“A Study on Role of Behavioural Finance In An Investment Decision of Equity Investors of Selected Cities of the Saurashtra Region”

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CHAPTER 1: INTRODUCTION

Investment decision-making in equity markets has long been explained through traditional financial theories that assume investors act rationally and make decisions based solely on available information. However, practical market behaviour often contradicts this assumption, as investors are influenced by psychological factors, emotions, and personal experiences. Behavioural finance emerged to address this gap by integrating insights from psychology with financial decision-making (Kahneman & Tversky, 1979)

Behavioural biases such as overconfidence, loss aversion, herd behaviour, anchoring, and regret aversion frequently affect how investors perceive risk and return, leading to irrational investment choices (Barberis & Thaler, 2003). These biases can result in excessive trading, poor diversification, and suboptimal portfolio performance. Understanding behavioural finance is therefore essential for explaining real-world investor behaviour and improving investment outcomes.

This study focuses on examining behavioural biases influencing equity investors in selected cities of the Saurashtra region—Junagadh, Rajkot, and Jamnagar—where limited region-specific research exists. By analyzing investor behaviour at the regional level, the study aims to provide meaningful insights that can assist investors, financial advisors, and policymakers in promoting more informed and rational equity investment decisions.

The thesis will be organized into Five chapters with a clear demarcation of content.

Chapter 1: Introduction

The chapter Introduction provides the conceptual foundation of the study by explaining the meaning and basic concepts of behavioural finance in comparison with traditional and modern finance theories. It discusses how investor behaviour often departs from rational assumptions due to psychological influences. The chapter also explains key behavioural biases affecting equity investors, including overconfidence bias, familiarity bias, confirmation bias, regret aversion,

narrow framing, shadow of the past, loss aversion, and herd instincts, highlighting their relevance to investment decision-making.

Chapter 2: Review of The Literature

This Chapter presents a comprehensive review of 112 research studies on behavioural finance sourced from Web of Science, Scopus, Springer, Google Scholar, ResearchGate, and the Vikram Sarabhai Library at IIMA, Ahmedabad. The review covers the period from 2011 to 2025 and is organized into three five-year scenarios. The first scenario (2011–2015) focuses on identifying key biases such as overconfidence, loss aversion, and herd behaviour. The second scenario (2016–2020) examines the interaction of multiple biases and the influence of culture, demographics, and technology. The third scenario (2021–2025) highlights the role of AI, FinTech, and modern tools in understanding investor behaviour, emphasizing the importance of combining financial knowledge with awareness of behavioural biases.

Chapter 3: Materials and Methods (Research Methodology)

This chapter completely outlines the research framework for the study. It includes the statement of the problem, the need for the study, the research objectives, and the hypotheses. The chapter also presents the variables, conceptual model, research design, and sampling plan, along with data collection methods. It discusses the reliability and validity of the questionnaire, the data analysis tools employed, and the study's limitations. Finally, it highlights the possible societal impact of the findings and concludes with the research approach adopted.

Chapter 4: Results and Discussions (Data Analysis)

This Chapter Presents the analysis of the collected data using various statistical techniques and software. Reliability of the data was assessed using Cronbach's Alpha and also through PLS-SEM in Smart PLS, while convergent and discriminant validity were evaluated with the help of PLS-SEM in Smart PLS. Descriptive statistics, cross-tabs, ANOVA, and multiple regression were used to examine relationships and effects between demographic variables, behavioural biases, and

equity investment decisions with the help of IBM SPSS-2022. Structural Equation Modeling (SEM) using Smart PLS was applied to study interrelationships among behavioural biases and investment Decisions, justify the research objectives, and test the research hypotheses.

Chapter 5: Summary and conclusion

This Chapter summarizes the key findings of the study on behavioural biases and their impact on equity investment decisions. It highlights how different biases, such as overconfidence, loss aversion, and herd behaviour, influence investor behaviour in the Saurashtra region. The chapter also presents conclusions drawn from the data analysis, discusses implications for investors, financial advisors, and policymakers, and provides recommendations for promoting more informed and rational investment decisions.

- **References**
- **Appendix**

CHAPTER 2: REVIEW OF THE LITERATURE

In this Literature reviews expresses the key theoretical and empirical contributions that have shaped the evolution of behavioural finance from the year 2011 to 2025. It Consists Mainly of Three Scenarios of the Behavioural Finance field.

The first Scenario begins by presenting the growth stage in the field of Behavioural Finance from 2011 to 2015. During the period from 2011 to 2015, much of the academic focus was on identifying key psychological biases such as overconfidence, loss aversion, anchoring, herd behaviour, Mental accounting, and Regret Aversion. This initial research study, which was largely based on Questionnaire survey data, tended to focus on established financial markets, more over this scenario shows that the research laid an important foundation for understanding investor psychology regarding investment decisions; it was somewhat limited by narrow methodologies and a lack of regional variation.

The Second Scenario begins by presenting the more recent developments in the field of Behavioural Finance year 2016 to 2020. During the period from 2016 to 2020, Behavioural finance expanded its focus, examining how multiple Behavioural biases interact rather than studying them alone. Researchers adopted more modern methods and techniques, while also exploring the roles of culture, demographics, and technology in shaping investor behaviour when making investment decisions. This period laid the groundwork for future studies on digital finance and behavioural patterns.

The Third Scenario begins by presenting the Solid Dominance of Behavioural biases in the field of Behavioural Finance year 2016 to 2020. During the Period from 2021 to 2025, Behavioural finance saw rapid progress driven by technological innovation. Researchers increasingly applied AI (artificial intelligence) and machine learning to study investor behaviour, especially in areas like cryptocurrencies and FinTech platforms. During this time period, it has become clear that improving financial decisions for investments requires more than just education and knowledge.

Studies emphasised the value of combining knowledge with behavioural biases and supportive policies and strategies for improving decisions. Today, the field plays an important role in helping individuals make better decisions in a fast-growing financial world.

Table No. 2.1 Comparative Study Table for Scenarios of Behavioural Finance.

	Scenario-1	***Scenario-2***	***Scenario-3***
Context	**2011–2015**	**2016–2020**	**2021–2025**
Research Study Focus	Theoretical Research, Questionnaire surveys, and also Finding Behavioural Biases	Developing empirical research, experimental Models, and testing and analysis	Solid Dominance on real-world applications and applicability of behavioural biases, identification of bias, and its management.
Data Collection Techniques	Primary Data as well as Secondary data	Primary data through Surveys combined with controlled experiments	Primary data through Surveys with questionnaires, experiments, and real-time digital data (e.g., fintech platforms)
Data Analysis Methods	Basic statistics, ANOVA and regression or Multiple Regression	Advanced econometrics, factor analysis, and SEM (Structural Equation Modelling)	SEM (Structural Equation Modeling), AI/machine learning, econometric models (VAR, IRF), and bibliometric analysis, etc.
Usage of Technology	More limited use of technology, mainly traditional statistical software like Excel	Increasing usage of software like SPSS, AMOS, and early AI applications	SPSS, AMOS, SmartPLS, with Widespread use of AI, machine learning, big data analytics, and digital tools
Working area of Research (Scope)	Focused on traditional financial markets and Behavioural biases	Inclusion of experimental research studies and diverse investor profiles towards investment decisions.	Explore fintech, cryptocurrencies, emerging markets, and Individual Behavioural bias detection tools

Interdisciplinary Perspectives	Core disciplines are economics and psychology.	Core disciplines are behavioural psychology and finance.	Core disciplines are Cross-subjects Mixture with data science, education, Behavioural psychology, and technology.
Major Biases and Worked Upon	**Overconfidence Bias, Herding Bias, Loss Aversion, Anchoring Bias, Regret Aversion Bias, Mental Accounting,** Representativeness Bias, Availability Bias.	**Overconfidence Bias, Loss Aversion, Herding Behaviour, Anchoring Bias, Mental Accounting, Regret Aversion,** Availability Bias, Representativeness Bias, Disposition Effect, Optimism Bias, Gambler's Fallacy, Familiarity Bias, Self-Attribution Bias, Framing Effect, Risk Perception Bias.	**Overconfidence Bias, Herding Bias, Loss Aversion, Anchoring Bias, Mental Accounting,** Disposition Effect, Confirmation Bias, Status Quo Bias, Myopia (Present Bias), **Regret Aversion,** Self-Attribution Bias, Availability Bias, Endowment Effect, Representativeness Bias, Optimism Bias, Emotional Biases (Fear, Greed, Sentiment)
Common Biases out of Three Scenarios	**Overconfidence Bias, Herding Bias, Loss Aversion, Anchoring Bias, Regret Aversion Bias, Mental Accounting,**	**Overconfidence Bias, Loss Aversion, Herding Behaviour, Anchoring Bias, Mental Accounting, Regret Aversion,**	**Overconfidence Bias, Herding Bias, Loss Aversion, Anchoring Bias, Mental Accounting, Regret Aversion**
Availability of Study Regarding Equity Investors	**Yes**	**Yes**	**Yes**

(Source: Authors' Compilation)

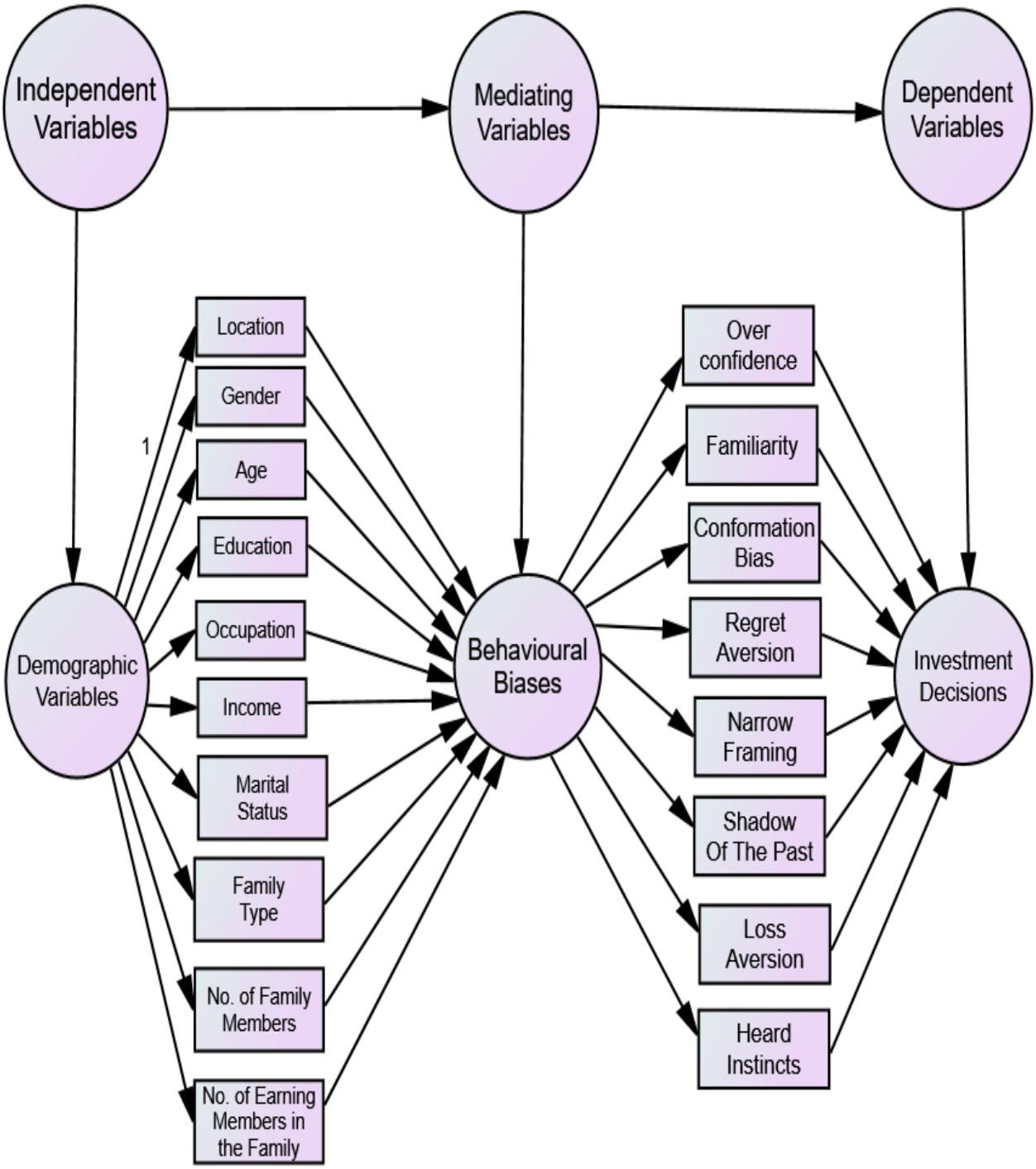
2.1 Research Gap

While behavioural finance has been extensively studied, most research focuses on national or international markets, with limited attention to specific regions like Saurashtra in Gujarat. Cities such as Junagadh, Rajkot, and Jamnagar remain underexplored, leaving a gap in understanding how local equity investors respond to behavioural biases. This study addresses this gap by examining whether and how these biases influence investment decisions in these cities, providing fresh insights into investor behaviour at a regional level.

CHAPTER 3: RESEARCH METHODOLOGY

Conceptual Model / Conceptual Framework

Diagram 3.1 Conceptual Model /Conceptual Framework



(Source: Author's Compilation Based on LR with the help of IBM Amos-2023)

3.1 Statement of Problem

Investment decisions in equity markets are influenced not only by financial data but also by psychological factors. Investors often face hesitation or uncertainty due to behavioural biases such as overconfidence, anchoring, representativeness, cognitive dissonance, regret aversion, narrow framing, and mental accounting (Kahneman & Tversky, 1979). These biases can lead to irrational and emotional decision-making, preventing investors from achieving optimal financial outcomes. While traditional finance theories assume rational behaviour, real-world evidence shows that psychological influences strongly shape investment choices (Barberis & Thaler, 2003). This study aims to examine how behavioural biases affect the equity investment decisions of investors in selected cities of the Saurashtra region, including Junagadh, Rajkot, and Jamnagar. Insights from this research can help investors, advisors, and policymakers adopt strategies to reduce biases and encourage more rational investment behaviour.

3.3 Need for the study

This study was basically done by a researcher to identify the Behavioural biases that influence the investors of cities like Junagadh, Rajkot, and Jamnagar of the Saurashtra region. Also in the study, researcher showcase how demographic factors affect these behavioural biases while making equity investment decisions. From the existing literature review, lots of studies have been done in the field of behavioural finance and behavioural biases, but the significant thing is that there are very few studies that have taken place in the Saurashtra region, and especially, there were no studies that have been done for these three cities, Junagadh, Rajkot, and Jamnagar. In this study, efforts were made to indicate how such behavioural biases influence the investors while making equity investment decisions of the investors in the Saurashtra Region

3.4 Limitation of the Study

- This Research Consists of only Eight Behavioural Biases
- This Research covered only three cities, viz. Junagadh, Rajkot, and Jamnagar of the Saurashtra region.

3.5 Possible Outcome / Impact On Society

This research shows the investment behaviour of people of Junagadh, Rajkot, and Jamnagar cities of the Saurashtra region, Demographic factors affecting behavioural biases, and also represents the influencing Behavioural biases, which affect the behaviour of equity investors while making equity investment decisions.

This research is useful for listed companies, Public Companies, Merchant bankers, stock brokers, Mutual Fund companies, and many more investment companies, and also for researchers or research scholars for further research.

3.6 Research Objectives

1. To study the Demographic variables of equity investors.

2. To know the preference of people towards equity Investment.

3. To study the impact of Demographic Variables on Behavioural Biases in the Investment Decision of equity investors.

4. To Measure the Levels of Different Behavioural Biases among Individual Equity Investors

5. To Study the Impact of Behavioural Biases on Equity Investors while Making Investment Decisions.

Table 3.1: Summary of Sample Plan and Research Type

<table>
<tr><th>Component</th><th>Details</th></tr>
<tr><td>Research Type</td><td>Descriptive Research</td></tr>
<tr><td>Population</td><td>Residents of three selected cities of the Saurashtra region: Junagadh, Rajkot, and Jamnagar</td></tr>
<tr><td>Study Area</td><td>Junagadh, Rajkot, and Jamnagar cities of Gujarat</td></tr>
<tr><td>Sample Frame</td><td>Individuals residing in the selected cities who invest in equity markets</td></tr>
<tr><td>Sampling Unit</td><td>Individual equity investor</td></tr>
<tr><td>Sampling Technique</td><td>Non-probability convenience sampling</td></tr>
<tr><td>Inclusion Criteria</td><td>Equity investors willing to participate in the study, irrespective of gender, age, education, income level, or marital status</td></tr>
<tr><td>Exclusion Criteria</td><td>Individuals who do not invest in equity</td></tr>
<tr><td>Sample Size Determination</td><td>Estimated using Cochran’s (1977) formula at a 95% confidence level</td></tr>
<tr><td>Minimum Sample Size</td><td>246 respondents per city (as per Cochran’s (1977) formula)</td></tr>
<tr><td>Target Sample Size</td><td>300 respondents from each city</td></tr>
<tr><td>Actual Sample Collected</td><td>Total 1,061 valid responses</td></tr>
<tr><td>City-wise Data Collected</td><td>
<table>
<tr><th>City</th><th>Total Data Collected</th><th>Questionnaire</th><th>Google Form</th></tr>
<tr><td>Junagadh</td><td>306</td><td>146</td><td>160</td></tr>
<tr><td>Rajkot</td><td>372</td><td>274</td><td>98</td></tr>
<tr><td>Jamnagar</td><td>383</td><td>180</td><td>203</td></tr>
<tr><td>Total</td><td>1061</td><td>600</td><td>461</td></tr>
</table>
</td></tr>
<tr><td>Data Collection Tool</td><td>Structured questionnaire</td></tr>
<tr><td>Mode of Data Collection</td><td>Physical survey (600 out of 850 Distributed) and Google Form (461)</td></tr>
<tr><td>Source of Data</td><td>Primary data collected by the researcher</td></tr>
</table>

(Source: Authors’ Compilation)

CHAPTER 4: DATA ANALYSIS AND INTERPRETATION

The Present chapter discusses the Statistical tools and data analysis techniques used to analyze the data collected for the present study. The core objective is to interpret the data in a meaningful way so that the research objectives and established hypotheses can be properly examined. In this study, every statistical tool has been carefully selected to ensure that the findings are accurate, reliable, and relevant to the objective of the study.

This chapter evaluates the reliability and validity of the measurement instruments used in the study. Internal consistency of the structured questionnaire is assessed using **Cronbach's Alpha** through **IBM SPSS Statistics (2022)**, with all values meeting the acceptable threshold of 0.70, indicating reliable measurement in the following table 4.1.

Table 4.1: Reliability Test Cronbach's Alpha

Parameter	**Junagadh**	**Rajkot**	**Jamnagar**	**Overall**
Valid Cases	306	372	383	1061
Cronbach's Alpha	**0.864**	**0.832**	**0.864**	**0.867**
Number of Items	27	27	27	27

(Source: IBM SPSS-22 Cronbach's Alpha Output)

To further validate the measurement model, **PLS-SEM** analysis is conducted using **SmartPLS 4**. Construct reliability is examined through **Composite Reliability**, while **convergent validity** is established using the **Average Variance Extracted (AVE)**. All constructs satisfy the recommended criteria. **Discriminant validity** is assessed using the **Fornell–Larcker criterion** and the **HTMT ratio**, confirming that the constructs are distinct. Overall, the results demonstrate that the collected data are **statistically reliable and valid**, conforming to established methodological requirements. Detailed results are presented in the **(A) Measurement Model** on **Page No. 57-58**

OBJECTIVE 1:

To study the Demographic variables of equity investors.

Table 4.2: Demographic Variables Comparison Table of Junagadh, Rajkot, and Jamnagar.

Sr. No.	Variable	Category	Junagadh	Rajkot	Jamnagar	Key Points	Overall Interpretation
1	**Location**	–	306	372	383	Jamnagar has the highest number of investors	Jamnagar (383) has the largest investor base, followed by Rajkot (372) and Junagadh (306).
2	**Gender**	Male	250 (81.7%)	231 (62.1%)	276 (72.1%)	Male investors dominate	Male investors dominate in all cities — Junagadh (81.7%), Jamnagar (72.1%), and Rajkot (62.1%). Rajkot has the highest female participation at 37.9%.
		Female	56 (18.3%)	141 (37.9%)	107 (27.9%)	Rajkot has better female participation	
3	**Age Group**	18–25	182 (59.5%)	232 (62.4%)	121 (31.6%)	Youth-driven in Rajkot and Junagadh	Rajkot (62.4%) and Junagadh (59.5%) have the youngest investor base, while Jamnagar has a more balanced distribution with 27.2% aged 36–45.
		26–35	84 (27.5%)	89 (23.9%)	115 (30.0%)	Jamnagar attracts more mid-20s investors	
		36–45	24 (7.8%)	43 (11.6%)	104 (27.2%)	Jamnagar has more mature investors	
		46–55	12 (3.9%)	8 (2.2%)	36 (9.4%)	The older age bracket is higher in Jamnagar	
		56+	4 (1.3%)	0 (0%)	7 (1.8%)	Very few senior investors	

4	**Education**	Below HSC	16 (5.2%)	3 (0.8%)	6 (1.6%)	Low-educated mostly in Junagadh	Jamnagar has the most highly educated professionals (50.9%). Rajkot leads in undergrads (44.4%), while Junagadh shows a spread — Postgraduates (29.7%), Graduates (26.1%), and Undergraduates (23.9%).
		12th/HSC	32 (10.5%)	3 (0.8%)	13 (3.4%)	Moderate education is more in Junagadh	
		Undergraduate	73 (23.9%)	165 (44.4%)	86 (22.5%)	Rajkot leads in undergraduates	
		Graduate	80 (26.1%)	71 (19.1%)	44 (11.5%)	Junagadh has more graduates	
		Postgraduate	91 (29.7%)	57 (15.3%)	39 (10.2%)	Most postgraduates in Junagadh	
		Professional	14 (4.6%)	68 (18.3%)	195 (50.9%)	Jamnagar dominates in professionals	
		Others	–	5 (1.3%)	–	Rare category, only in Rajkot	
5	**Occupation**	Salaried	104 (34.0%)	123 (33.1%)	129 (33.7%)	The salaried class is consistent	Jamnagar has the highest number of professionals (30.0%), Rajkot shows a broader mix, and Junagadh leans toward business (19.6%) and students (33.7%).
		Businessman	60 (19.6%)	51 (13.7%)	19 (5.0%)	More businesspeople in Junagadh	
		Professional	15 (4.9%)	28 (7.5%)	115 (30.0%)	Jamnagar leads in professionals	
		Retired	2 (0.7%)	0 (0%)	2 (0.5%)	Very few retired investors	
		Housewife	4 (1.3%)	9 (2.4%)	3 (0.8%)	Highest in Rajkot	

		Student	103 (33.7%)	123 (33.1%)	107 (27.9%)	Active student base in all cities	
		Equity Trader	9 (2.9%)	7 (1.9%)	6 (1.6%)	Rare category	
		Others	9 (2.9%)	31 (8.3%)	2 (0.5%)	Rajkot has more diverse jobs	
6	**Annual Income**	Up to ₹2.5L	159 (52.0%)	228 (61.3%)	132 (34.5%)	Low-income dominates in Rajkot	Income rises from Rajkot (61.3% earn ≤ ₹2.5L), to Junagadh (30.7% earn ₹2.5L–₹5L), to Jamnagar (35.8% earn ₹5L–₹10L and 20.1% earn ₹10L+).
		₹2.5L–₹5L	94 (30.7%)	38 (10.2%)	37 (9.7%)	Mid-income more in Junagadh	
		₹5L–₹10L	41 (13.4%)	83 (22.3%)	137 (35.8%)	Jamnagar leads in mid-high earners	
		₹10L+	12 (3.9%)	23 (6.2%)	77 (20.1%)	High earners mostly in Jamnagar	
7	**Marital Status**	Married	93 (30.4%)	104 (28.0%)	218 (56.9%)	Jamnagar has more married investors	Jamnagar has a more settled investor base (56.9% married), while unmarried investors dominate Rajkot (70.7%) and Junagadh (69.0%).
		Unmarried	211 (69.0%)	263 (70.7%)	163 (42.6%)	Single investors dominate in Rajkot and Junagadh	
		Separated/Others	2 (0.6%)	5 (1.3%)	2 (0.6%)	Minimal	
8	**Family Type**	Nuclear	110 (35.9%)	131 (35.2%)	115 (30.0%)	More nuclear families in Rajkot and Junagadh	Joint families are common in all cities: Jamnagar (70.0%), Rajkot (64.8%), Junagadh (64.1%). Nuclear families are a minority.
		Joint	196 (64.1%)	241 (64.8%)	268 (70.0%)	Joint families dominate	
9	**Family Size**	Two	9 (2.9%)	14 (3.8%)	16 (4.2%)	Rare	Most families have more than four members: Jamnagar (64.5%), Rajkot

		Three	54 (17.6%)	49 (13.2%)	50 (13.1%)	Slightly more in Junagadh	(50.8%), Junagadh (46.4%). Shows a stronger joint family culture.
		Four	101 (33.0%)	120 (32.3%)	70 (18.3%)	Common in Junagadh & Rajkot	
		More than Four	142 (46.4%)	189 (50.8%)	247 (64.5%)	Most common in Jamnagar	
10	**Earning Members**	One	77 (25.2%)	142 (38.2%)	104 (27.2%)	More single earners in Rajkot	Dual-income families dominate — Jamnagar (54.0%), Rajkot (44.1%), Junagadh (45.4%). Rajkot also has the highest single-earner families (38.2%).
		Two	139 (45.4%)	164 (44.1%)	207 (54.0%)	Dual earners are the most in Jamnagar	
		Three	64 (20.9%)	43 (11.6%)	51 (13.3%)	More mid-sized earning families in Junagadh.	
		Four	18 (5.9%)	11 (3.0%)	11 (2.9%)	Slightly more in Junagadh.	
		More than Four	8 (2.6%)	12 (3.2%)	10 (2.6%)	Rare to find families with more than four earners.	

(Source: Authors' Compilation)

OBJECTIVE: 2

To know the preference of people towards equity Investment.

Table 4.3: Summary of Cross-tabulation of Junagadh, Rajkot, and Jamnagar Cities

Sr.No	Cross-Tabulation	Junagadh	Rajkot	Jamnagar
1	**Gender & Purpose of Investment**	Out of 306 respondents, 185 males and 47 females preferred investment, showing a strong focus on safe financial choices, particularly among women.	Of 372 respondents, 175 males and 113 females chose investment, reflecting a clear preference for long-term investment, especially among women.	Among 383 respondents, 202 males and 91 females opted for investment, indicating a dominant investment preference over trading or speculation, with women more inclined.
2	**Age & Trading Frequency**	Out of 306 respondents, the 18–25 age group (182) is most active in trading, with daily (36), weekly (51), monthly (41), and random (48) trades. Older age groups show less frequent trading.	Among 372 respondents, the 18–25 group (232) leads in trading, including daily (33), weekly (56), monthly (66), and random (66) trades. Trading declines with age.	Out of 383 respondents, the 26–35 (115) and 36–45 (104) groups trade most, mainly monthly or weekly. Younger (18–25) trade more randomly, while older groups trade less.
3	**Education & Preferred Mode of Trading**	Out of 306 respondents, 257 prefer online, 15 offline, and 34 both. Most postgraduates, graduates, and undergraduates mainly trade online.	Among 372 respondents, 331 choose online, 15 offline, and 26 both. Undergraduates, graduates, postgraduates, and all professionals mostly prefer online trading.	Out of 383 respondents, 361 prefer online, 5 offline, and 17 both. Professionals, undergraduates, graduates, and postgraduates largely trade online.

4	**Gender & Experience in Equity Investment**	Out of 306 respondents, 250 males and 56 females invest in equity. Most males have under 3 years of experience, while most females (37) have less than 1 year.	Among 372 respondents, 231 males and 141 females invest. Males are mostly new (<1 year) or experienced (>6 years), while most females (96) are new investors.	Out of 383 respondents, 276 males and 107 females invest. Males are largely experienced (>6 years), while females' experience is spread, with the highest in 3–6 years (33).
5	**Age & Self-Description as an Investor**	Out of 306 respondents, most investors are 18–25 (182), with 74 careful, 58 willing to take risks after research, and 18 high-risk takers. Older age groups show declining risk appetite.	Among 372 respondents, the 18–25 group (232) dominates, with 119 careful, 54 research-based risk-takers, and 36 high-risk. Risk-taking declines with age, with 26–35 showing mostly calculated risk.	Out of 383 respondents, 18–25 (121) prefer research-based risk (62) or careful investing (29). The 26–35 and 36–45 groups also favor informed risk-taking, while older groups are more cautious.
6	**Education & Preferred Mode of Trading**	Most investors trade up to ₹10,000, especially salaried (57) and students (54). Businessmen trade more in higher ranges, with 12 in ₹20,000–30,000 and 2 above ₹50,000.	Out of 372 respondents, 191 trade up to ₹10,000, mainly students (86) and salaried (42). Mid-range trades (₹10,000–30,000) are mostly salaried and professionals, while higher trades (>₹30,000) are less common.	Out of 383 respondents, 134 trade up to ₹10,000 (students 82, salaried 37). Higher trades (₹10,000–50,000+) are dominated by salaried and professionals, with the top bracket (>₹50,000) mainly professionals (32).

7	**Income & The number of companies**	Most investors earn up to ₹2.5 lakh (159), with 93 investing in 1–5 companies. Higher income groups invest slightly more widely, but the majority still limit themselves to 1–5 companies.	Out of 372 respondents, 228 earn up to ₹2.5 lakh, with 161 investing in 1–5 companies. Higher income groups (₹5–10 lakh and above) diversify more, investing in 5–20+ companies.	Among 383 respondents, lower-income investors (≤₹2.5 lakh) mostly invest in 1–5 companies, while higher-income groups (₹5–10 lakh and >₹10 lakh) increasingly diversify, with many investing in 15–20 or 20+ companies.
8	**Age & Source of Investment**	Out of 306 respondents, most rely on their own funds. In the 18–25 group, 152 use personal money, 26 both, and 4 borrow. Older age groups almost entirely use owned funds.	Among 372 respondents, younger investors (18–25) show more borrowing (44) or mixed funds (35), while older groups predominantly invest using their own money.	Of 383 respondents, self-funding dominates across all ages. For 18–25, 113 use personal funds, and older groups almost exclusively rely on owned money.
9	**Education & Preferred Sectors of Equity Investment**	Out of 306 respondents, highly educated investors—Postgraduates (91), Graduates (80), and Undergraduates (73)—prefer Banking, IT, and Energy. Lower-educated groups participate minimally.	Among 372 respondents, Undergraduates (165), Graduates (71), and Professionals (68) dominate, favoring Banking (225), IT (168), and FMCG (130). Lower education levels show minimal involvement.	Out of 383 respondents, Professionals (195) and Undergraduates (86) lead investments across all sectors, mainly Banking (262), IT (250), and FMCG (192). Lower-educated groups contribute very little.

10	**Gender, Source of Income/Investment & Education**	Most of 306 respondents treat money as both income and investment (135) or mainly as investment (133). Men, especially highly educated, dominate these groups.	Out of 372 respondents, 200 view money as investment, 98 as both, and 74 as income. Men lead, while women and undergraduates also prefer investment	Among 383 respondents, 239 see money as investment, 58 as both, and 86 as income. Men, particularly Professionals, dominate, with female undergraduates also active.

(Source: Authors' Compilation)

OBJECTIVE: 3

To study the impact of Demographic Variables on Behavioural Biases in the investment decision of equity investors.

In this study, the choice of statistical tools was made after considering the type of data collected and the purpose of each research objective. For **the present objective**, which focuses on understanding how demographic factors influence different behavioural biases among equity investors, **one-way ANOVA** was used. This test is appropriate because most demographic characteristics—such as gender, education level, occupation, marital status, and family structure—fall under categorical or group-based data. Behavioural biases, on the other hand, were measured on continuous scales. **one-way** ANOVA allows the comparison of the mean scores of these biases across several demographic groups at the same time. This makes it a suitable and efficient technique for identifying whether behavioural biases vary significantly according to differences in demographic backgrounds.

Table 4.4: Summary of ANOVA Test Results and Interpretation of Behavioural Biases Across Demographic Factors

Variables	Hypothesis					Interpretation
Age Groups **Behavioural Biases**	**H0:** Different **Age Groups** of respondents assign the same mean towards behavioural biases **H1:** Different **Age Groups** of respondents do not assign the same mean towards behavioural biases					**H0 Rejected for All Biases**
	Behavioural Bias	**F-value**	**P-value**	**Significant (p < 0.05)**	**Results**	The results show that people of different age groups differ significantly in all the behavioural biases studied, suggesting that age affects these tendencies.
	Overconfidence	6.634	**.000**	Yes	H0 Rejected	
	Familiarity	5.229	**.000**	Yes	H0 Rejected	
	Conformation Bias	9.17	**.000**	Yes	H0 Rejected	
	Regret Aversion	34.359	**.000**	Yes	H0 Rejected	
	Narrow Framing	20.203	**.000**	Yes	H0 Rejected	
	Shadow of the Past	12.522	**.000**	Yes	H0 Rejected	
	Loss Aversion	23.091	**.000**	Yes	H0 Rejected	
	Herd Instincts	11.901	**.000**	Yes	H0 Rejected	
Education Level **Behavioural Biases**	**H0:** Different **Education Levels** of respondents assign the same mean towards behavioural biases **H1:** Different **Education Levels** of respondents do not assign the same mean towards behavioural biases					**H0 Rejected for All Biases**
	Behavioural Bias	**F-value**	**P-value**	**Significant (p < 0.05)**	**Results**	The Result Shows That Different education levels
	Overconfidence	11.202	**.000**	Yes	H0 Rejected	

	Familiarity	13.609	**.000**	Yes	H0 Rejected	lead to significant differences in all the behavioural biases, suggesting that education affects all behavioural Biases
	Conformation Bias	12.947	**.000**	Yes	H0 Rejected	
	Regret Aversion	26.502	**.000**	Yes	H0 Rejected	
	Narrow Framing	19.205	**.000**	Yes	H0 Rejected	
	Shadow of the Past	9.641	**.000**	Yes	H0 Rejected	
	Loss Aversion	15.603	**.000**	Yes	H0 Rejected	
	Herd Instincts	13.62	**.000**	Yes	H0 Rejected	
Occupation **Behavioural Biases**	**H0:** Different **Occupations** of respondents assign the same mean towards behavioural biases **H1:** Different **Occupations** of respondents do not assign the same mean towards behavioural biases					**H0 Rejected for All Biases**
	Behavioural Bias	**F-value**	**P-value**	**Significant (p < 0.05)**	**Results**	The analysis shows that occupation significantly affects all behavioural biases, with different occupational groups exhibiting varying tendencies
	Overconfidence	10.051	**.000**	Yes	H0 Rejected	
	Familiarity	4.75	**.000**	Yes	H0 Rejected	
	Conformation Bias	8.864	**.000**	Yes	H0 Rejected	
	Regret Aversion	19.423	**.000**	Yes	H0 Rejected	
	Narrow Framing	20.385	**.000**	Yes	H0 Rejected	
	Shadow of the Past	7.841	**.000**	Yes	H0 Rejected	
	Loss Aversion	12.163	**.000**	Yes	H0 Rejected	

	Herd Instincts	12.423	**.000**	Yes	H0 Rejected	
Income **Behavioural Biases**	**H0:** Different **Income Levels** of respondents assign the same mean towards behavioural biases **H1:** Different **Income Levels** of respondents do not assign the same mean towards behavioural biases					**H0 Rejected for All Biases**
	Behavioural Bias	**F-value**	**P-value**	**Significant (p < 0.05)**	**Results**	The results show that people with different income levels vary significantly in all the behavioural biases studied, suggesting that income plays a role in these tendencies
	Overconfidence	27.24	**.000**	Yes	H0 Rejected	
	Familiarity	15.733	**.000**	Yes	H0 Rejected	
	Conformation Bias	16.832	**.000**	Yes	H0 Rejected	
	Regret Aversion	48.754	**.000**	Yes	H0 Rejected	
	Narrow Framing	31.545	**.000**	Yes	H0 Rejected	
	Shadow of the Past	18.092	**.000**	Yes	H0 Rejected	
	Loss Aversion	39.278	**.000**	Yes	H0 Rejected	
	Herd Instincts	18.875	**.000**	Yes	H0 Rejected	
Marital Status **Behavioural Biases**	**H0:** Different **Marital statuses** of respondents assign the same mean towards behavioural biases **H1:** Different **Marital Statuses** of respondents do not assign the same mean towards behavioural biases					**H0 Rejected for All Biases**
	Behavioural Bias	**F-value**	**P-value**	**Significant (p < 0.05)**	**Results**	The findings indicate that respondents' marital status
	Overconfidence	5.042	**0.002**	Yes	H0 Rejected	

	Familiarity	3.805	**0.01**	Yes	H0 Rejected	significantly affects all behavioural biases, showing that these tendencies vary across different marital groups.
	Conformation Bias	6.515	**.000**	Yes	H0 Rejected	
	Regret Aversion	26.038	**.000**	Yes	H0 Rejected	
	Narrow Framing	16.021	**.000**	Yes	H0 Rejected	
	Shadow of the Past	7.165	**.000**	Yes	H0 Rejected	
	Loss Aversion	16.432	**.000**	Yes	H0 Rejected	
	Herd Instincts	12.191	**.000**	Yes	H0 Rejected	
Family Type **Behavioural Biases**	**H0:** Different **Family types** of respondents assign the same mean towards behavioural biases **H1:** Different **Family types** of respondents do not assign the same mean towards behavioural biases					**H0 Rejected for 7 Biases** **H0 Accepted for** Familiarity
	Behavioural Bias	**F-value**	**P-value**	**Significant ($p < 0.05$)**	**Results**	The results indicate that family type affects most behavioural biases, except familiarity, which does not vary significantly across family types
	Overconfidence	7.15	**0.008**	Yes	H0 Rejected	
	Familiarity	1.576	**0.21**	No	H0 Accepted	
	Conformation Bias	4.941	**0.026**	Yes	H0 Rejected	
	Regret Aversion	9.974	**0.002**	Yes	H0 Rejected	
	Narrow Framing	6.745	**0.01**	Yes	H0 Rejected	
	Shadow of the Past	9.115	**0.003**	Yes	H0 Rejected	
	Loss Aversion	8.277	**0.004**	Yes	H0 Rejected	
	Herd Instincts	6.733	**0.01**	Yes	H0 Rejected	

Number of Family Members **Behavioural Biases**	**H0:** Different **numbers of Family Members** of respondents assign the same mean towards behavioural biases **H1:** Different **numbers of Family Members** of respondents do not assign the same mean towards behavioural biases					**H0 Rejected for 4 Biases** **H0 Accepted for** Overconfidence, Familiarity, Conformation Bias, Narrow Framing
	Behavioural Bias	**F-value**	**P-value**	**Significant ($p < 0.05$)**	**Results**	The number of family members significantly affects certain behavioural biases—regret aversion, shadow of the past, loss aversion, and herd instincts—while having no significant impact on overconfidence, familiarity, confirmation bias, or narrow framing
	Overconfidence	0.669	**0.571**	No	H0 Accepted	
	Familiarity	0.501	**0.681**	No	H0 Accepted	
	Conformation Bias	1.709	**0.163**	No	H0 Accepted	
	Regret Aversion	4.939	**0.002**	Yes	H0 Rejected	
	Narrow Framing	0.957	**0.412**	No	H0 Accepted	
	Shadow of the Past	3.278	**0.02**	Yes	H0 Rejected	
	Loss Aversion	3.703	**0.011**	Yes	H0 Rejected	
	Herd Instincts	5.076	**0.002**	Yes	H0 Rejected	
Number of Earning Members **Behavioural Biases**	**H0:** Different **Numbers of Earning Members** of respondents assign the same mean towards behavioural biases **H1:** Different **Numbers of Earning Members** of respondents do not assign the same mean towards behavioural biases					**H0 Rejected for 6 Biases** **H0 Accepted for** Overconfidence, Familiarity

	Behavioural Bias	F-value	P-value	Significant ($p < 0.05$)	Results	
	Overconfidence	0.47	**0.758**	No	H0 Accepted	The number of earning members in a family significantly influences several behavioural biases—confirmation bias, regret aversion, narrow framing, shadow of the past, loss aversion, and herd instincts—while it has no significant effect on overconfidence and familiarity.
	Familiarity	2.125	**0.076**	No	H0 Accepted	
	Conformation Bias	4.399	**0.002**	Yes	H0 Rejected	
	Regret Aversion	4.254	**0.002**	Yes	H0 Rejected	
	Narrow Framing	3.132	**0.014**	Yes	H0 Rejected	
	Shadow of the Past	2.807	**0.025**	Yes	H0 Rejected	
	Loss Aversion	3.549	**0.007**	Yes	H0 Rejected	
	Herd Instincts	3.854	**0.004**	Yes	H0 Rejected	

(Source: Authors' Compilation)

Findings

Age

To examine the effect of age on behavioural biases, an ANOVA was conducted, revealing significant differences across age groups ($p < 0.05$). **Overconfidence** was highest in the 56+ group (4.32) and lowest in the 18–25 (3.39). **Familiarity** was highest in 46–55 (4.07) and lowest in 18–25 (3.77). **Confirmation bias** peaked in 46–55 (3.86) and was lowest in 18–25 (3.54). **Regret aversion** was highest in 36–45 (3.89) and lowest in 56+ (2.91). **Narrow framing** was highest in 56+ (4.24) and lowest in 18–25 (3.63). **Shadow of the past** and **loss aversion** were highest in 36–45 (4.01 and 3.92) and lowest in 56+ (3.23 and 3.16). **Herd instincts** were highest in 36–45 (3.59) and lowest in 18–25 (3.13). In short, All the behavioural

biases generally increase with age, peaking in middle-aged to older adults, with some decline in the oldest group.

Education Level:

To examine the effect of education level on behavioural biases, an ANOVA was conducted, revealing significant differences across education groups ($p < 0.05$). **Overconfidence** was highest in the Professional group (3.80) and lowest in Others (2.35). **Familiarity** was highest in the Professional group (4.23) and lowest in Others (2.30). **Confirmation bias** peaked in the Professional group (3.92) and was lowest in Others (2.80). **Regret aversion** was highest in the Professional group (3.98) and lowest in Others (2.40). **Narrow framing** was highest in the Professional group (4.20) and lowest in Others (3.40). **Shadow of the past** and **loss aversion** were highest in the Professional group (4.05 and 3.94) and lowest in Others (2.80 and 3.12). **Herd instincts** were highest in the Professional group (3.74) and lowest in Undergraduates (3.07). Overall, behavioural biases generally increase with higher education levels, with Professionals consistently exhibiting the highest means across all factors.

Occupation:

To examine the effect of occupation on behavioural biases, an ANOVA was conducted, revealing significant differences across occupational groups ($p < 0.05$). **Overconfidence** was highest among Professionals (3.90) and lowest among Housewives (2.78). **Familiarity** peaked in Professionals (4.21) and was lowest in Retired participants (3.38). **Confirmation bias** was highest in Professionals (3.96) and lowest in Others (3.28). **Regret aversion** was highest in Professionals (3.92) and lowest in Equity Traders (2.83). **Narrow framing** was highest in Professionals (4.26) and lowest in Others (3.07). **Shadow of the past** and **loss aversion** were highest in Professionals (4.00 and 3.91) and lowest in Retired participants (2.63) and Others (3.02), respectively. **Herd instincts** were highest in Retired participants (3.75) and

Professionals (3.74) and lowest in Equity Traders (2.64). Overall, behavioural biases tend to be strongest among professionally employed participants, while the lowest means are observed in retirees, housewives, equity traders, and other minor occupational groups, indicating occupation plays a significant role in shaping decision-making tendencies.

Income:

To examine the effect of income on behavioural biases, an ANOVA was conducted, revealing significant differences across income groups ($p < 0.05$). **Overconfidence** was highest in the 10,00,000 and above group (4.03) and lowest in the up to 2,50,000 group (3.31). **Familiarity** peaked in the 5,00,000 to 10,00,000 group (4.17) and was lowest in the up to 2,50,000 group (3.73). **Confirmation bias** was highest in the 5,00,000 to 10,00,000 group (3.86) and lowest in the up to 2,50,000 group (3.53). **Regret aversion** reached its maximum in the 5,00,000 to 10,00,000 group (4.02) and minimum in the up to 2,50,000 group (3.23). **Narrow framing** was highest in the 10,00,000 and above group (4.21) and lowest in the up to 2,50,000 group (3.61). **Shadow of the past** and **loss aversion** were highest in the 5,00,000 to 10,00,000 group (4.07 and 4.01) and lowest in the up to 2,50,000 group (3.60 and 3.45), respectively. **Herd instincts** were highest in the 5,00,000 to 10,00,000 group (3.68) and lowest in the up to 2,50,000 group (3.15). Overall, behavioural biases generally increase with higher income levels, with the 5,00,000 to 10,00,000 and 10,00,000+ groups showing the highest means across most factors, while the lowest-income group consistently shows the lowest means.

Marital Status:

To examine the effect of marital status on behavioural biases, an ANOVA was conducted, revealing significant differences across marital groups ($p < 0.05$). **Overconfidence** was highest among Married participants (3.61) and lowest in the Others category (3.19). **Familiarity** peaked in Married participants (3.998) and was lowest in the Unmarried group (3.81).

Confirmation bias was highest in Married participants (3.77) and lowest in Separated participants (3.32). **Regret aversion** reached its maximum in Married participants (3.78) and minimum in Unmarried participants (3.29). **Narrow framing** was highest in Married participants (4.03) and lowest in Others (3.33). **Shadow of the past** and **loss aversion** were highest in Married participants (3.89 and 3.81) and lowest in Others (3.25 and 3.20), respectively. **Herd instincts** were highest in Others (3.58) and Married participants (3.55) and lowest in Unmarried participants (3.18). Overall, behavioural biases tend to be strongest among married individuals, while unmarried and other minor groups generally exhibit lower mean scores, indicating marital status significantly influences decision-making tendencies.

Family Type:

To examine the effect of the number of family members on behavioural biases, an ANOVA was conducted. For most biases, no significant differences were observed across family sizes ($p > 0.05$), including overconfidence, familiarity, confirmation bias, and narrow framing. However, significant differences were found in regret aversion ($p = 0.002$), shadow of the past ($p = 0.020$), loss aversion ($p = 0.011$), and herd instincts ($p = 0.002$). **Regret aversion** was highest among families with more than four members (3.57) and lowest in families of four members (3.32). **Shadow of the past** peaked in families with more than four members (3.81) and was lowest in four-member families (3.62). **Loss aversion** was highest in families with more than four members (3.68) and lowest in four-member families (3.51). **Herd instincts** were also highest in families with more than four members (3.43) and lowest in four-member families (3.17). Overall, larger family sizes tend to exhibit slightly higher tendencies for certain behavioral biases, particularly in regret aversion, past experiences, loss aversion, and herd behavior, while other biases remain largely unaffected by family size.

Number of Family Members:

The ANOVA was conducted to examine the effect of the number of family members on behavioral biases. The results showed significant differences for regret aversion, shadow of the past, loss aversion, and herd instincts ($p < 0.05$), while overconfidence, familiarity, confirmation bias, and narrow framing were not significant ($p > 0.05$). **Regret aversion** was highest in families with more than four members (3.5681) and lowest in families with four members (3.3184). The **shadow of the past** was highest in families with more than four members (3.8140) and lowest in families with three members (3.7059). **Loss aversion** was highest in families with more than four members (3.6796) and lowest in families with four members (3.5086). **Herd instincts** were highest in families with more than four members (3.4308) and lowest in families with four members (3.1684). Overall, behavioural biases tend to be higher in families with more than four members and relatively lower in families with four or fewer members.

Number of Earning Members:

To examine the effect of the number of earning members in a family on behavioural biases, an ANOVA was conducted. The results showed significant differences for confirmation bias, regret aversion, narrow framing, shadow of the past, loss aversion, and herd instincts ($p < 0.05$), while overconfidence and familiarity were not significant ($p > 0.05$). **Confirmation bias** was highest in families with three earning members (3.78) and lowest in families with more than four earning members (3.35). **Regret aversion** peaked in families with three earning members (3.62) and was lowest in families with more than four earning members (3.07). **Narrow framing** was highest in families with three earning members (3.93) and lowest in families with one earning member (3.71). **Shadow of the past** was highest in families with two earning members (3.80) and lowest in families with more than four earning members (3.40). **Loss**

aversion was highest in families with three earning members (3.74) and lowest in families with four earning members (3.46). **Herd instincts** were highest in families with three earning members (3.44) and lowest in families with more than four earning members (3.03). Overall, behavioral biases tend to be higher in families with two to three earning members and relatively lower in families with more than four earning members.

OBJECTIVE:4

To measure the Levels of Different Behavioural Biases among Individual Equity Investors of Selected cities of the Saurashtra Region.

Equity investment decisions are often influenced by psychological factors rather than pure rational analysis. Investors commonly rely on mental shortcuts and emotions, leading to behavioural biases such as overconfidence, loss aversion, herd behaviour, anchoring, and regret aversion, which directly affect investment outcomes. Understanding these biases helps explain why investors frequently deviate from rational financial theories under uncertainty and market pressure. To examine this, the study develops a Behavioural Bias Index covering eight key biases among equity investors from Junagadh, Rajkot, and Jamnagar. The index is constructed using responses from 1,061 participants to 27 Likert-scale statements, with weighted scoring applied to quantify behavioural tendencies (Bozorg-Haddad, et al., 2021)

PTO

Research Design

This study uses a descriptive and quantitative research design to examine behavioural biases among equity investors. Primary data were collected through a structured questionnaire from 1,061 respondents in the Saurashtra region, covering Junagadh (306), Rajkot (372), and Jamnagar (384). The questionnaire included 27 statements representing eight behavioural biases, which respondents rated on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5), allowing effective measurement and comparison of investor behaviour.

Weighted Likert Scoring:

Concept and Procedure

Since each statement reflects the respondent's behavioural inclination, the study used a **weighted Likert scoring system** to convert the responses into numerical values. In this method, every category on the scale is assigned a weight (w_i), and the number of people selecting each category is recorded as a frequency (f_i).(Bozorg-Haddad, et al., 2021)

The weighted value for each statement is determined using the following formula:

Weighted Score =

$$\sum_{i=1}^{5}(f_i \times w_i)$$

Explanation of the Sigma (∑) Symbol

The summation sign (∑) indicates that the values inside the expression are repeatedly added. The upper value "5" represents the total number of response options on the Likert scale. Thus, for each statement, the calculation adds together five separate products.

Table 4.5: Explanation of equation with Frequency and weight

▪ ***(f1* x *w1)***	▪ (frequency of Strongly Disagree × weight 1)
▪ ***(f2* x *w2)***	▪ (frequency of Disagree × weight 2)
▪ ***(f3* x *w3)***	▪ (frequency of Neutral × weight 3)
▪ ***(f4* x *w4)***	▪ (frequency of Agree × weight 4)
▪ ***(f5* x *w5)***	▪ (frequency of Strongly Agree × weight 5)

(Source: Authors' Compilation)

Table 4.6: Likert Scale Response Categories and Corresponding Weights

Response Category (f_i)	**Weight (w_i)**
Strongly Disagree (1)	1
Disagree (2)	2
Neutral (3)	3
Agree (4)	4
Strongly Agree (5)	5

(Source: Authors' Compilation)

This structure ensures that stronger agreement carries a higher numerical value, which helps in identifying the strength of a given Behavioural Bias.

Illustrative Calculation

For clarity, consider the statement of overconfidence Bias:

"I take more risks because I have confidence in my abilities."

Assume the following frequencies were recorded:

- 78 respondents – Strongly Disagree
- 164 respondents – Disagree
- 263 respondents – Neutral
- 357 respondents – Agree
- 199 respondents – Strongly Agree

The weighted score becomes:

(78×1) + (164×2) + (263×3) + (357×4) + (199×5) =3618

A single number, such as **3618,** summarizes both how many people responded in each category and the strength of their selection.

Construction of the Behavioural Bias Index

Let a behavioural bias be measured with **k** different statements. The weighted score for each statement is calculated separately. The index value for that bias is then obtained by either summing or averaging these scores. In this study, indexing was done using the mean of the weighted scores (Bozorg-Haddad, et al., 2021)

$$\text{Bias Index} = \frac{\sum_{j=1}^{k} S_j}{k}$$

Where:

- $\mathbf{S_j}$ = weighted score of statement j
- **k** = number of items used to measure the bias

Example: Overconfidence Index

Table 4.7: four statements, the Overconfidence Index with weighted scores:

Statement		Weighted Score
S1	I have sufficient knowledge of Indian stock market.	3505
S2	I am confident of my ability to pick better stocks than others.	3663
S3	I take more risks because I have confidence in my abilities.	3618
S4	I trust my ability to start and manage the investments.	4011

(Source: Authors' Compilation)

The index becomes:

$$\frac{3505+3663+3618+4011}{4} = \mathbf{3699.25}$$

This value represents the average intensity of overconfidence bias among all surveyed investors.

Classification of Bias Intensity

To interpret the index values meaningfully, theoretical minimum and maximum values were computed:

- **Minimum** possible score = total respondents × 1
  = 1061 × 1 = **1061**
- **Maximum** possible score = total respondents × 5
  = 1061 × 5 = **5305**

Based on this scale, the following interpretation ranges were used:

Table 4.8: Behavioural Bias Index Score Range

Score Range	Interpretation
1061–2122	Unbiased
2123–3183	Neutral
3184–4244	Biased
4245–5305	Highly Biased

(Source: Authors' Compilation)

These ranges help determine whether a particular bias is weak, moderate, or strong in the target population.

Table 4.9: Behavioural Bias Impact Index (BBII)

Behavioural Bias	1061–2122 = Unbiased	2123–3183 = Neutral	3184–4244 = Biased	4245–5305 = Highly Biased
Overconfidence Bias	-	-	**3699.25**	-
Familiarity Bias	-	-	**4123**	-
Confirmation Bias	-	-	**3881.2**	-
Regret Aversion	-	-	**3696.66**	-
Narrow Framing	-	-	**4061.13**	-
Shadow Of The Past	-	-	**3971.5**	-
Loss Aversion	-	-	**3843.4**	-
Heard Instincts	-	-	**3530.66**	-

(Source: Authors' Compilation)

Interpretation:

All eight behavioural bias indices are firmly in the Biased range (3184–4244), confirming that investors in Junagadh, Rajkot, and Jamnagar are heavily influenced by Behavioural Biases. Familiarity Bias and Narrow Framing are particularly strong, showing comfort-driven and segmented decision-making. Even Herd Instincts, although lower than other biases, still contribute to investment decisions. The Neutral (2123–3183) and Unbiased (1061–2122) ranges serve as benchmarks, emphasizing how far investors' actions diverge from rational and balanced behaviour.

Findings

The findings indicate that Investors located in the three cities, namely Junagadh, Rajkot, and Jamnagar, consistently exhibit behavioural biases, indicating a strong psychological component in their financial decision-making. The widespread presence of bias across the

sample suggests that cognitive shortcuts and emotional tendencies significantly influence investment behaviour, regardless of demographic differences.

Familiarity Bias emerged as the most dominant. Investors gravitate toward what feels safe or well-known, which aligns with established behavioural finance research. While familiarity creates comfort, it also increases exposure to company-specific risk due to poor diversification.

Narrow Framing and Shadow of the Past also scored high, suggesting that many investors focus narrowly on specific securities or rely on previous experiences rather than evaluating overall portfolio strategy or current market data. Such tendencies can distort risk perceptions and hinder objective decision-making.

Overconfidence Bias indicates that a significant number of investors assume they have superior judgment or expertise, which can lead to overtrading and greater risk exposure—an observation commonly discussed in behavioural finance research.

Confirmation Bias and Loss Aversion were also prominent. These biases strengthen pre-existing beliefs and lead investors to retain losing positions longer than optimal, thereby diminishing potential returns. Even though Herd Instincts scored lowest among the eight biases, their presence still indicates that peer decisions influence investor actions, particularly during market volatility.

Overall, the findings reaffirm that investor behaviour is shaped by predictable psychological patterns rather than pure rationality. This emphasizes the importance of tailored investor education programs, behaviourally informed financial advice, and policy interventions that help investors make more thoughtful and informed decisions.

Table 4.10: Calculation of Behavioural Biases Index - Weighted Behavioural Bias Scale (WBBS)

Behavioural Bias	No.	Statement	Total Respondents [Junagadh-306] [Rajkot-372] [Jamnagar-384]	Strongly Disagree (n x 1)	Disagree (n x 2)	Neutral (n x 3)	Agree (n x 4)	Strongly Agree (n x 5)	Weighted Likert Scale Scoring	Weighted by Behavioural Bias
Overconfidence Bias	1	**I have sufficient knowledge of Indian stock market.** (Prosad, 2014)	1061	54 × 1 = 54	195 × 2 = 390	287 × 3 = 861	425 × 4 = 1700	100 × 5 = 500	**3505**	Overconfidence Bias **3699.25**
	2	**I am confident of my ability to pick better stocks than others.** (Prosad, 2014)	1061	44 × 1 = 44	180 × 2 = 360	252 × 3 = 756	422 × 4 = 1688	163 × 5 = 815	**3663**	
	3	**I take more risks because I have confidence in my abilities.** (Malik, 2020)	1061	78 × 1 = 78	164 × 2 = 328	263 × 3 = 789	357 × 4 = 1428	199 × 5 = 995	**3618**	
	4	**I trust my ability to start and manage the investments.** (Parvathy, 2022)	1061	36 × 1 = 36	76 × 2 = 152	204 × 3 = 612	514 × 4 = 2056	231 × 5 = 1155	**4011**	
Familiarity Bias	5	**I have a tendency to make investment in only those avenues in which I am familiar with.** (Sukanya, 2019)	1061	26 × 1 = 26	99 × 2 = 198	191 × 3 = 573	447 × 4 = 1788	298 × 5 = 1490	**4075**	Familiarity Bias **4123**
	6	**I select the Shares of companies which I already know.** (Sudarshan, 2022)	1061	29 × 1 = 29	87 × 2 = 174	151 × 3 = 453	455 × 4 = 1820	339 × 5 = 1695	**4171**	
Confirmation Bias	7	**I hold into securities that I have inherited, regardless of whether retaining those**	1061	72 × 1 = 72	196 × 2 = 392	270 × 3 = 810	358 × 4 = 1432	165 × 5 = 825	**3531**	Confirmation Bias **3881.2**

		securities is financially wise or not. (Sukanya, 2019)								
	8	**I collect maximum information from experts about Equities to confirm my investment decisions.** (Sudarshan, 2022)	1061	33 × 1 = 33	110 × 2 = 220	193 × 3 = 579	436 × 4 = 1744	289 × 5 = 1445	**4021**	
	9	**I hold the Equities when the price decreases, even if it increases the loss.** (Sudarshan, 2022)	1061	68 × 1 = 68	200 × 2 = 400	203 × 3 = 609	392 × 4 = 1568	198 × 5 = 990	**3635**	
	10	**I study the nature of Equity and search for information while making investments.** (Sudarshan, 2022)	1061	35 × 1 = 35	74 × 2 = 148	131 × 3 = 393	516 × 4 = 2064	305 × 5 = 1525	**4165**	
	11	**I seek market news that confirms my investment decision as correct.** (Sudarshan, 2022)	1061	31 × 1 = 31	81 × 2 = 162	171 × 3 = 513	542 × 4 = 2168	236 × 5 = 1180	**4054**	
Regret Aversion	12	**I regret when I find a stock; I have considered buying it but did not went up in value.** (Swati, 2021)	1061	52 × 1 = 52	143 × 2 = 286	247 × 3 = 741	381 × 4 = 1524	238 × 5 = 1190	**3793**	**Regret Aversion 3696.66**
	13	**While selling a stock, you become emotionally affected by the price at which you purchased the stock.** (Swati, 2021)	1061	66 × 1 = 66	170 × 2 = 340	220 × 3 = 660	351 × 4 = 1404	254 × 5 = 1270	**3740**	
	14	**I avoid selling a stock to avoid the regret of having made a bad investment.** (Swati, 2021)	1061	86 × 1 = 86	179 × 2 = 358	224 × 3 = 672	419 × 4 = 1676	153 × 5 = 765	**3557**	
Narrow Framing	15	**I tend to treat each element of my investment portfolio separately.** (Sudarshan, 2022)	1061	22 × 1 = 22	80 × 2 = 160	202 × 3 = 606	499 × 4 = 1996	258 × 5 = 1290	**4074**	**Narrow Framing 4061.13**
	16		1061						**4135**	

		I save a part of my income for investing in the stock market. (Sudarshan, 2022)		50 × 1 = 50	81 × 2 = 162	142 × 3 = 426	443 × 4 = 1772	345 × 5 = 1725		
	17	**I classify my money into different accounts based on investment objectives, like money kept aside for insurance, money kept aside for investing in retirement schemes, Equity shares, etc.** (Sukanya, 2019)	1061	35 × 1 = 35	115 × 2 = 230	197 × 3 = 591	451 × 4 = 1804	263 × 5 = 1315	**3975**	
Shadow Of The Past	18	**I avoid investing in Equity that have performed poorly in the recent past.** (Sudarshan, 2022)	1061	57 × 1 = 57	142 × 2 = 284	181 × 3 = 543	435 × 4 = 1740	246 × 5 = 1230	**3854**	**Shadow Of The Past 3971.5**
	19	**I tend to invest more when I am successful in my previous Equity investments.** (Sudarshan, 2022)	1061	24 × 1 = 24	82 × 2 = 164	191 × 3 = 573	492 × 4 = 1968	272 × 5 = 1360	**4089**	
Loss Aversion	20	**The pain of financial loss is greater than the pleasure of financial gain.** (Sudarshan, 2022)	1061	37 × 1 = 37	100 × 2 = 200	200 × 3 = 600	415 × 4 = 1660	309 × 5 = 1545	**4042**	**Loss Aversion 3843.4**
	21	**I tend to hold onto losing Equity too long, hoping for a reversal.** (Sudarshan, 2022)	1061	60 × 1 = 60	141 × 2 = 282	243 × 3 = 729	404 × 4 = 1616	213 × 5 = 1065	**3752**	
	22	**I feel more sorrow about holding onto losing Equity too long than about selling winning Equity too soon.** (Sudarshan, 2022)	1061	50 × 1 = 50	167 × 2 = 334	256 × 3 = 768	399 × 4 = 1596	189 × 5 = 945	**3693**	
	23	**I would feel very bad if I buy something and it goes down.** (Parvathy, 2022)	1061	37 × 1 = 37	129 × 2 = 258	202 × 3 = 606	456 × 4 = 1824	237 × 5 = 1185	**3910**	

	24	**I am willingly remain in a risky stock position, hoping the price will bounce back.** (Swati, 2021)	1061	52 × 1 = 52	137 × 2 = 274	214 × 3 = 642	438 × 4 = 1752	220 × 5 = 1100	**3820**	
Heard Instincts	25	**Other investors' decisions of buying and selling stocks have impact on my investment decisions.** (Swati, 2021)	1061	79 × 1 = 79	220 × 2 = 440	231 × 3 = 693	365 × 4 = 1460	166 × 5 = 830	**3502**	**Heard Instincts 3530.66**
	26	**I usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market.** (Swati, 2021)	1061	105 × 1 = 105	236 × 2 = 472	218 × 3 = 654	344 × 4 = 1376	158 × 5 = 790	**3397**	
	27	**Discussing my investment decisions with colleagues reduces my pressure of being successful.** (Prosad, 2014)	1061	89 × 1 = 89	162 × 2 = 324	197 × 3 = 591	376 × 4 = 1504	237 × 5 = 1185	**3693**	

(Source: Authors' Compilation)

Individual Equity Investor Behavioural Bias Index

(Behavioural Bias Level Index) (BBLI)

Introduction

Behavioural biases play a crucial role in shaping investors' decisions in the stock market. Identifying these biases is crucial, as they may result in irrational or emotionally influenced decisions that can adversely affect investment performance. Key behavioural biases include overconfidence, familiarity bias, confirmation bias, regret aversion, narrow framing, past performance influence, loss aversion, and herd behaviour.

To measure these tendencies, surveys using a Likert-scale format are commonly employed. Respondents indicate their level of agreement with statements related to their investment behaviour, allowing a quantitative assessment of biases.

Methodology

Questionnaire Survey Design:

- A total of 27 statements covering eight behavioural biases were presented to respondents.
- Responses were recorded on a 5-point Likert scale:
    - 1 = Strongly Disagree
    - 2 = Disagree
    - 3 = Neutral
    - 4 = Agree
    - 5 = Strongly Agree

Data Collection:

- A structured questionnaire survey was carried out among 1061 Equity investors across Junagadh, Rajkot, and Jamnagar cities of the Saurashtra Region.

Scoring and Bias Assessment:

- Each respondent's score is obtained by adding their responses to all 27 statements.
- Maximum possible score: 27 × 5 = 135
- Behavioural Bias percentage is calculated using the formula:

$$\text{Behavioural Bias (\%)} = \frac{\text{Respondent's Total Score}}{\textbf{Maximum Possible Score (135)}} \times 100$$

For Illustration, Respondent No. 1 of this survey is considered.

4 + 4 + 4 + 4 + 2 + 4 + 2 + 4 + 2 + 4 + 4 + 3 + 4 + 2 + 4 + 4 + 4 + 3 + 4 + 2 + 4 + 2 + 3 + 4 + 3 + 4 + 4 = **91**

$$\text{Behavioural Bias (\%)} = \frac{\text{Respondent's Total Score}}{\text{Maximum Possible Score (135)}} \times 100 = \frac{91}{135} \times 100 = 67.41$$

A bias percentage of 67.41% places the respondent in the **High Bias** category, indicating that their investment decisions are notably influenced by behavioural tendencies.

Table 4.11: Behavioural Bias Level Classification:

Bias Percentage	Interpretation
0–40%	Unbiased
41–60%	Moderate Bias
61–80%	High Bias
81–100%	Very High Bias

(Source: Authors' Compilation)

Table 4.12: Bias Level Evaluation Based on Percentages

Respondent No.	Total Score	% of Biasedness	Interpretation
1	91	67.41%	High Bias
2	92	68.15%	High Bias
3	83	61.48%	High Bias
4	92	68.15%	High Bias
5	90	66.67%	High Bias
6	86	63.70%	High Bias
7	86	63.70%	High Bias
8	92	68.15%	High Bias
9	91	67.41%	High Bias
10	93	68.89%	High Bias

(Source: Authors' Compilation)

The table presents the total scores and corresponding percentages for the first 10 respondents, along with an interpretation indicating whether the respondents display behavioural bias. Using this method, the Behavioural Bias Level Index (BBLI) or Score can be calculated for all 1,061 respondents from the cities of Junagadh, Rajkot, and Jamnagar. This index provides a standardized measure of each investor's behavioural bias, categorizing it into four levels: Unbiased, Moderate Bias, High Bias, or Very High Bias.

This concept allows each respondent's behavioural bias level to be quantified and categorized. Measuring bias percentages across multiple participants or regions can reveal patterns and highlight areas where investor education or behavioural interventions may be most needed.

Individual Equity Investor Behavioural Bias Scale

Equity Investment Behavioural Bias Assessment Scale (EIBBAS)

Introduction:

This study examines eight prominent behavioural biases—Overconfidence, Familiarity, Confirmation, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instinct—through a structured 27-item questionnaire using a Likert scale. Scores for each bias are computed, expressed as percentages, and categorized into four levels: Low, Moderate, High, and Very High. The findings provide insights into the primary Behavioural Biases influencing the respondent's investment decision-making process.

The study adopted a quantitative approach to examine the behavioural biases affecting investors' decision-making. The design focused on measuring the extent to which eight specific biases influence investment choices.

Equation for Scoring and Calculation of Individual Behavioural Bias

The score for each bias was calculated by summing the responses of the items related to that bias:

Bias Score = ∑ (responses for that bias)

The maximum possible score for each bias was determined as:

Maximum Score = Number of Items x 5

The percentage of each bias was then calculated using:

$$\text{Bias\%} = \frac{\text{Bias Score}}{\text{Maximum Score}} \times 100$$

Illustrative Calculation:

1. **Overconfidence (Q1-Q4)**

   OC Score = Q1 + Q2 + Q3 + Q4 = 4 + 4 + 4 + 4 = 16

   Maximum Score = 4 × 5 = 20

   OC% = $\frac{16}{20}$ **× 100 = 80%**

Interpretation: High Bias – respondent shows strong overconfidence in decision-making.

2. **Familiarity Bias (Q5-Q6)**

   FB Score = Q5 + Q6 = 2 + 4 = 6

   Maximum Score = 2 × 5 = 10

   FB% = $\frac{6}{10}$ **× 100 = 60%**

Interpretation: Moderate Bias – respondent moderately prefers familiar investments.

3. **Confirmation Bias (Q7-Q11)**

   CB Score = Q7 + Q8 + Q9 + Q10 + Q11 = 2 + 4 + 2 + 4 + 4 = 16

   Maximum Score = 5 × 5 = 25

   CB% = $\frac{16}{25}$ **× 100 = 64%**

Interpretation: High Bias – respondent tends to seek information that confirms existing beliefs.

4. **Regret Aversion (Q12-Q14)**

   RA Score = Q12 + Q13 + Q14 = 3+4+2 = 9

   Maximum Score = 3 × 5 = 15

   RA% = $\frac{9}{15}$ **× 100 = 60%**

Interpretation: Moderate Bias – respondent moderately avoids decisions that may lead to regret.

5. **Narrow Framing (Q15-Q17)**

   NF Score = Q15 + Q16 + Q17 = 4 + 4 +4 = 12

   Maximum Score = 3 × 5 = 15

   NF% = $\frac{12}{15}$ **× 100 = 80%**

Interpretation: High Bias – respondent evaluates investments in a narrow, limited perspective.

6. Shadow of the Past (Q18-Q19)

SOP Score = Q18 + Q19 = 3 + 4 = 7

Maximum Score = 2 × 5 = 10

SO P% = $\frac{7}{10}$ **× 100 = 70%**

Interpretation: High Bias – past performance strong influences current investment decisions.

7. Loss Aversion (Q20-Q24)

LA Score = Q20 + Q21 + Q22 + Q23 + Q24 = 2 + 4 + 2 + 3 + 4 = 15

Maximum Score = 5 × 5 = 25

LA% = $\frac{15}{25}$ **× 100 = 60%**

Interpretation: Moderate Bias – respondent moderately avoids losses over potential gains.

8. Herd Instinct (Q25-Q27)

HI Score = Q25 + Q26 + Q27 = 3 + 4 + 4 = 11

Maximum Score = 3 × 5 = 15

HI% = $\frac{11}{15}$ **× 100 ≈ 73.33%**

Interpretation: High Bias – respondent is strongly influenced by the behavior of other investors.

Table 4.13: Behavioural Bias Level Classification:

Bias Percentage	Interpretation
0–40%	Unbiased
41–60%	Moderate Bias
61–80%	High Bias
81–100%	Very High Bias

(Source: Authors' Compilation)

Table 4.14: Equity Investment Behavioural Bias Assessment Scale (EIBBAS)

Behavioural Bias	No.	Statement (Q1–Q27)	Likert Scale Response (1–5)	Cumulative Score Calculation	Cumulative Score	Max Score (Cumulative)	Bias % Equation	Bias %	Interpretation
Overconfidence	**Q1**	I have sufficient knowledge of the Indian stock market. (Prosad, 2014)	4	4+4+4+4	16	4x5 = 20	16/20×100	80%	**High Bias**
	Q2	I am confident in my ability to pick better stocks than others. (Prosad, 2014)	4						
	Q3	I take more risks because I have confidence in my abilities. (Malik, 2020)	4						
	Q4	I trust my ability to start and manage investments. (Parvathy, 2022)	4						
Familiarity Bias	**Q5**	I invest only in avenues I am familiar with. (Sukanya, 2019)	2	2+4	6	2x5 = 10	6/10×100	60%	**Moderate Bias**
	Q6	I select shares of companies I already know. (Sudarshan, 2022)	4						

Confirmation Bias	**Q7**	I hold inherited securities even if not financially wise. (Sukanya, 2019)	2	2+4+2+4+4	16	5x5 = 25	16/25×100	64%	**High Bias**
	Q8	I collect information to confirm my decisions. (Sudarshan, 2022)	4						
	Q9	I hold equities even when price decreases, increasing losses. (Sudarshan, 2022)	2						
	Q10	I study equity nature and gather information before investing. (Sudarshan, 2022)	4						
	Q11	I seek market news that confirms my decisions. (Sudarshan, 2022)	4						
Regret Aversion	**Q12**	I regret not buying a stock that later increases. (Swati, 2021)	3	3+4+2	9	3x5 = 15	9/15×100	60%	**Moderate Bias**
	Q13	Selling stock affects me emotionally based on buying price. (Swati, 2021)	4						
	Q14	I avoid selling stock to avoid regret. (Swati, 2021)	2						

Narrow Framing	**Q15**	I treat each investment separately. (Sudarshan, 2022)	4	4+4+4	12	5x3 = 15	12/15×100	80%	**High Bias**
	Q16	I save part of income for stock market investment. (Sudarshan, 2022)	4						
	Q17	I classify money into accounts for different investment objectives. (Sukanya, 2019)	4						
Shadow of the Past	**Q18**	I avoid investing in equities that performed poorly recently. (Sudarshan, 2022)	3	3+4	7	2x5 = 10	7/10×100	70%	**High Bias**
	Q19	I invest more when successful previously. (Sudarshan, 2022)	4						
Loss Aversion	**Q20**	Loss pain is greater than gain pleasure. (Sudarshan, 2022)	2	2+4+2+3+4	15	5x5 = 25	15/25×100	60%	**Moderate Bias**
	Q21	I hold losing equity too long. (Sudarshan, 2022)	4						
	Q22	I feel sorrow for holding losers too long. (Sudarshan, 2022)	2						
	Q23	I feel bad if a purchase goes down. (Parvathy, 2022)	3						

	Q24	I stay in risky stock hoping for bounce-back. (Swati, 2021)	4						
Herd Instinct	**Q25**	Others' decisions affect my investment.(Swati, 2021)	3	3+4+4	11	3x5 = 15	11/15×100	73.33%	**High Bias**
	Q26	I react quickly to others' decisions. (Swati, 2021)	4						
	Q27	Discussing decisions reduces pressure. (Prosad, 2014)	4						

(Source: Authors' Compilation)

OBJECTIVE: 5

To Study the Impact of Behavioural Biases on Equity Investors while Making Investment Decisions.

For the present objective, which examines the extent to which behavioural biases shape equity investment decisions, **Multiple Regression Analysis** was applied. This method is ideal because behavioural biases serve as continuous independent variables, while the investment decision is treated as a continuous dependent variable. Multiple regression helps determine which specific biases have a meaningful impact on investment decisions and also measures the strength and direction of these relationships. In addition, regression provides an overall explanation of how much the set of behavioural biases collectively accounts for variations in investment choices. These features make it a strong and appropriate statistical tool for fulfilling this objective for R and R^2, Adjusted R Square, Std. Error of the Estimate, Durbin-Watson values (Cohen, Cohen, West, & Aiken, 2003) was considered.

The following table on the next page presents the Hypothesis testing, results, and Interpretation of multiple Regression of the present objective.

PTO

Table 4.15: Summary of the Effect of Behavioural Biases on Investment Decisions of Equity Investors in Selected Cities of the Saurashtra Region

Variables	Hypothesis Statements	Statistical Test Used	Key Finding (Summary)	Decision
Behavioural biases **Investment experience**	**H_0:** Behavioural biases do not significantly affect the investment experience of equity investors in selected Saurashtra cities. **H_1:** Behavioural biases significantly affect the investment experience of equity investors in selected Saurashtra cities.	Multiple Regression	The regression model shows a moderate positive relationship between behavioural biases and investment experience ($R = 0.419$, $R^2 = 0.175$, Adjusted $R^2 = 0.169$). The model is statistically significant ($F = 27.964$, $p < 0.001$). Among the predictors, regret aversion ($\beta = 0.202$, $p < 0.001$), narrow framing ($\beta = 0.166$, $p < 0.001$), and overconfidence ($\beta = 0.150$, $p < 0.001$) have the strongest effect.	H_0 Rejected
Behavioural biases **Trading frequency**	**H_0:** Behavioural biases do not significantly affect trading frequency of equity investors. **H_1:** Behavioural biases significantly affect trading frequency of equity investors.	Multiple Regression	The regression model shows a weak to moderate positive relationship between behavioural biases and trading frequency ($R = 0.302$, $R^2 = 0.091$, Adjusted $R^2 = 0.084$). The model is statistically significant ($F = 13.172$, $p < 0.001$). Overconfidence ($\beta = -0.273$, $p < 0.001$) has a significant negative effect, while familiarity ($\beta = 0.084$, $p = 0.012$) has a significant positive effect.	H_0 Rejected
Behavioural biases **Amount of single trade**	**H_0:** Behavioural biases do not significantly affect the amount of single trade.	Multiple Regression	The regression model shows a weak to moderate positive relationship between behavioural biases and amount of single trade ($R = 0.329$, $R^2 = 0.109$, Adjusted $R^2 = 0.102$).	H_0 Rejected

	H_1: Behavioural biases significantly affect the amount of single trade.		The model is statistically significant ($F = 16.010$, $p < 0.001$). Overconfidence ($\beta = 0.253$, $p < 0.001$) and narrow framing ($\beta = 0.182$, $p < 0.001$) are significant positive predictors.	
Behavioural biases **The number of companies invested**	**H_0:** Behavioural biases do not significantly affect the number of companies invested by equity investors. **H_1:** Behavioural biases significantly affect the number of companies invested by equity investors.	Multiple Regression	The regression model shows a moderate positive relationship between behavioural biases and the number of companies invested ($R = 0.426$, $R^2 = 0.182$, Adjusted $R^2 = 0.176$). The model is statistically significant ($F = 29.238$, $p < 0.001$). Significant predictors include overconfidence ($\beta = 0.298$, $p < 0.001$), regret aversion ($\beta = 0.123$, $p = 0.001$), narrow framing ($\beta = 0.117$, $p < 0.001$), and loss aversion ($\beta = 0.075$, $p = 0.044$).	H_0 Rejected
Behavioural biases **Objective of Regular Return**	**H_0:** Behavioural biases do not significantly affect the objective of regular returns of equity investors. **H_1:** Behavioural biases significantly affect the objective of regular returns of equity investors.	Multiple Regression	The regression model shows a moderate positive relationship between behavioural biases and objective of regular returns ($R = 0.342$, $R^2 = 0.117$, Adjusted $R^2 = 0.110$). The model is statistically significant ($F = 17.365$, $p < 0.001$). Significant predictors include overconfidence ($\beta = 0.119$, $p < 0.001$), familiarity ($\beta = 0.117$, $p < 0.001$), narrow framing ($\beta = 0.089$, $p = 0.008$), shadow of the past ($\beta = 0.079$, $p = 0.022$), and loss aversion ($\beta = 0.101$, $p = 0.009$).	H_0 Rejected
Behavioural biases **The objective of safety of principal**	**H_0:** Behavioural biases do not significantly affect the objective of safety of principal amount of equity investors. **H_1:** Behavioural biases significantly affect the	Multiple Regression	The regression model shows a moderate positive relationship between behavioural biases and objective of safety of principal amount ($R = 0.320$, $R^2 = 0.103$, Adjusted $R^2 = 0.096$). The model is statistically significant ($F = 15.040$, $p < 0.001$). Narrow framing ($\beta = 0.169$, $p < 0.001$), loss aversion ($\beta = 0.101$, $p = 0.010$), confirmation bias ($\beta = 0.089$, $p = 0.013$), and	H_0 Rejected

	objective of safety of principal amount of equity investors.		familiarity (β = 0.084, p = 0.012) are significant positive predictors.	
Behavioural biases **The usage of broking apps**	**H_0:** Behavioural biases do not significantly affect the usage of broking apps and financial news portals by equity investors. **H_1:** Behavioural biases significantly affect the usage of broking apps and financial news portals by equity investors.	Multiple Regression	The regression model shows a weak to moderate positive relationship between behavioural biases and usage of broking apps and financial news portals (R = 0.336, R^2 = 0.113, Adjusted R^2 = 0.106). The model is statistically significant (F = 16.725, p < 0.001). Significant predictors include overconfidence (β = -0.090, p = 0.003), familiarity (β = -0.085, p = 0.011), regret aversion (β = -0.091, p = 0.016), narrow framing (β = -0.086, p = 0.011), and loss aversion (β = -0.122, p = 0.002).	H_0 Rejected

(Source: Authors' Compilation)

Findings

Trading Frequency:

The regression analysis indicates a weak to moderate positive relationship between behavioural biases and the trading frequency of equity investors in the selected cities of the Saurashtra region ($R = 0.302$, $R^2 = 0.091$). The model is statistically significant ($F = 13.172$, $p < 0.001$), suggesting that behavioural biases collectively influence how often investors trade. Among the biases studied, overconfidence shows a significant negative effect, whereas familiarity shows a significant positive effect. This confirms that behavioural tendencies play a role in shaping trading habits.

Amount of Single Trade:

Behavioural biases have a weak to moderate positive impact on the amount invested in a single trade ($R = 0.329$, $R^2 = 0.109$), with the regression model being statistically significant ($F = 16.010$, $p < 0.001$). Specifically, overconfidence and narrow framing are positively associated with higher trade amounts, while other biases show no significant effect. This suggests that certain biases drive investors to invest larger amounts in individual trades.

Number of Companies Invested:

The model shows a moderate positive relationship between behavioural biases and the number of companies in which investments are made ($R = 0.426$, $R^2 = 0.182$). The ANOVA results ($F = 29.238$, $p < 0.001$) confirm that behavioural biases significantly influence investment diversification. Overconfidence, regret aversion, narrow framing, and loss aversion are the key biases impacting the number of companies investors choose to invest in.

Objective of Regular Return:

Behavioural biases demonstrate a weak to moderate positive effect on investors' objective of earning regular returns ($R = 0.342$, $R^2 = 0.117$), with the regression model being statistically significant ($F = 17.365$, $p < 0.001$). Overconfidence, familiarity, narrow framing, shadow of the

past, and loss aversion significantly affect investors' preference for steady returns, indicating that biases shape return-related investment goals.

Objective of Safety of Principal:

The analysis reveals a weak to moderate positive relationship between behavioural biases and the objective of maintaining the safety of the principal investment ($R = 0.320$, $R^2 = 0.103$), and the model is significant ($F = 15.040$, $p < 0.001$). Narrow framing, loss aversion, conformation bias, and familiarity significantly influence investors' focus on protecting their capital, showing that risk-related biases are important determinants of conservative investment behaviour.

Broking Apps as Source of Information:

Behavioural biases exhibit a weak to moderate positive relationship with the use of broking apps for investment information ($R = 0.336$, $R^2 = 0.113$), with the model being statistically significant ($F = 16.725$, $p < 0.001$). Overconfidence, familiarity, regret aversion, narrow framing, and loss aversion negatively affect the use of broking apps, suggesting that investors with stronger biases may rely less on digital tools for investment decisions.

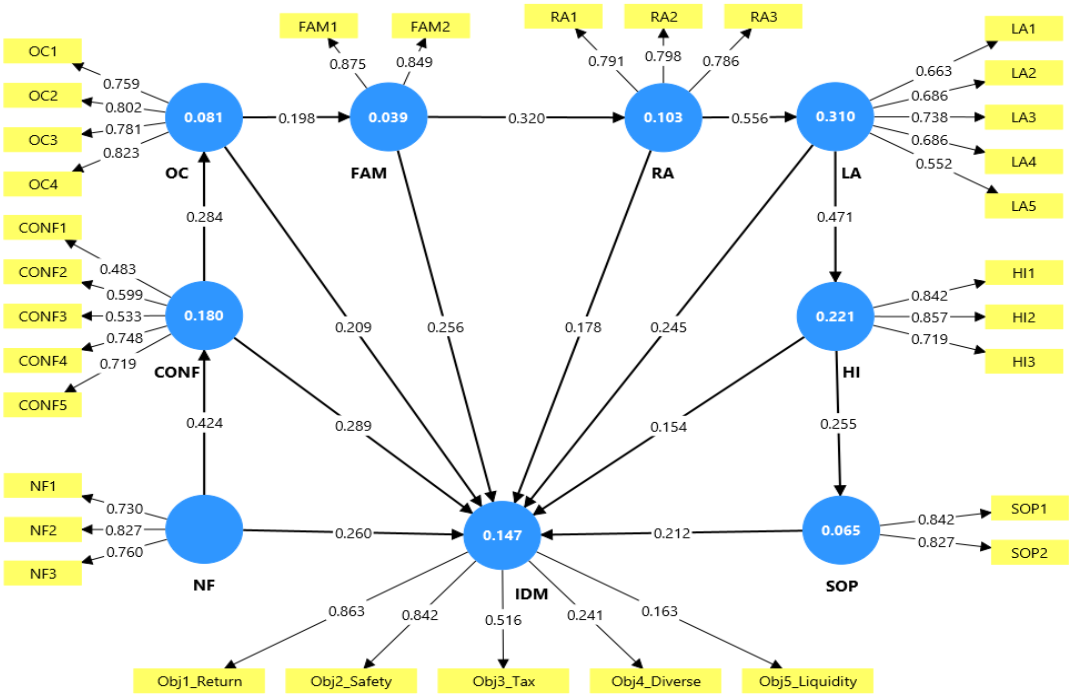
Investment Experience:

Finally, the regression results indicate a moderate positive relationship between behavioural biases and the overall investment experience of equity investors ($R = 0.419$, $R^2 = 0.175$), with a statistically significant model ($F = 27.964$, $p < 0.001$). Among the predictors, regret aversion, narrow framing, and overconfidence have the strongest effects, confirming that behavioural biases play a notable role in shaping investors' knowledge, confidence, and experience in equity markets.

Structural Equation Model

To Study the Impact of Behavioural Biases on Equity Investors while Making Investment Decisions.

Diagram 1: PLS- SEM Analysis of Behavioural Biases and Investment Decisions



PLS-SEM Analysis of Behavioural Biases and Investment Decisions

Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed in this study to examine the relationships between eight behavioural biases—Overconfidence (OC), Familiarity Bias (FAM), Confirmation Bias (CONF), Regret Aversion (RA), Narrow Framing (NF), Shadow of the Past (SOP), Loss Aversion (LA), and Herd Instinct (HI)—and equity investment decisions (IDM) among investors in selected cities of the Saurashtra region with the help of Smart- PLS 4 (Hair J. F. et al., 2017; Hair et al., 2019)

(A) Measurement Model (Outer Model)

The measurement model assesses how well the observed indicators represent their respective latent constructs. In the Table 4.16 Most indicators exhibit satisfactory outer loadings above 0.70, indicating good reliability and convergent validity (Hair J. et al., 2021). Constructs such as Overconfidence, Familiarity, Regret Aversion, Narrow Framing, Herd Instinct, and Shadow of the

Past show strong loadings. Some indicators under Confirmation Bias, Loss Aversion, and Investment Decision-Making fall slightly below the threshold but were retained to preserve theoretical completeness and content validity (Fornell & Larcker, 1981; Shahani & Ahmed, 2022).

Table 4.16: Indicator (Outer) Loadings

Construct	Indicator	Outer Loading	Threshold (≥ 0.70)	Interpretation
Overconfidence (OC)	OC1	0.759	≥ 0.70	Acceptable
	OC2	0.802	≥ 0.70	Excellent
	OC3	0.781	≥ 0.70	Excellent
	OC4	0.823	≥ 0.70	Excellent
Familiarity Bias (FAM)	FAM1	0.875	≥ 0.70	Excellent
	FAM2	0.849	≥ 0.70	Excellent
Confirmation Bias (CONF)	CONF1	0.483	≥ 0.70	Below threshold – consider removal
	CONF2	0.599	≥ 0.70	Marginal – may retain for content validity
	CONF3	0.533	≥ 0.70	Weak loading
	CONF4	0.748	≥ 0.70	Acceptable
	CONF5	0.719	≥ 0.70	Acceptable
Regret Aversion (RA)	RA1	0.791	≥ 0.70	Excellent
	RA2	0.798	≥ 0.70	Excellent
	RA3	0.786	≥ 0.70	Excellent
Narrow Framing (NF)	NF1	0.73	≥ 0.70	Acceptable
	NF2	0.827	≥ 0.70	Excellent
	NF3	0.76	≥ 0.70	Excellent
Loss Aversion (LA)	LA1	0.663	≥ 0.70	Slightly below threshold – acceptable
	LA2	0.686	≥ 0.70	Slightly below threshold – acceptable
	LA3	0.738	≥ 0.70	Acceptable
	LA4	0.686	≥ 0.70	Slightly below threshold – acceptable
	LA5	0.552	≥ 0.70	Weak
Herd Instinct (HI)	HI1	0.842	≥ 0.70	Excellent
	HI2	0.857	≥ 0.70	Excellent
	HI3	0.719	≥ 0.70	Acceptable
Shadow of the Past (SOP)	SOP1	0.842	≥ 0.70	Excellent
	SOP2	0.827	≥ 0.70	Excellent
Investment Decision-Making (IDM)	Obj1_Return	0.863	≥ 0.70	Excellent
	Obj2_Safety	0.842	≥ 0.70	Excellent
	Obj3_Tax	0.516	≥ 0.70	Below threshold
	Obj4_Diverse	0.241	≥ 0.70	Poor
	Obj5_Liquidity	0.163	≥ 0.70	Poor

(Source: Smart-PLS4 Output)

Table 4.17: Construct Reliability and Validity

Construct	Cronbach's Alpha (α)	Composite Reliability (ρc)	Threshold (α & ρc ≥ 0.70)	Average Variance Extracted (AVE)	Threshold (AVE ≥ 0.50)	Interpretation
Confirmation Bias (CONF)	0.620	0.757	≥ 0.70	0.391	≥ 0.50	Marginal reliability; AVE below threshold
Familiarity Bias (FAM)	0.655	0.853	≥ 0.70	0.743	≥ 0.50	Reliable and valid construct
Herd Instinct (HI)	0.738	0.849	≥ 0.70	0.654	≥ 0.50	Reliable and valid construct
Investment Decision Making (IDM)	0.678	0.683	≥ 0.70	0.361	≥ 0.50	Marginal internal consistency and low convergent validity
Loss Aversion (LA)	0.687	0.800	≥ 0.70	0.446	≥ 0.50	Reliable but AVE slightly below acceptable limit
Narrow Framing (NF)	0.662	0.817	≥ 0.70	0.598	≥ 0.50	Reliable and acceptable convergent validity
Overconfidence (OC)	0.806	0.870	≥ 0.70	0.626	≥ 0.50	Highly reliable and valid construct
Regret Aversion (RA)	0.702	0.834	≥ 0.70	0.626	≥ 0.50	Reliable and valid construct
Shadow of the Past (SOP)	0.565	0.821	≥ 0.70	0.697	≥ 0.50	Reliable based on CR and AVE despite lower α

(Source: Smart-PLS4 Output)

Construct reliability and validity were further evaluated using Cronbach's alpha, Composite Reliability, and Average Variance Extracted (AVE). Presenting in the Table 4.17 Most constructs show satisfactory reliability (α ≥ 0.65; ρc ≥ 0.7) and convergent validity (AVE ≥ 0.50), while a few exhibit marginal values but remain acceptable based on theoretical considerations. (Hair J. et al., 2021; Hair et al., 2019; Shahani & Ahmed, 2022).

Discriminant validity

Table 4.18: Discriminant validity Fornell and Larcker criterion

	CONF	FAM	HI	IDM	LA	NF	OC	RA	SOP
CONF	**0.625**								
FAM	0.386	**0.862**							
HI	0.266	0.209	**0.809**						
IDM	0.289	0.256	0.154	**0.601**					
LA	0.385	0.313	0.471	0.245	**0.668**				
NF	0.424	0.278	0.228	0.26	0.287	**0.773**			
OC	0.284	0.198	0.141	0.209	0.145	0.286	**0.791**		
RA	0.368	0.32	0.432	0.178	0.556	0.347	0.135	**0.791**	
SOP	0.299	0.36	0.255	0.212	0.462	0.303	0.135	0.419	**0.835**

(Source: Smart-PLS4 Output)

The square root of AVE Table 4.18 shows that each construct exceeded its correlations with other constructs, confirming that each construct measures a unique concept. (Fornell & Larcker, 1981; Jain et al., 2023)

Table 4.19: Discriminant Validity HTMT Matrix

	CONF	FAM	HI	IDM	LA	NF	OC	RA	SOP
CONF									
FAM	0.618								
HI	0.456	0.306							
IDM	0.357	0.308	0.237						
LA	0.636	0.463	0.643	0.334					
NF	0.639	0.422	0.342	0.327	0.425				
OC	0.363	0.244	0.198	0.28	0.211	0.383			
RA	0.606	0.469	0.593	0.25	0.793	0.507	0.173		
SOP	0.533	0.593	0.382	0.24	0.741	0.497	0.183	0.664	

(Source: Smart-PLS4 Output)

All HTMT values were below the threshold of 0.85–0.90, showing no excessive overlap and supporting discriminant validity showing in the Table 4.19. (Henseler et al., 2015; Jain et al., 2023).

(B) Structural Model Assessment (Inner Model)

Coefficient of Determination (R^2 and Adjusted R^2)

Table 4.20: R^2 and Adjusted R^2

Construct	R-square	R-square adjusted
CONF	0.18	0.179
FAM	0.039	0.038
HI	0.221	0.221
IDM	0.147	0.141
LA	0.31	0.309
OC	0.081	0.08
RA	0.103	0.102
SOP	0.065	0.064

(Source: Smart-PLS4 Output)

Table 4.20 shows the **Coefficient of Determination (R^2)** values indicate the proportion of variance in an endogenous construct explained by its exogenous variables (Hair J. et al., 2021). Following R^2 values of **0.75, 0.50, and 0.25** are considered substantial, moderate, and weak, respectively (Hair et al., 2019) . In this study, the **R^2 for Investment Decision Making (IDM)** is **0.147**, suggesting that the behavioural biases collectively explain around **14.7% of the variance** in equity investment decisions. Among predictors, Loss Aversion and Herd Instinct show moderate R^2 values, whereas Overconfidence and Regret Aversion are weaker predictors.

Table 4.21: Effect Size (f^2) Values

Path	f^2	Path	f^2
CONF → IDM	0.012	OC → FAM	0.041
CONF → OC	0.088	OC → IDM	0.010
FAM → IDM	0.012	RA → IDM	0.001
FAM → RA	0.114	RA → LA	0.449
HI → IDM	0.000	SOP → IDM	0.002
HI → SOP	0.069	LA → IDM	0.008

LA → HI	0.284	NF → CONF	0.219
NF → IDM	0.011		

(Source: Smart-PLS4 Output)

According to (Cohen, 1988), f^2 values of **0.02, 0.15, and 0.35** represent small, medium, and large effects, respectively. Effect sizes (f^2) reveal that Regret Aversion strongly predicts Loss Aversion ($f^2 = 0.449$), and Loss Aversion substantially influences Herd Instinct ($f^2 = 0.284$), while most other direct effects are small.

Table 4.22: Predictive Relevance and Predictive Accuracy (PLS Predict – Q^2, RMSE, and MAE Values)

	Q^2predict	**PLS-SEM_RMSE**	**PLS-SEM_MAE**	**LM_RMSE**	**LM_MAE**	**IA_RMSE**	**IA_MAE**
CONF1	**0.045**	1.119	0.925	1.116	0.915	1.145	0.974
CONF2	**0.069**	1.015	0.784	1.017	0.785	1.052	0.833
CONF3	**0.027**	1.159	0.967	1.159	0.974	1.175	1.012
CONF4	**0.104**	0.938	0.69	0.939	0.691	0.992	0.691
CONF5	**0.091**	0.915	0.666	0.918	0.668	0.96	0.708
OC1	**0.035**	1.018	0.858	1.004	0.837	1.037	0.878
OC2	**0.031**	1.053	0.889	1.046	0.863	1.07	0.912
OC3	**0.028**	1.154	0.973	1.15	0.955	1.17	0.994
OC4	**0.039**	0.958	0.724	0.947	0.702	0.978	0.745
FAM1	**0.01**	1.01	0.781	0.986	0.753	1.015	0.786
FAM2	**0.009**	1.012	0.739	0.99	0.745	1.016	0.742
RA1	**0.003**	1.121	0.944	1.084	0.878	1.122	0.946
RA2	**0.003**	1.192	1.02	1.15	0.946	1.194	1.021
RA3	**0.004**	1.156	0.985	1.078	0.854	1.159	0.987
LA1	**0.001**	1.065	0.842	1.028	0.804	1.066	0.843
LA2	**0.001**	1.121	0.941	1.11	0.909	1.121	0.942
LA3	**0.001**	1.098	0.932	1.078	0.894	1.098	0.933
LA4	**0.001**	1.056	0.858	1.038	0.822	1.057	0.859
LA5	**0.001**	1.099	0.911	1.086	0.877	1.1	0.911

HI1	**0.001**	1.177	1.013	1.157	0.978	1.178	1.014
HI2	**0.001**	1.225	1.054	1.204	1.023	1.225	1.054
HI3	**0.001**	1.228	1.047	1.195	0.98	1.228	1.048
SOP1	**0**	1.135	0.936	1.103	0.877	1.135	0.937
SOP2	**0**	0.964	0.724	0.927	0.695	0.964	0.724
Obj1_Return	**0.042**	1.238	0.964	1.236	0.957	1.264	1.004
Obj2_Safety	**0.053**	1.085	0.833	1.081	0.84	1.115	0.856
Obj3_Tax	**0.004**	1.21	0.999	1.209	0.996	1.213	1.005
Obj4_Diverse	**0.005**	1.195	1.016	1.194	1.011	1.198	1.019
Obj5_Liquidity	**0.003**	1.345	1.161	1.34	1.152	1.346	1.164

(Source: Smart-PLS4 Output)

The PLS-Predict assessment was performed to examine the **out-of-sample predictive capability** of the model, following the guidelines of (Hair J. et al., 2021). The table presents Q^2_predict, RMSE, and MAE values for each indicator of the behavioural biases and investment decision constructs. A **positive Q^2_predict** value greater than zero demonstrates **predictive relevance**, indicating that the exogenous constructs possess the ability to predict the indicators of the endogenous variables better than a naive benchmark.

The Q^2 values for the indicators of **Confirmation Bias (CONF)** range from **0.027 to 0.104**, suggesting small to moderate predictive relevance. Similarly, **Overconfidence (OC)** indicators show Q^2 values between **0.028 and 0.039**, while **Familiarity (FAM)** and **Regret Aversion (RA)** record relatively lower Q^2 values ranging from **0.003 to 0.01**, implying limited predictive power. **Loss Aversion (LA)** and **Herd Instinct (HI)** indicators exhibit marginal predictive relevance ($Q^2 \approx 0.001$), and **Shadow of the Past (SOP)** shows almost no predictive relevance ($Q^2 = 0$).

Among the investment-objective indicators, **Obj1_Return (0.042)** and **Obj2_Safety (0.053)** display the highest Q^2 values, confirming that the model can moderately predict these aspects of

investment decision making. Other investment-objective indicators such as **Obj3_Tax (0.004)**, **Obj4_Diverse (0.005)**, and **Obj5_Liquidity (0.003)** demonstrate weaker predictive capacity.

When comparing the **PLS-SEM RMSE and MAE** values with the **LM (Linear Model)** and **IA (Individual Analysis)** benchmarks, it is evident that the **PLS-SEM model generally yields lower or comparable prediction errors**. This supports the model's satisfactory predictive accuracy and confirms that the inclusion of behavioural biases contributes to explaining variation in investment decision outcomes beyond what a simple linear benchmark would predict.

In summary, the PLS-Predict results indicate that the model possesses **acceptable predictive relevance and accuracy** for several constructs, particularly for **Confirmation Bias, Overconfidence, and Investment Objectives related to Return and Safety**. These findings reinforce the notion that behavioural biases significantly influence the investment decision process of equity investors, consistent with behavioural finance theory (Hair J. et al., 2021; Shmueli et al., 2019)

The Q^2 value shows how well a model can predict outcomes. Values above 0 indicate predictive ability, with 0.00–0.25 considered low, 0.25–0.50 moderate, and anything over 0.50 high.(Hair J. et al., 2021; Shmueli et al., 2019)

Table 4.23: Q^2 Results Table

Construct / Indicator	**Q^2_predict**	**Predictive Relevance Based on Threshold**
Confirmation Bias (CONF)	0.027 – 0.104	**Small to Moderate**
Overconfidence (OC)	0.028 – 0.039	**Small**
Familiarity (FAM)	0.003 – 0.010	**Very Low (Near Zero)**
Regret Aversion (RA)	0.003 – 0.010	**Very Low (Near Zero)**
Loss Aversion (LA)	≈ 0.001	**Negligible**

Herd Instinct (HI)	≈ 0.001	**Negligible**
Shadow of the Past (SOP)	0.000	**No Predictive Relevance**
Obj1_Return	0.042	**Small to Moderate**
Obj2_Safety	0.053	**Small to Moderate**
Obj3_Tax Benefit	0.004	**Very Low**
Obj4_Diversification	0.005	**Very Low**
Obj5_Liquidity	0.003	**Very Low**

(Source: Authors' Compilation)

Predictive relevance (Q^2_predict) is modest for some constructs, such as Confirmation Bias, Overconfidence, and key investment objectives (Return and Safety), but very low for others, reflecting the complex nature of behavioural influences.

Limitation

Despite the model's overall adequacy, its predictive capacity is constrained by the low Q^2_predict values for several behavioural constructs. These results imply that certain biases contribute minimally to prediction within the current sample. While this does not diminish the legitimacy of the model, it highlights the need for future research to consider expanded measurement frameworks, additional behavioural indicators, or alternative analytical techniques to better capture the predictive influence of these constructs.

Bootstrapping Analysis for Path Coefficients and Hypothesis Testing

Table 4.24: Summary of Hypothesis Testing Results

Hypothesis	Path	Original Sample (β)	t-Statistic	p-Value	Decision H0 Rejected / H0 Accepted
H1	CONF → IDM	0.123	3.198	0.001	**Rejected (significant effect)**
H2	CONF → OC	0.284	8.487	0.000	**Rejected (significant effect)**
H3	FAM → IDM	0.117	3.465	0.001	**Rejected (significant effect)**
H4	FAM → RA	0.320	9.952	0.000	**Rejected (significant effect)**
H5	HI → IDM	0.011	0.310	0.757	**Accepted (not significant)**
H6	HI → SOP	0.255	8.341	0.000	**Rejected (significant effect)**
H7	LA → HI	0.471	18.771	0.000	**Rejected (significant effect)**
H8	LA → IDM	0.111	2.440	0.015	**Rejected (significant effect)**
H9	NF → CONF	0.424	13.048	0.000	**Rejected (significant effect)**
H10	NF → IDM	0.112	3.154	0.002	**Rejected (significant effect)**
H11	OC → FAM	0.198	5.709	0.000	**Rejected (significant effect)**

H12	OC → IDM	0.101	2.727	0.006	**Rejected (significant effect)**
H13	RA → IDM	-0.044	1.110	0.267	**Accepted (not significant)**
H14	RA → LA	0.556	21.803	0.000	**Rejected (significant effect)**
H15	SOP → IDM	0.050	1.408	0.159	**Accepted (not significant)**

(Source: Smart-PLS4 Output)

Bootstrapping is used in PLS-SEM to test the statistical significance of relationships, with t-values greater than 1.96 and p-values less than 0.05 indicating significance (Hair J. F. et al., 2017) Hypothesis testing indicates that most paths are statistically significant ($p < 0.05$), confirming the influence of specific biases on investment decisions, while some relationships, such as HI → IDM, RA → IDM and SOP → IDM, are not significant.

Model Fit Indices

Table 4.25: Model Fit

	Saturated model	**Estimated model**
SRMR	0.078	0.124
d_ULS	3.192	8.072
d_G	0.688	0.838
Chi-square	4272.264	4838.186
NFI	0.548	0.489

(Source: Smart-PLS4 Output)

Model fit indices (SRMR, Chi-square, NFI) were reported for transparency. The SRMR value for the saturated model (0.078) meets acceptable thresholds, while other global fit measures are not decisive in PLS-SEM and are supplementary (Hair J. et al., 2021; Henseler et al., 2015)

CHAPTER 5: CONCLUSION

The demographic analysis of equity investors in Junagadh, Rajkot, and Jamnagar reveals distinct patterns across location, gender, age, education, occupation, income, and family characteristics. Jamnagar has the largest and more mature investor base, with a higher proportion of married, professional, and high-income investors, while Rajkot and Junagadh are dominated by younger, male, and student investors. Joint families are prevalent in all cities, with dual-income households common in Jamnagar. Overall, investor profiles indicate regional variations in experience, income, and educational background, which may influence investment behaviour and decision-making.

The cross-tabulation analysis reveals clear patterns in equity investment behaviour across Junagadh, Rajkot, and Jamnagar. Male investors dominate in all cities, while female participation is highest in Rajkot. Younger investors (18–25) are more active in trading, especially in daily or weekly trades, whereas older investors prefer cautious, research-based decisions. Online trading is overwhelmingly preferred by educated and professional investors. Investment amounts correlate with occupation and income, with higher-income groups diversifying across more companies. Self-funding is the primary source of investment, and Banking, IT, and FMCG sectors are the most favoured, particularly among highly educated and professional investors. Overall, the Results highlights the influence of demographic factors on investment preferences, risk appetite, and trading behaviour.

The results show that demographic factors such as age, education, occupation, income, and marital status significantly influence all behavioural biases studied. Family type, number of family members, and number of earning members affect only some biases, including regret aversion, shadow of the past, loss aversion, and herd instincts, while other biases like overconfidence and familiarity, remain unaffected. This highlights that both personal and household characteristics play an important role in shaping decision-making tendencies.

The Behavioural bias Index provides a comprehensive overview of behavioural biases influencing investors in Junagadh, Rajkot, and Jamnagar. The Behavioural Bias Index, developed through weighted Likert scoring, effectively captures the intensity of eight key biases. All biases fall within the "Biased" category, confirming that psychological tendencies strongly influence investment choices. The most significant biases—Familiarity, Narrow Framing, and Shadow of the Past—highlight a tendency toward comfort-driven, segmented, and historically anchored decision-making. Although Herd Instincts were relatively lower, the overall pattern indicates widespread reliance on subjective judgment and emotional reasoning. Understanding these biases is essential for improving financial decision-making. Recognizing and addressing them can reduce risk exposure, enhance diversification, and support more rational investment strategies.

The analysis of multiple regression results indicates that behavioural biases significantly influence various aspects of equity investment decisions among investors in Junagadh, Rajkot, and Jamnagar. Biases such as overconfidence, regret aversion, narrow framing, loss aversion, and familiarity consistently affect investment experience, trading frequency, trade amounts, diversification, and objectives like regular returns and safety of principal. They also impact the usage of broking apps and financial news portals. Across all hypotheses, the null hypotheses were rejected, confirming that behavioural biases play a meaningful role in shaping investment behaviour, risk-taking, and decision-making patterns among equity investors in the selected Saurashtra cities.

The study concludes that behavioural biases significantly shape investment decisions among equity investors in the Saurashtra region. Investors are influenced by pre-existing beliefs, familiarity with financial instruments, narrow framing, emotional sensitivity to losses, and overconfidence. While biases like Herd Instinct, Regret Aversion, and Shadow of the Past have indirect effects, their role reinforces overall decision-making patterns. These findings support behavioural finance theories, highlighting that psychological factors, cognitive distortions, and emotional tendencies are central to understanding investor behaviour.

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Questionnaire

A Study on Role of Behavioural Finance In An Investment Decision of Equity Investors of Selected Cities of Saurashtra Region

Dear Respondents,

Myself, Vipul Sundavadara I am a Ph.D. scholar, and I am researching on behavioural finance. This questionnaire is aimed at identifying the role of behavioural biases in the investment decision-making process of equity investors. The findings of this study will help to determine the influence of the identified behavioural biases on the investment decisions of equity investors. The data collected through this questionnaire will be kept confidential as it is academic research.

The questionnaire consists of three parts:

Part 1: Demographic Profile of the Respondents

Part 2: Equity Information Profile of Respondents

Part 3: Behavioural biases in investment decisions

Note: Kindly tick **[✓]** the box you feel appropriate for your feedback.

Name of equity Investor: _____

Contact No.: _____

Part- 1 Demographic Profile of Respondents

1. **Location (City):**

Junagadh ☐	Rajkot ☐	Jamnagar ☐	Others ☐

2. **Gender:**

Male ☐	Female ☐	Transgender ☐

3. **Age:**

18-25 ☐	26-35 ☐	36-45 ☐	46-55 ☐	56 and above ☐

4. **Education:**

Below HSC ☐	12th/HSC ☐	Under Graduate ☐
Graduate ☐	Post Graduate ☐	Professional ☐
Others ☐		

5. **Occupation:**

Salaried ☐	Businessman ☐	Professional ☐
Retired ☐	House Wife ☐	Student ☐
Equity Trader ☐	Others ☐	

6. **Individual Annual Income? (Your Annual Income)**

Up to 2,50,000		2,50,000 to 5,00,000	
5,00,000 to 10,00,000		10,00,000 and Above	

7. **Marital Status:**

Married	Unmarried	Separated	Others

8. **Family Type:**

Nuclear Family	Joint Family

9. **No. of Family Members:**

Two	Three
Four	More than Four

10. **No. of Earning Members in the Family:**

One	Two	Three
Four	More than Four	

Part- 2 Equity Information Profile of Respondents

11. **At Which Age Have You Started Investing in Equity?**

18-25	26-35	36-45	46-55	56 and above
☐	☐	☐	☐	☐

12. **Your Purpose?**

Trading ☐	Investment ☐	Speculation ☐

13. **Is It Your Source of Income or Investment?**

Income ☐	Investment ☐	Both ☐

14. **How much Experience do you have in equity investment?**

Less than 1 Year	☐
1 Year to 3 Years	☐
3 Years to 6 Years	☐
6 Years and more	☐

15. **Please specify your trading frequency.**

Daily	☐
Weekly	☐
Forth nightly	☐
Monthly	☐
Randomly in a year	☐

16. **Your source of information for equity investment.**
(You can tick more than one option.)

Newspaper	☐
Electronic Media: TV	☐
Internet- Google	☐
Business apps (Like Money control, Business Standards, The ET market, etc.)	☐
Broking apps (Like Share Khan, Marvadi, Angel Broking, etc.)	☐
Own Analysis	☐
Friends and colleagues	☐
Financial Advisors and Agents	☐

17. **How much amount of single trade do you execute?**

Up to 10,000	☐	10,000 to 20,000	☐
20,000 to 30,000	☐	30,000 to 40,000	☐
40,000 to 50,000	☐	More than 50,000	☐

18. **The number of companies in which investments are made?**

1-5	☐	5-10	☐	10-15	☐
15-20	☐	More than 20	☐		

19. **Your Source of Investment?**

Owned Funds	☐	Borrowed Funds	☐	Both	☐

20. **Your Preferred Mode of trading?**

Online	☐	Offline	☐	Both	☐

21. **You Describe yourself as:**

A high-risk gambler		Careful	
Eager to take a risk after completing sufficient research		Risk avoider	

22. **You prefer to invest your money in which sector?** (You can tick more than one option.)

FMCG Sector		Banking Sector	
IT Sector		Energy Sector	
Pharmaceutical Sector		Capital Goods Sector	
Others			

23. **What are your investment objectives?**

Investment objectives	**SD 1**	**D 2**	**N 3**	**A 4**	**SA 5**
Regular Returns					
Safety of the Principal Amount					
Income tax benefits					
Diversification					
Liquidity					

Part- 3 Behavioural biases in equity investment decisions.

Read each Statement carefully and tick ☑ your Preferred Response.

SD – 1	D- 2	N- 3	A-4	SA-5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Statement	SD 1	D 2	N 3	A 4	SA 5
24. I have sufficient knowledge of Indian stock market.					
25. I am confident of my ability to pick better stocks than others.					
26. I take more risks because I have confidence in my abilities.					
27.I trust my ability to start and manage the investments.					
28. I have a tendency to make investment in only those avenues in which I am familiar with.					
29. I select the Shares of companies which I already know.					
30.I hold into securities that I have inherited, regardless of whether retaining those securities is financially wise or not.					
31. I collect maximum information from experts about Equities to confirm my investment decisions.					
32.I hold the Equities when the price decreases, even if it increases the loss.					
33. I study the nature of Equity and search for information while making investments.					
34. I seek market news that confirms my investment decision as correct.					
35. I regret when I find a stock; I have considered buying it but did not went up in value.					
36.While selling a stock, you become emotionally affected by the price at which you purchased the stock.					

37.I avoid selling a stock to avoid the regret of having made a bad investment.					
38. I tend to treat each element of my investment portfolio separately.					
39. I save a part of my income for investing in the stock market.					
40.I classify my money into different accounts based on investment objectives, like money kept aside for insurance, money kept aside for investing in retirement schemes, Equity shares, etc.					
41. I avoid investing in Equity that have performed poorly in the recent past.					
42. I tend to invest more when I am successful in my previous Equity investments.					
43. The pain of financial loss is greater than the pleasure of financial gain.					
44. I tend to hold onto losing Equity too long, hoping for a reversal.					
45. I feel more sorrow about holding onto losing Equity too long than about selling winning Equity too soon.					
46. I would feel very bad if I buy something and it goes down.					
47.I am willingly remain in a risky stock position, hoping the price will bounce back.					
48.Other investors' decisions of buying and selling stocks have impact on my investment decisions.					
49.I usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market.					
50.Discussing my investment decisions with colleagues reduces my pressure of being successful.					

Thank You!!

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SPECIAL ISSUE-DECEMBER 2024

Behavioural Finance: A Systematic Literature Review

Author 1: Vipul Sundavadara, Ph.D. Research scholar, The Department of Commerce, Faculty of Management and Commerce, Noble University, Junagadh- Gujrat

Author 2: Prof. (Dr.) Riddhi Sanghvi, Dean, Faculty of Doctoral Studies, Noble University, Junagadh-Gujrat.

Dear author,

The above manuscript, after positive review reports, is accepted for publication. This will be published in *The Scientific Temper* as Special Issue, December 2024, and will be uploaded online in the last week of December 2024.

Thank you for your interest with this journal

Thanks, and good wishes

Prem Narayan Tripathi

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DIRECTOR

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ORIGINAL RESEARCH PAPER

Behavioral finance: A systematic literature review

Vipul Sundavadara[1*], Riddhi Sanghvi[2]

Abstract

Purpose: The goal of this research is to identify the various behavioral biases that influence individual investors' investment decisions in order to create a conceptual model of behavioral biases and a historical framework of behavioral biases. These efforts will also serve to provide future directions for behavioral finance and behavioral bias research.

Design/Methodology: This study's foundation is an analysis of pertinent behavioral finance research papers published between 2011 and 2023 as well as behavioral biases. Google Scholar, Research Gate, Emerald Inside, Taylor and Francis, Shodh Ganga, Science Direct Etc. are the core sources of the papers reviewed in this study. The tabular form is used for Discussing reviews of the present paper.

Findings: The present paper describes the literature review on behavioral finance and biases from 2011 to 2023 and it is still continuous in underdeveloped and developed nations. Also, find out that the study on behavioral finance increased in the past few years.

Originality/Value: The present paper caters to different types of classification and review of behavioral finance and behavioral biases and also presents the collection in the form of a systematic review matrix of behavioral finance, this will help students, Researchers, academicians for next level research on the topic of behavioral finance.

Keywords: Behavioral Finance, Equity investors, Behavioral Biases, Investment Decision Making.

Introduction

Finance is an inherent part of every Individual, firm or huge corporate house. As said 'finance is the lifeblood of the economy '. The term Finance stands for making decisions regarding money viz. Decisions regarding Procurement of funds, investment of funds and Decisions regarding payment of dividends in most companies and the concept of finance for households to earn money, payment of expenses and savings and investing in some fields which give handsome returns. (Upadhyay & Shah, 2019) An investment is a decision that includes risk in either short-term or long-term return on investment. That's why before taking a risk in any investment decision first of all the information regarding the calculation of return must be taken into consideration. The plus point of the financial market is that there is tremendous information related to financial decisions but the minus point of this market is an investor cannot get exact information that where to invest and where not to invest to get a handsome return. So, the estimation of Risk and return is difficult for the investors. In this situation, investors are not always rational while making investment decisions. (Krishna Deshmukh Pt Ravishankar, 2016) An individual investor has lots more options for investing their funds like Gold, Fixed Deposits, Mutual funds, SIP (Small Investment Plan), Equity market Etc. but when they are supposed to invest in any kind of avenue they are affected by some factors and those behavioral factors are called Behavioral Biases. Behavioral biases are an integral part of behavioral finance and it believes that in behavioral finance the investors are not always rational to make investment decisions. To understand Behavioral finance must clear the concepts of Traditional finance and Behavioral finance.

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Vedant acknowledges the meaningful contribution made and wishes the best for future endeavours.

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Behavioural Finance: A Systematic Literature Review

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"A Study on Impact of Behavioural Biases in An Investment Decision of Equity Investors of Junagadh City"

[1]Vipul Sundavadara, [2]Prof. (Dr.) Riddhi Sanghvi
[1]Ph.D. Research scholar, Department of Commerce, Noble University, Junagadh 362001, India
[2]Dean and Professor, Department of Commerce, Noble University, Junagadh 362001, India

Abstract:

Purpose:

This study aims to analyze the demographic characteristics of investors in Junagadh city, understand their inclination towards equity investment, identify the factors influencing their investment decisions, and examine the impact of behavioural biases on their investment choices.

Design/Methodology/Approach:

I collected primary as well as secondary data for this study. To gather primary data, I designed a structured questionnaire and surveyed 250 equity investors in Junagadh city. Additionally, I obtained secondary data from various sources such as the internet, articles, journals, and blogs. The research design I employed is descriptive because it is utilised to portray the characteristics of a population or phenomenon, in this case, the equity investors of Junagadh City.

Findings:

The majority of equity investors in Junagadh are young, unmarried individuals from lower-income backgrounds. They prefer online trading and focus on long-term investments, emphasizing regular returns and the safety of their principal. Their investments primarily target sectors such as Banking, IT, and Energy. Tax benefits, diversification, and liquidity are not prioritized. Additionally, there are no significant differences in behavioural biases based on age, education, or income. The only factor that influences perceptions is occupation, particularly in relation to the "Shadow of the Past" bias furthermore Overconfidence and herd instincts are key behavioural biases influencing investment decisions.

Originality/Value:

The present paper provides a comprehensive overview of the demographic characteristics and behavioural biases of equity investors in Junagadh city. It serves as a valuable resource for students, researchers, and academicians interested in conducting advanced research on the topic of behavioural finance in different cities or regions.

Keywords: *Behavioural Biases, Behavioural Finance, Equity Investors, Investment Decision Making*

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"A Comparative Study of the Impact of Behavioural Finance on Equity Investment Decisions: Evidence from Investors in Junagadh and Rajkot"

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Abstract:

This research explores how behavioural finance influences equity investment decisions among investors in Junagadh and Rajkot. The study is based on primary data collected through structured questionnaires from 200 respondents, equally divided between the two cities. It focuses on key behavioural biases—Overconfidence, Familiarity, Regret Aversion, and Narrow Framing—and examines the role of demographic factors, particularly age and education, in shaping these biases. The analysis using t-tests and ANOVA shows that while most biases are similar across both locations, Junagadh investors exhibit notably higher Narrow Framing. In contrast, age and education have a stronger effect on investor behaviour in Rajkot, highlighting regional differences. The study emphasizes the importance of understanding behavioural biases and promoting financial awareness to improve investment decision-making.

Keywords: *Behavioural Finance, Equity Investment Decisions, Demographic Factors, Junagadh, Rajkot*

Introduction

Finance is an essential part of decision-making for both individuals and organizations, irrespective of their size. It mainly deals with how funds are raised, allocated, and utilized in the most efficient way. Every investor, whether an individual or a business entity, is required to make choices regarding investment, distribution of returns, and overall financial planning. Therefore, finance can be understood as the process of making informed investment decisions (Upadhyay & Shah, 2019)

With the passage of time, the discipline of finance has evolved considerably. One of the most notable developments in this area is the emergence of behavioural finance, which offers a different perspective compared to traditional financial theories. Traditional finance is based on the assumption that investors act rationally and make decisions after carefully analyzing all available information. However, behavioural finance suggests that real-world investors do not always behave in a perfectly rational manner. Their decisions are often influenced by psychological tendencies, emotions, and personal experiences.

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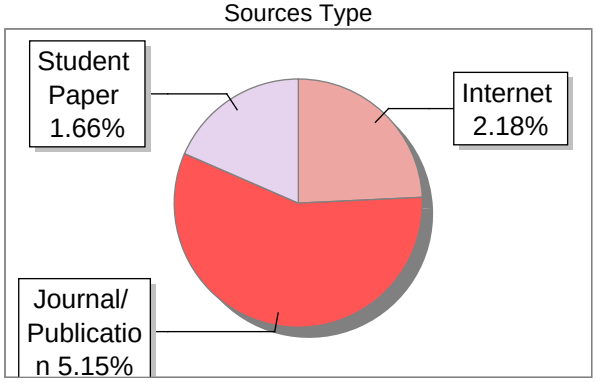

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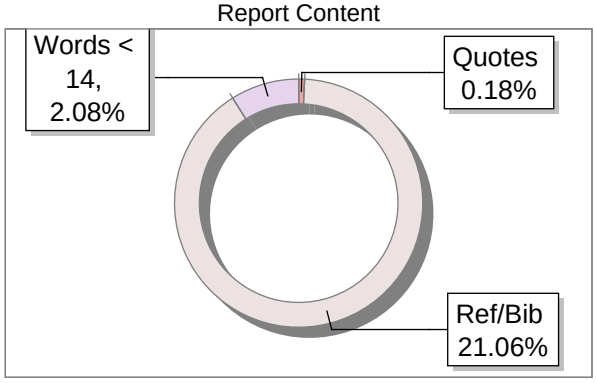

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