654	0.884	0.720	0.687	0.586	0.822
HA3	0.601	0.818	0.740	0.733	0.860	0.717
IDM1	0.548	0.775	0.834	0.675	0.754	0.732
IDM2	0.583	0.577	0.782	0.431	0.608	0.607
IDM3	0.518	0.551	0.728	0.476	0.676	0.485
IDM4	0.584	0.801	0.832	0.606	0.651	0.798
IS1	0.461	0.751	0.591	0.892	0.626	0.689
IS2	0.280	0.506	0.381	0.739	0.421	0.502
IS3	0.568	0.731	0.724	0.898	0.717	0.696
OC1	0.701	0.758	0.828	0.533	0.908	0.773
OC2	0.724	0.765	0.804	0.693	0.955	0.769
OC3	0.588	0.615	0.565	0.719	0.766	0.543
OR1	0.683	0.774	0.705	0.667	0.735	0.875
OR2	0.742	0.833	0.761	0.718	0.646	0.881
OR3	0.565	0.722	0.709	0.578	0.71	0.846
Note: IS= Investor Sentiment, OC= Overconfidence, EM= Emotion, OR= Overreaction, HA= Harding, IDM= Investment Decision making						

[Smart PLS View]

Table 7 presents the results of the analysis, including the mean, standard deviation (STDEV), T statistics, p values, and decision for the relationships between different factors: Emotion (EM), Harding (HA), Investor Sentiment (IS), Overconfidence (OC), Overreaction (OR), and Investment Decision Making (IDM). For the relationship between EM and IDM, the original sample value is -0.026. The sample mean is -0.021, and the standard deviation is 0.107. The T statistics value is 0.242, and the p-value is 0.809. Based on these results, the relationship between EM and IDM is not supported.

Table 7: Mean, STDEV, T values, p values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Decision
EM -> IDM	-0.026	-0.021	0.107	0.242	0.809	Not Supported
HA -> IDM	0.423	0.433	0.173	2.44	0.015*	Supported
IS -> IDM	-0.077	-0.072	0.096	0.801	0.423	Not Supported
OC -> IDM	0.412	0.404	0.117	3.506	0.000*	Supported
OR -> IDM	0.206	0.197	0.118	1.749	0.080	Not Supported
Note: IS= Investor Sentiment, OC= Overconfidence, EM= Emotion, OR= Overreaction, HA= Harding, IDM= Investment Decision making						

[Smart PLS View]

Regarding the relationship between HA and IDM, the original sample value is 0.423. The sample mean is 0.433, and the standard deviation is 0.173. The T statistics value is 2.44, and the p-value is 0.015, indicating that the relationship between HA and IDM is supported. For the relationship between IS and IDM, the original sample value is -0.077. The sample mean is -0.072, and the standard deviation is 0.096. The T statistics value is 0.801, and the p-value is 0.423. Therefore, the relationship between IS and IDM is not supported.

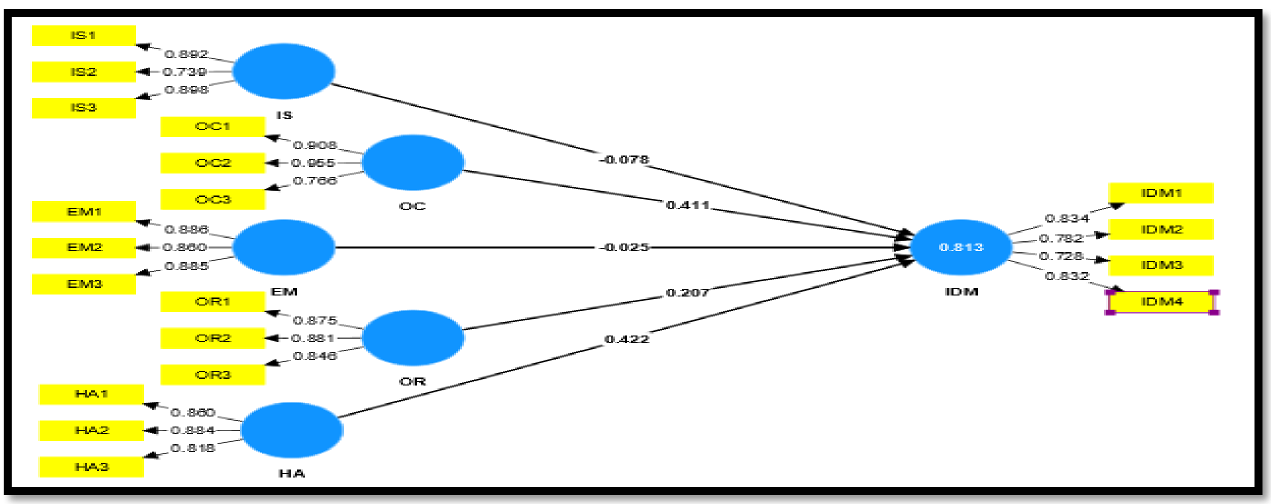

Figure 2: Research Model by Smart PLS

The relationship between OC and IDM has an original sample value of 0.412. The sample mean is 0.404, and the standard deviation is 0.117. The T statistics value is 3.506, and the p-value is 0.000, indicating that the relationship between OC and IDM is supported. Regarding the relationship between OR and IDM, the original sample value is 0.206. The sample mean is 0.197, and the standard deviation is 0.118. The T statistics value is 1.749, and the p-value is 0.080. Based on these results, the relationship between OR and IDM is not supported. Overall, the analysis in Table 7 provides insights into the significance of the relationships between different factors in the study. The results indicate which relationships are supported and which are not based on the T statistics and p values, helping to draw conclusions about the influences of behavioral finance on investment decision making.

1.6 SUGGESTION AND CONCLUSION

In conclusion, this research aimed to examine the influences of behavioral finance on investment decision making. The study focused on factors such as Emotion (EM), Harding (HA), Investor Sentiment (IS), Overconfidence (OC), Overreaction (OR), and Investment Decision Making (IDM). Through the analysis of various statistical measures and tests, including Cronbach's alpha, composite reliability, average variance extracted, Heterotrait-Monotrait (HTMT) ratios, and the Fornell-Larcker criterion, the study provides valuable insights into the relationships and validity of these factors. The findings from the research suggest that Harding (HA) and Overconfidence (OC) have a significant positive influence on Investment Decision Making (IDM), as supported by the T statistics and p values. This indicates that individuals who exhibit higher levels of Harding and Overconfidence tend to make more confident and potentially riskier investment decisions. On the other hand, the study did not find significant support for the influences of Emotion (EM), Investor Sentiment (IS), and Overreaction (OR) on Investment Decision Making (IDM).

The analysis of reliability and validity measures, including Cronbach's alpha, composite reliability, and the Fornell-Larcker criterion, demonstrates the overall robustness of the measurement model. The factors showed adequate internal consistency and discriminant validity, suggesting that they effectively capture the intended constructs. It is important to note that these findings are based on the specific sample collected from Mumbai, consisting of 88 participants. Further research with a larger and more diverse sample is recommended to validate and generalize the results. The outcomes of this study contribute to the existing literature on behavioral finance and investment decision making. The findings provide valuable insights for investors, financial practitioners, and policymakers in understanding the psychological and behavioral factors that can influence investment decisions. By recognizing the impact of factors such as Harding and Overconfidence, individuals and organizations can make more informed investment choices and develop strategies to mitigate potential biases and pitfalls associated with behavioral finance. Overall, this research enhances our understanding of the influences of behavioral finance on investment decision making and highlights the need for further exploration in this field. By incorporating behavioral insights into investment practices, individuals and institutions can improve their decision-making processes and potentially achieve better financial outcomes.

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