

**A STUDY ON ROLE OF BEHAVIOURAL
FINANCE IN AN INVESTMENT DECISION OF
EQUITY INVESTORS OF SELECTED CITIES OF
THE SAURASHTRA REGION**

**FOR THE AWARD OF THE DEGREE OF
DOCTOR OF PHILOSOPHY**

**IN
COMMERCE**

BY

VIPUL SUNDAVADARA

(Registration No.: 002)

SUPERVISOR

DR. RIDDHI SANGHVI



FACULTY OF MANAGEMENT & COMMERCE

NOBLE UNIVERSITY

JUNAGADH - 362310

JUNE - 2026

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Ph.D.

COMMERCE

JUNE- 2026

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**A THESIS SUBMITTED TO
NOBLE UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE
OF**

DOCTOR OF PHILOSOPHY

IN

COMMERCE

BY

VIPUL SUNDAVADARA

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Date: 13/07/2026

This is to certify that the thesis entitled **“A STUDY ON ROLE OF BEHAVIOURAL FINANCE IN AN INVESTMENT DECISION OF EQUITY INVESTORS OF SELECTED CITIES OF THE SAURASHTRA REGION”** submitted for the degree of **DOCTOR OF PHILOSOPHY** in the subject of **COMMERCE (BEHAVIOURAL FINANCE)** is a record of bonafide research work carried out by **VIPUL SUNDAVADARA** under my guidance and supervision and that no part of this thesis has been submitted for any other degree, diploma, associateship, fellowship, or other similar titles. The assistance and help received during the course of the investigation have been fully acknowledged.

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LIST OF ABBREVIATIONS

Sr. No.	Abbreviation	Full Form
1	ANOVA	Analysis of Variance
2	AVE	Average Variance Extracted
3	BBII	Behavioural Bias Impact Index
4	BBLI	Behavioural Bias Level Index
5	BSE	Bombay Stock Exchange
6	CONF	Confirmation Bias
7	EIBBAS	Equity Investment Behavioural Bias Assessment Scale
8	FAM	Familiarity Bias
9	H0	Null Hypothesis
10	H1	Alternative Hypothesis
11	HI	Herd Instinct
12	HTMT	Heterotrait-Monotrait Ratio
13	IDM	Investment Decision-Making
14	LA	Loss Aversion
15	LM	Linear Model
16	MAE	Mean Absolute Error
17	NF	Narrow Framing
18	NSE	National Stock Exchange
19	OBJ	Objective
20	OC	Overconfidence
21	PLS-SEM	Partial Least Squares Structural Equation Modelling
22	RA	Regret Aversion
23	RMSE	Root Mean Squared Error
24	SEBI	Securities and Exchange Board of India
25	SOP	Shadow of the Past
26	VIF	Variance Inflation Factor

ABSTRACT

**“A STUDY ON ROLE OF BEHAVIOURAL FINANCE IN AN
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SELECTED CITIES OF THE SAURASHTRA REGION”**

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ABSTRACT

The present study examines the role of behavioural biases in shaping the investment decision-making process of individual equity investors in Junagadh, Rajkot, and Jamnagar cities of the Saurashtra region. Although traditional financial theories assume that investors act rationally and make decisions based on available financial information, real-world evidence suggests that investment behaviour is often influenced by psychological and emotional factors. Behavioural finance explains these deviations by highlighting the impact of cognitive biases on financial decision-making.

This study focuses on key behavioural biases, including overconfidence, familiarity bias, confirmation bias, regret aversion, narrow framing, loss aversion, shadow of the past, and herd instinct, and investigates their influence on equity investment behaviour. Descriptive research Method was used for the present study. A structured questionnaire was used for primary data collection from equity investors from Junagadh, Rajkot, and Jamnagar respectively. With the help of physical questionnaire and Google forms 1,061 valid responses were obtained. The sampling technique was

Convenience sampling. The Collected data were analyzed with the help of various statistical tools and techniques, Viz. descriptive statistics, cross-tabulation, ANOVA, correlation analysis, multiple regression analysis, Behavioural Bias Impact Index (BBII), Cronbach's Alpha, and Partial Least Squares Structural Equation Modeling (PLS-SEM). The collected data of the study were tested using SPSS and SmartPLS.

The results of the given study show that demographic features such as age, education levels, occupation of investors, income, marital status, and family structure have a notable influence on behavioural biases of equity investors of the Saurashtra region. With the help of this research, the young investors were seen to be more actively participating in trading activities, while higher earner investors and professional equity investors exhibited stronger behavioural tendencies such as overconfidence, narrow framing, and familiarity bias. Also, Behavioural Bias Impact Index shows that all eight Behavioural biases are seen in all three cities of the Saurashtra region.

This analysis also suggests that behavioural biases affect the decision-making of investors, such as trading frequency, investment amount, portfolio diversification, and investment objectives like regular return and capital investment. Out of eight biases, overconfidence, familiarity bias, loss aversion, narrow framing, and confirmation bias, these biases strongly create an effect. Further, SEM results describe that all behavioural biases collectively have a meaningful influence on the investment decision.

In conclusion of present study, equity investment decisions in all three cities viz. Junagadh, Rajkot, and Jamnagar of the Saurashtra region are not purely rational but are significantly influenced by behavioural biases. The Study provides a valuable contribution to the behavioural finance literature by researching in the Saurashtra region.

It also highlights the need for equity investor awareness initiatives to reduce bias-driven decisions and promote more rational investment decision.

Keywords: Behavioural Finance, Behavioural Biases, Investment decisions, Saurashtra region.

CHAPTER- 1

INTRODUCTION

CHAPTER- 1 INTRODUCTION

1.1 Introduction:

Traditional financial theories basically assume that investors behave rationally, possess all the information, and make investment decisions with the ambition of maximizing expected utility. Fundamental theories such as the Efficient Market Hypothesis (Fama, 1970) and Modern Portfolio Theory suggest that financial markets efficiently process available information regarding investments, and asset prices fully reflect such information. In spite of the wide acceptance of these theories, real-world market behaviour often contradicts these underlying assumptions. The market situations, such as speculative bubbles, ongoing mispricing, excessive trading practices, and market anomalies, indicate that investment decisions are not always purely rational, suggesting that the presence of psychological and behavioural factors plays an important role in investors' financial decision-making.

Behavioural finance came up as a response to the limitations of traditional finance theories by incorporating concepts from disciplines like psychology, sociology, and behavioural economics. The behavioural finance field suggests that investment decisions are often affected by cognitive biases, human emotions, and social factors instead of strict rational judgment (Shefrin, 2000). The fundamental research by Kahneman & Tversky (1979) showed that individual investors often rely on heuristics while making investment decisions under uncertainty. As a result, investors may face biases such as loss aversion, overconfidence, anchoring, and representativeness.

The importance of behavioural finance is particularly relevant in emerging economies like India, where investment behaviour and investors choice is shaped by diverse socio-economic situations and varying by different levels of financial literacy. In India, especially Individual investors are constantly influenced by personal experiences, social norms, and emotional biases alongside formal financial analysis (Ritter, 2003).

The Economic and cultural diversity of the Saurashtra region make it more relatable for examining behavioural finance aspects in an investment related decisions. Cities such as Junagadh, Rajkot, and Jamnagar show diverse economic activities,

different levels of industrial development, and notable variation in income distribution and education levels. Behavioural finance has explored more at the national level, research studies focusing on specific cities or regions comparatively limited. Investor behaviour is often influenced by local economic structures, social environment, and cultural diversity (Statman, 2014). The study focuses on Junagadh, Rajkot, and Jamnagar, to better understand that, how behavioural factors affect equity investment decisions in the Saurashtra region.

The present study, titled “*A Study on Role of Behavioural Finance in an Investment Decision of Equity Investors of Selected Cities of the Saurashtra Region,*” aims to identify key behavioural biases that influence investor choices, evaluate their impact on risk perception and portfolio management, and compare behavioural patterns across the selected cities. The findings are expected to contribute to academic literature by offering empirical evidence from a region-specific context while providing practical insights for investors, financial advisors, and policymakers. Enhanced understanding of investor psychology may aid in the development of targeted financial literacy programs and investment advisory services tailored to the region’s specific needs.

In conclusion, analyzing the role of behavioural finance in the investment decisions of equity investors in Junagadh, Rajkot, and Jamnagar offers a comprehensive framework for understanding the psychological and social factors that influence financial behaviour. By moving beyond the assumptions of classical financial theory, this research aims to provide a more realistic and contextually grounded perspective on equity investment decision-making, bridging the gap between theory and practice in the Saurashtra region.

1.2 Background and Evolution of Behavioural Finance:

The foundations of traditional finance are rooted in the assumption that individuals act rationally and consistently seek to maximize their economic utility. Initial financial theories, such as Expected Utility Theory and the Efficient Market Hypothesis (EMH), assume that investors behave rationally, use information logically, and make unbiased investment decisions (Fama, 1970). For many years, these assumptions create the foundation for financial research and influenced theories related to market situation and asset pricing.

Over time, empirical studies began to question the ability of the explanatory power of classical financial models for actual market behaviour. Researchers identified lots more market anomalies, including excessive volatility, overreaction to news related to the market, speculative bubbles, etc.—such market behaviour could not be fully explained by rational models alone (Shiller, 1981). All these limitations motivate scholars to consider alternative explanations rooted in human behaviour and the decision-making processes of investors.

The development of behavioural finance was strongly influenced by research in the field of psychology and behavioural economics. An important contribution occurred with the work of (Kahneman & Tversky, 1979), who introduced Prospect Theory as another alternative to Expected Utility Theory. Their study showed that individuals do not evaluate gains and losses equally. Investors often display loss aversion and rely on heuristics while making decisions under different certain and uncertain situations. These findings indicated that financial decision-making is often influenced by cognitive biases despite strict rational calculation.

Behavioural finance and behavioural biases gained greater attention in financial market research during the 1980s and 1990s. According to (De Bondt & Thaler, 1985) psychological biases can lead to overreaction, which affects stock prices in the market. This time duration marked the slow integration of behavioural insights into finance. which leads to a growing recognition that markets are influenced by irrational investors.

During the 1990s and early 2000s, behavioural finance recognized as an independent field of study. (Shefrin, 2000) emphasized the role of emotions such as fear and greed in shaping investment decisions, while (Barberis et al., 1998) proposed models that incorporated investor sentiment and belief updating into asset pricing. Over time, the behavioural finance field became a systematic discipline for the psychological aspects of decision-making.

Today, behavioural finance, now considered as an extension of traditional finance instead of its replacement. The field examines how psychological, emotional, and social factors affect financial decision-making. The growth of behavioural finance shows how financial research has changed over time—from fully rational to more realistic behaviour.

1.3 Traditional Finance VS Behavioural Finance

Traditional finance and behavioural finance represent two distinct approaches to understanding investor behaviour and financial market functioning. Traditional finance theory is basically rooted in neoclassical economic theory and is based on the assumption that investors are rational and can make their financial decisions properly. Under this theory, investors make decisions that maximise expected utility. Also, market prices are assumed to be efficient, with prices fully reflecting relevant information (Fama, 1970). Financial models such as Modern Portfolio Theory and the Capital Asset Pricing Model are built on these assumptions and focus on balancing risk and return in the construction of investment portfolios.

Another important difference between these two approaches is connected to the perception of risk. Traditional finance treats risk as an objective concept, commonly represented by statistical indicators such as variance or standard deviation. While behavioural finance suggests that investors interpret risk differently based on their emotions and personal experiences, which play a critical role in shaping risk-taking behaviour (Shefrin, 2000). For instance, investors may ignore losses more than they seek profit, as described in Prospect Theory (Kahneman & Tversky, 1979).

The Market efficiency represents another major difference between traditional and behavioural finance. According to traditional finance theory, mispriced assets are rectified quickly through arbitrage, which helps to balanced market efficiency. Behavioural finance questions this assumption by highlighting the presence of limits to arbitrage, where rational traders may be unable or unwilling to correct mispricing due to risk, transaction costs, or institutional constraints (Barberis et al., 1998). Because of these behavioural factors, asset prices are likely to deviate from their actual values for a considerable time.

A comparison between traditional finance and behavioural finance is presented in the table below

Table 1.1: Differences between Traditional Finance and Behavioural Finance

Basis of Comparison	Traditional Finance	Behavioural Finance	References
Assumption about Investors	Investors are rational and seek to maximize expected utility.	Investors are influenced by psychological, emotional, and social factors.	(Fama, 1970; Statman, 2014)
Nature of Decision-Making	Decisions are logical and consistent.	Decisions may be biased and inconsistent due to heuristics.	(Kahneman & Tversky, 1979)
Information Processing	Information is processed objectively and efficiently.	Information is interpreted subjectively, often imperfectly.	(Barberis et al., 1998)
View on Market Efficiency	Markets are assumed to be efficient.	Markets may exhibit inefficiencies due to investor behaviour.	(Shiller, 1981; Fama, 1970)
Treatment of Risk	Risk is measured objectively using statistical tools.	Risk perception is subjective and emotion-driven.	(Kahneman & Tversky, 1979)
Reaction to New Information	Investors react rationally and promptly.	Investors may overreact or underreact.	(De Bondt & Thaler, 1985)
Role of Emotions	Emotions are not considered in decision-making.	Emotions such as fear and greed influence decisions.	(Shefrin, 2000)
Cognitive Biases	Biases are largely ignored.	Biases such as overconfidence and loss aversion are central.	(Ritter, 2003)
Market Anomalies	Difficult to explain persistent anomalies.	Explains anomalies through behavioural factors.	(Shiller, 1981)
Practical Relevance	More theoretical and model-driven.	More realistic and applicable to actual investor behaviour.	(Statman, 2014)
Applicability to Equity Investors	Assumes optimal portfolio choices based on rationality.	Explains deviations from optimal equity investment decisions.	(Ritter, 2003)

(Source: Author's Compilation from Review of Literature)

1.4 Behavioural Finance in India

The application of behavioural finance in India has gained considerable attention in recent years due to the rapid expansion of financial markets and the increasing participation of individual investors. Traditional finance theories include how financial markets work, but they do not fully explain the actual investment behaviour of investors in India. Because differences in socio-economic conditions, culture, and financial literacy, influence how Indian investors make investment decisions, especially, this makes behavioural finance highly relevant in the Indian context (Sahi & Arora, 2012).

Studies shows in India that investors are affected by behavioural biases as well as several times depend on the suggestions from the friends and relatives. (Barber & Odean, 2001).

In India, social and cultural factors strongly affect investor psychology. Many investors make decisions based on family atmosphere and sometimes advice from friends. Indian investors usually prefer companies those they already know or the companies much popular in the country (Sahi & Arora, 2012; Statman, 2014). This clearly shows that investors in India not always make rational decisions.

Financial literacy is also an important aspect of investor behaviour in India. Although SEBI has worked hard to improve financial awareness and financial education of investors. However, many investors continues to have a limited understanding of basic investment concepts (SEBI, 2020). Due to limited financial understanding, equity investors often react emotionally not rationally to market movements. They became panic and sell their investments during market decline, and take excessive risk during rising market periods. (Gupta & Ahmed, 2016; Shiller R. J., 2015)

Academic research on behavioural finance in India has expanded steadily, with studies examining the influence of psychological biases on equity investment decisions, mutual fund selection, and trading behaviour.

These Research studies show that behavioural biases affect investment choices and portfolio performance among Indian equity investors (Chandra & Kumar, 2012). Most behavioural finance studies in India focuses on metropolitan cities or rely on

national-level context, because of this, limited understanding of region-specific or small region and city-level behavioural patterns.

Overall, behavioural finance helps to understand investor behaviour in India by considering psychological, emotional, and social influences that traditional financial theories do not purely explain. Behavioural finance in Indian growing more importance shows that the need for more focus on regional and demographic variations in investor behaviour.

1.4.1 Behavioural Finance in Gujarat / Saurashtra Region

Gujarat has long been recognized as one of India's most economically progressive states, characterized by a strong entrepreneurial culture, active participation in financial markets, and a high inclination toward business and investment activities. Gujarat's strong business environment and investment context make it an important region for studying investor behaviour. According to traditional finance theories, investors behave rationally, but in actual situations, many individual investors in Gujarat are influenced by psychological biases, social, and cultural factors.

The Saurashtra region of Gujarat, including cities such as Rajkot, Junagadh, and Jamnagar, is an important area for studying investor behaviour. This region has a diverse economy that includes trading, manufacturing, small businesses, and service-oriented basic occupations. Equity investors of these cities do not depend only on financial knowledge but their decisions are also affected by personal experience, advice from friends and relatives and also the market trends.

Research studies from Gujarat and other semi-urban areas in India show that many retail investors frequently exhibit behavioural biases. Investors often rely on informal networks, brokers, friends, and media sources for investment-related information rather than systematic financial analysis (Chandra & Kumar, 2012). These behavioural patterns can influence trading frequency, stock selection, and risk-taking behaviour, leading to deviations from rational investment models.

Gujarat is economically strong state, but only few behavioural finance studies focus on specific regions within whole state. Most of studies in India mainly focus on metro cities like Mumbai, Delhi, or Bengaluru etc. but small cities and semi-urban areas

receive less importance. Because of this, the equity investors behavioural biases of regions like Saurashtra has not been studied in detailed.

More people from Rajkot, Junagadh, and Jamnagar are now investing in equity markets. This increases the importance of Saurashtra region behavioural finance research. Studying behavioural biases in these cities can help lots of parties regarding the investment decisions. In short, Gujarat, especially the Saurashtra region, is becoming important for behavioural finance research because more people are participating in the stock market.

1.5 Equity market in India

1.5.1 Background of Equity Market:

The equity market represents a key pillar of the modern financial architecture, providing a formal mechanism through which ownership claims in business enterprises are generated and exchanged. The Equity market, stock market, and share market generally mean the same thing. These markets refer to a place or a platform where investors can buy and sell shares of companies. This market mainly operates through two main segments. The primary market and secondary market. In the primary market, companies issue new shares to raise capital. Especially in secondary market, shares are traded among investors after the initial issuance.

In financial terms, buying shares gives investors ownership in a company. It means an equity investor is the owner of a small part of the company's total capital. Investors may earn dividend income from the company's profit and can also benefit when share prices rise in the share market. Unlike debt funds such as bonds, equity share investment does not provide fixed returns. They involve higher risk, but they may also offer higher returns while share prices increase. Apart from financial benefits like dividends, shareholders can vote on important matters of a company. So shareholders can be a part of present and future policy decisions of the company.

1.5.2 Equity Investor:

An equity investor is an individual or institution that commits capital to the acquisition of shares with the objective of earning financial returns. These returns are generally come from rising share prices and dividend payments made by the company. Unlike other investment instruments, Equity investments carry higher risk because

share prices change daily to daily according to company performance and different market situations. Due to, investors may experience uncertainty in returns. However, over the long time, equity investments normally provide higher returns than any other secure and unsecure investment options. This happens mainly due to reflecting the long-term growth of companies earning and overall economic benefit.

Equity markets also support economic growth. They help direct the general public's savings towards productive investments. They also provide a regulated and transparent system for trading shares. So that investors can buy and sell their shares in a secure and organized market environment without any fear or fraud.

1.6 Behavioural Finance and the Equity Market in India

The Indian equity market has expanded significantly with the growth of organized stock exchanges, increased retail participation, and advancements in trading technology. Even though market efficiency and getting information regarding the market have improved. Still, investment decisions in India regarding the equity market are often not fully rational, like traditional financial theories. Behavioural finance clearly explains that investors are not fully rational but are affected by psychological biases and emotional factors when making equity investment decisions.

Behavioural finance comes from psychology and behavioural studies on how people make decisions when outcomes are completely uncertain.

Behavioural biases like loss aversion and risk perception, basically described in Prospect Theory (Kahneman & Tversky, 1979). Several studies on Indian investors indicated that these behavioural biases are common in an investment. Equity investors often ignore booking losses and continue hold losing stocks for long time (Baker et al., 2018). This behaviour reduces profit and affects equity investment decisions in the Indian stock market.

Similarly, overconfidence bias also affects investment decisions. Overconfidence bias means investors think they know more as well as they have complete knowledge and can predict the results better than they actually can (Shefrin, 2000).

This bias is commonly seen among retail investors in India. Several research studies in India clearly shows that overconfident investors tend to trade more. They also

take higher risks and they do not diversify their investments well due to overconfidence (Kumar & Goyal, 2016). This is especially relevant in Indian stock market because many investors are first-time or not fully informed.

Another mainly affected behavioural bias is herding. Herding means investors follow others' suggestions rather than making their own decisions. Herding behaviour, explained in behavioural finance as a response to social influence and information uncertainty (Shiller R. J., 2015), has been observed in the Indian equity market during periods of high volatility and speculative activity. Studies in India clearly show that retail investors often follow market trends, are also attracted towards friends' advice and media reports. This can lead to higher price ups and downs and short-term instability in the market price (Bikhchandani & Sharma, 2001; Sehgal & Tripathi, 2009).

Anchoring bias, when investors depend too much on firsthand information, such as purchase price or past stock return, when making decisions. Anchoring bias was first explained as a cognitive shortcut in behavioural decision theory (Tversky & Kahneman, 1974). Many research studies in India show that investors often rely on past prices when making decisions. Due to this, investors may react very slowly to new market information (Chandra & Kumar, 2012; Baker et al., 2018).

Apart from cognitive biases, emotions like fear, greed, and regret also affect investment behaviour in the Indian equity market. Emotional responses to the market, when the market falls, investors often behave in panic and sell all investments. When the market rises, they tend to buy more shares in expectation of more profit. Research studies in India show that emotions affect more investors to judge risk and decide when to invest or not, especially during uncertain market situations. (Statman, 2014).

Financial investment knowledge and experience reduce the impact of behavioural biases in investment decision-making. While behavioural finance theory acknowledges that biases cannot be completely eliminated, Indian empirical studies suggest that investors with higher financial knowledge and experience demonstrate relatively more disciplined investment behaviour (Kumar S. , 2017; SEBI, SEBI investor survey report, 2023) However, regulatory surveys reveal that a large segment of Indian households remains risk-averse and behaviourally inclined towards traditional

investment avenues, reinforcing the relevance of behavioural finance in the Indian equity market (SEBI, SEBI investor survey report, 2023).

In this context, behavioural finance provides a comprehensive framework for understanding the investment decision-making process of Indian equity investors. Since behavioural patterns may vary across regions due to differences in socio-economic conditions, financial awareness, and cultural influences, examining behavioural biases among equity investors from selected cities of the Saurashtra region becomes particularly relevant. Such a region-specific analysis contributes to a deeper understanding of investor behaviour within the broader Indian equity market framework.

1.7 Behavioural Biases

Behavioural biases are systematic deviations from rational thinking that affect how investors make decisions in financial markets. These biases arise from cognitive limitations, emotional influences, and psychological tendencies, leading investors to sometimes act in ways that are inconsistent with objective analysis or market fundamentals. In the context of equity investment, understanding these biases is essential, as they can significantly influence decision-making, risk assessment, and portfolio performance. The following discussion focuses on ten key behavioural biases—overconfidence, anchoring, familiarity bias, confirmation bias, regret aversion, mental accounting, narrow framing, shadow of the past, loss aversion, and herd instincts—which are commonly observed among individual investors and play a critical role in shaping investment behaviour.

A detailed explanation of each of these behavioural biases is provided in the sections below.

Table 1.2: Behavioural Biases

Bias	What It Means	Practical Example
Overconfidence	Believing your own skills or knowledge are better than they really are.	Thinking you can predict stock trends perfectly and taking big risks.
Anchoring	Letting the first number or piece of info you see shape your decisions.	Seeing a product at ₹200 and assuming ₹150 is a bargain without checking its true value.

Familiarity Bias	Favoring things you know well, even if better options exist.	Investing only in companies you've heard of instead of exploring diversified options.
Confirmation Bias	Only noticing information that supports what you already believe.	Ignoring negative reviews of your favorite brand while focusing on positive ones.
Regret Aversion	Avoiding choices that might make you feel regret later.	Not selling a losing investment to avoid feeling bad, even when it's wise to sell.
Mental Accounting	Treating money differently depending on its source or purpose.	Spending a bonus on luxury items instead of saving it like your regular income.
Narrow Framing	Looking at decisions in isolation, ignoring the bigger picture.	Judging an investment solely by this month's performance instead of long-term growth.
Shadow of the Past	Letting previous experiences overly influence current choices.	Avoiding a stock that once lost value, even if its outlook has changed.
Loss Aversion	Fearing losses more than valuing equivalent gains.	Holding onto a failing investment because losing money feels worse than gaining.
Herd Instincts	Doing what everyone else is doing rather than thinking independently.	Buying a stock because it's trending, without analyzing its fundamentals.

(Source: Author's Compilation)

1.7.1 Overconfidence

1.7.1.1. Concept of Overconfidence Bias

Overconfidence bias is one of the most studied and important psychological biases in the behavioural finance field. It happens when people think they know more than they actually do and they have more knowledge than others. They underestimate risks, and believe they can predict better results than they can. In financial decision-making, this overconfidence bias makes people think they have better information or skills than others, even when that is not actually correct according to market (Odean, 1998). Because of this, their investment decisions may not be rational.

The early work of Daniel Kahneman and Amos Tversky showed that people often make decisions that are not fully rational because they depend on mental shortcuts and biases (Kahneman & Tversky, 1979). Their research showed that mistakes in decision-making are not random.

Research in psychology shows that people often become overconfident about their ability to predict results. Financial markets are uncertain. Investors frequently think they can pick undervalued stocks, buy and sell at the right time, and beat the market, even though evidence shows this is not always true (Odean, 1998).

In behavioural finance, overconfidence is considered a key deviation from the rational behaviour of traditional finance. While rational models assume that investors analyse information more objectively.

In conclusion, overconfidence bias goes against the assumption that investors always behave rationally in traditional finance while making investment decisions.

By considering psychological behaviour, behavioural finance gives a more realistic understanding of how investors actually behave and why markets are sometimes uncertain. Clearing the concept of overconfidence is important for better investment decision-making, portfolio arrangement, and risk assessment and management.

1.7.1.2. Definitions of Overconfidence

Psychological context

Overconfidence is the tendency of individuals to overestimate their own abilities, knowledge, and the precision of their information, often resulting in excessive certainty in judgment and prediction (Bhandari & Deaves, 2006)

Behavioural Finance context

In behavioural finance, overconfidence refers to a psychological bias where investors overestimate their knowledge, underestimate risks, and exaggerate their ability to control investment outcomes (Pompian, 2011; Nofsinger, 2004)

Investment Context

Investors are overconfident when they overestimate their skill in picking stocks, timing the market, or interpreting information, often leading to excessive trading and under-diversified portfolios (Odean, 1998).

1.7.1.3. Overconfidence in Financial Decision-Making

1 Excessive Trading

One of the most robust empirical findings in behavioural finance is the relationship between overconfidence and excessive trading. Odean (1998) demonstrated that overconfident investors trade more frequently than rational investors, even when expected gains do not justify transaction costs.

2 Under-Diversification

Overconfident investors tend to under-diversify their portfolios. (Goetzmann & Kumar, 2008) observed that individual investors often hold only a few stocks despite evidence supporting diversification benefits. This behaviour arises because investors overestimate the reliability of their selected securities and underestimate risk exposure.

(Domian et al., 2007) suggest that optimal diversification may require holding over 100 stocks; however, many investors hold only three or four, exposing themselves to unsystematic risk.

3 Market Overreaction and Volatility

(Daniel et al., 1998) proposed a model in which overconfident investors overreact to private information and underreact to public signals. This behaviour leads to short-term price movement.

This behaviour helps to explain, if investors have complete knowledge of overconfidence, they can plan more careful investment and also divert their investments, and make some disciplined strategies for investment. This can help them for decisions and reduce the possibilities of losses in long term.

1.7.2. Anchoring

1.7.2.1. Basics of Anchoring Bias

Anchoring bias is one of the most important cognitive biases studied in behavioural finance field. Anchoring bias means people rely too much on first information when making decisions in non-fixed situations. In anchoring bias investors give too much importance to one piece of information while making financial decisions. In the research of (Tversky & Kahneman, 1974), first of all explained the anchoring-and-adjustment heuristic. Their research indicated that even any kind of random numbers also can strongly influence people's decisions.

In financial markets, Investors face uncertainty and a bundle of information, which makes anchoring bias more general. Investors generally trust on past prices and opinions related to previous market situations. All these aspects affect their return expectation and future stock investment.

1.7.2.2. Conceptual Foundations of Anchoring

Anchoring emerges from bounded rationality and the cognitive limitations inherent in human decision-making. In uncertain situations, individuals use simple mental shortcuts to make decisions with ease. Anchoring simply works in two steps. In the First step, Investor focus on an initial value or piece of information. As well, in the Second step, investor adjust their decisions when new information is available. However, these basic adjustments are often small and not enough to make proper financial decisions.

1.7.2.3. Definitions of Anchoring:

- 1.** Anchoring is a cognitive bias in which individuals rely excessively on an initial reference point and make insufficient adjustments when forming judgments (Tversky & Kahneman, 1974)
- 2.** Anchoring refers to the tendency to base decisions disproportionately on the first piece of information encountered, even when it may be arbitrary or irrelevant. (Pompian, 2011)

3. In behavioural finance, anchoring describes investors' fixation on specific benchmarks—such as purchase prices or historical levels—when evaluating securities (Bhatt & Chauhan, 2014).

1.7.2.4. Anchoring in Investment Behaviour

Anchoring bias manifests in multiple dimensions of investment decision-making.

(a) Purchase Price as a Reference Point

One of the most widely observed forms of anchoring involves fixation on the acquisition price of a security. Investors usually compare profits or losses with the actual price or starting point of the stock or investment. For example, an investor who purchased a stock at ₹1000 may not want to sell at ₹800, because he keeps the stock at the original price. The belief shows that clearly anchoring bias due to the decision taken by the investor is totally based on the basic purchase price, in place of the latest market information (Bose & Shah, 2022). Because of this kind of behaviour, investors keep losing stocks for a long time despite of reducing overall portfolio returns.

(b) Anchoring to Historical Price Levels

(Bhatt & Chauhan, 2014) found that investors commonly depend on 52-week highs or lows as an indicator. These reference points may not be surely connected with future return; still investors rely on that information which makes their decision more easier.

(c) Persistence of Initial Beliefs

Anchoring is not confined to numerical values; it also applies to qualitative expectations. Once investors form an opinion regarding a firm's long-term earnings potential, they may exhibit reluctance to revise that assessment even after receiving contradictory earnings reports (Upadhyay & Shah, 2019). This inertia in belief revision reflects insufficient adjustment from prior cognitive anchors.

(Misal, 2013) further highlights that investors tend to extrapolate recent experiences when making forecasts, assigning disproportionate weight to short-term trends. Such reliance on recent price behaviour may conflict with long-term averages and probabilistic reasoning, thereby reinforcing systematic bias.

(d) Salience and Attention Effects

The strength of anchoring is closely associated with the salience of the reference point. (Akin, 2022) notes that information which is vivid, frequently repeated, or easily recalled tends to attract greater cognitive attention. As a result, salient numerical values—such as widely publicized stock prices or heavily reported earnings figures—become powerful anchors.

When investors rely disproportionately on attention-grabbing data, they may overlook less visible but economically relevant information. For example, companies receiving extensive media coverage may attract investment interest independent of their underlying fundamentals. In this manner, anchoring interacts with salience effects, amplifying deviations from rational valuation.

1.7.2.5. Anchoring and Market Outcomes

Anchoring bias has implications beyond individual decision errors. At the aggregate level, systematic underreaction to new information may contribute to market anomalies. (Dickason & Ferreira, 2018) argue that anchoring can influence investor sentiment and portfolio selection patterns, leading to persistent inefficiencies.

Moreover, anchoring may encourage premature selling of appreciating assets and prolonged holding of declining securities (Akin, 2022). Such distortions can affect liquidity patterns and price dynamics, challenging the assumptions of informational efficiency embedded in traditional financial theory.

1.7.2.6. Empirical Identification of Anchoring

Empirical detection of anchoring typically involves structured surveys or experimental designs in which participants are exposed to predetermined numerical values prior to estimation tasks. The anchoring bias emerges when investors keep

constantly depend on a firsthand price point, however that information is not actually useful or relevant.

The anchoring bias can be seen when investor hold stocks or shares instead of big changes in the market situation or any kind of changes occur in company's conditions but investor's decisions always affected by the basic price at that price they originally buy the stock. (Bose & Shah, 2022)

Anchoring bias shows that investors do not always make fully rational decisions. in this context Anchoring bias shows why behavioural finance is important for examining investor behaviour.

1.7.3. Familiarity Bias

1.7.3.1. Basics of Familiarity Bias

Familiarity bias is a common behavioural bias in behavioural finance, in which investors invest only in those investment options that they already know, whether it can be any kind of shares of a company or any assets (Upadhyay & Shah, 2019; Mittal, 2022). This bias happens due to investor usually feeling more comfortable with known things and avoiding unfamiliar situations. This is sometimes basic human nature. While investing, Investors may choose familiar investments instead of carefully studying all available investment options. Due to this bias investors may ignore investing unfamiliar investment options even when they able to provide big future returns or better diversification advantages.

Investors usually believe that familiar investment options are easy to clearly understand and manage. On the other side unfamiliar or new investment options seen more risky (Chira et al., 2011). For instance, an employee may confidently invest in their owner's company's stock just because he knows more about it, in the same way some investor may avoid foreign stocks because they do not more understand about international markets and its working patterns.

Although this preference provides psychological comfort, it often leads to an over-concentration in a limited set of investments, increasing portfolio risk and

reducing the potential benefits of diversification (Barberis & Huang, Mental Accounting, Loss Aversion, and Individual Stock Returns, 2001; Gennaioli et al., 2015)

Familiarity bias is closely linked to other behavioural biases such as overconfidence and status quo bias. Research shows that familiarity bias can lead to inefficient allocation of resources in the market, as investors neglect potentially high-performing assets simply because they are unfamiliar or complex to understand (Gennaioli et al., 2015)

In practical terms, familiarity bias emphasizes the human tendency to prioritize comfort and perceived understanding over objective evaluation. While investing in familiar assets can reduce uncertainty and provide emotional reassurance, unchecked reliance on this bias can hinder portfolio performance and limit long-term wealth accumulation. Recognizing and addressing familiarity bias is therefore critical for financial advisors and investors alike, as awareness can encourage more diversified portfolios and improve decision-making by balancing comfort with rational analysis.

In summary, familiarity bias illustrates the intersection of psychology and finance, showing how emotional comfort, perceived knowledge, and aversion to the unknown can strongly influence investment decisions. It underscores the importance of diversification, objective analysis, and conscious reflection in mitigating the natural human preference for the familiar. By understanding this bias, investors can make more informed choices, reduce concentration risk, and take advantage of opportunities beyond their immediate knowledge set.

1.7.3.2. Conceptual Foundation of Familiarity Bias

Familiarity bias is a behavioural finance phenomenon where investors tend to prefer investments that are familiar or well-known to them. This bias arises from the human inclination to seek comfort in the known and avoid uncertainty associated with unfamiliar assets (Upadhyay & Shah, 2019). Familiarity bias reflects a cognitive shortcut: individuals perceive familiar investments as easier to understand, monitor, and evaluate, whereas unfamiliar options are associated with ambiguity and perceived as higher risk (Mittal, 2022).

Psychological research suggests that this preference stems not only from familiarity but also from risk aversion and the desire to reduce cognitive load while making investment decisions (Chira et al., 2011)

Familiarity bias can influence both individual and institutional investors, leading to concentrated portfolios that may increase exposure to specific market or company risks. While it offers emotional comfort and perceived control, unchecked familiarity bias can reduce diversification, limit access to high-performing assets, and result in suboptimal investment outcomes (Gennaioli et al., 2015). Understanding this bias allows investors and advisors to consciously diversify portfolios, make informed decisions, and balance comfort with rational evaluation.

1.7.3.3. Definitions of Familiarity Bias

- 1.** Familiarity bias is a tendency to prefer investments that are familiar or well-known, such as domestic or employer-related stocks, over potentially better but unfamiliar alternatives. (Upadhyay & Shah, 2019)
- 2.** It is a behavioural bias in which investors concentrate on assets they recognize, avoiding unfamiliar investments due to perceived risk or uncertainty. (Mittal, 2022).
- 3.** Familiarity bias reflects the human preference for the known, influencing investors to allocate resources disproportionately to familiar companies, markets, or assets. (Gennaioli et al., 2015).

To summarize, familiarity bias shows that investors often prefer assets and markets they recognize, prioritizing comfort over potentially better opportunities. This behaviour can result in portfolios that are heavily concentrated, less diversified, and more vulnerable to risk. Although familiar investments may offer a sense of security and easier monitoring, relying too heavily on them can reduce overall returns and cloud objective judgment. Recognizing this tendency helps investors make more thoughtful decisions, spread their investments across different opportunities, and take advantage of options beyond what is immediately known or familiar.

1.7.4. Confirmation Bias

1.7.4.1. Basics of Confirmation Bias

Confirmation bias is a prominent behavioural finance bias in which individuals favour information that supports their pre-existing beliefs while disregarding or underweighting contradictory evidence. This selective perception often leads investors to seek out reasons supporting their opinions and avoid information that challenges them, resulting in decisions based on incomplete or biased data (Upadhyay & Shah, 2019; Mittal, 2022). In financial markets, this bias manifests when investors become overly attached to their investment strategies or stock choices, interpreting ambiguous information as validation for their initial assumptions while ignoring signals that indicate potential risks or errors (Pompian, 2011).

Confirmation bias can significantly distort decision-making. Investors may overvalue evidence that aligns with their expectations and undervalue contradictory evidence, creating a feedback loop that reinforces existing beliefs. For example, an investor convinced that a particular stock will rise may focus exclusively on positive news, while dismissing negative reports or warning signs, ultimately making decisions on a skewed information set (Akin, 2022). This behaviour not only perpetuates overconfidence but can also lead to suboptimal financial outcomes, such as misallocation of capital or unnecessary concentration in particular assets (K C & Cirappa, 2023).

In conclusion, confirmation bias is a critical factor influencing investor behaviour, characterized by a preference for information that aligns with existing beliefs and the neglect of opposing evidence. Its effects can lead to overconfidence, poor diversification, and suboptimal investment outcomes.

1.7.4.2. Conceptual Foundation of Confirmation Bias

Confirmation bias occurs when individuals prioritize information that confirms their prior beliefs while ignoring contradictory evidence (Upadhyay & Shah, 2019; Mittal, 2022). In investing, this leads to selective perception, overconfidence, and reliance on incomplete information. The bias is rooted in cognitive psychology and self-deception, where decision-makers reinforce their existing opinions rather than

objectively evaluating all available evidence (Kapor, 2014; Hammond et al., 1998). Awareness of confirmation bias is crucial for mitigating its impact and promoting rational, evidence-based financial decision-making (Rappaport & Mauboussin, 2001).

1.7.4.3. Definition of Confirmation Bias

1. “Confirmation bias is a behavioural tendency in which individuals overlook information that contradicts their existing views, favouring information that confirms their prior beliefs. In investing, this leads to selective attention to supportive data while ignoring contradictory evidence.” (Upadhyay & Shah, 2019)
2. “Investors will fully seek information that supports their preconceptions and avoid information that challenges them, often making decisions based on incomplete or biased data, resulting in suboptimal financial outcomes.” (Mittal, 2022)
3. “Confirmation bias, also called self-confirmation bias, is the practice of collecting information to confirm one’s previously held beliefs rather than acquiring new knowledge. Challenging or contradictory information is often ignored.” (Kapor, 2014)

In conclusion, confirmation bias plays a significant role in shaping investor behaviour by encouraging individuals to favour information that supports their existing beliefs while disregarding opposing evidence. This selective processing of information can lead to overconfidence, flawed judgment, and poor investment decisions. When investors focus only on supportive data, they risk forming inaccurate assessments and maintaining ineffective strategies. Over time, such behaviour may result in concentrated portfolios, missed opportunities, and financial losses. Recognizing confirmation bias is therefore essential for promoting objective analysis, critical thinking, and well-informed investment decisions that are based on balanced and comprehensive evaluation rather than personal assumptions.

1.7.5. Regret Aversion

1.7.5.1. Basics of Regret Aversion

Regret aversion is an important bias in the field of behavioural finance. Regret aversion refers to the tendency of people to make such decisions that strongly help them to ignore feelings of regret for making any decisions. This bias happens because people

do not like accepting mistakes and always worry that another decision might have been better (Bhatt & Chauhan, 2014). In financial markets, people affected by regret aversion often hesitate to make decisions because they worry they may regret making that decision later. Such behaviour can lead to holding losing investments for longer than rational analysis would suggest, as well as hesitating to enter the market even when conditions indicate favourable opportunities (Misal, 2013).

The conceptual foundation of regret aversion lies in Regret Theory, introduced by (Loomes & Sugden, 1982). According to this theory, the utility derived from a chosen option is influenced not only by its outcome but also by the outcomes of alternatives that were rejected. Two central assumptions form the basis of this theory: first, individuals compare the results of the chosen option with those of the unchosen alternatives, experiencing regret when foregone options yield better results; second, potential negative outcomes are anticipated and factored into decision-making, influencing choices before the consequences occur (Zeelenberg et al., 1996; Mittal, 2022). In practical terms, this implies that investors often avoid unconventional or high-risk decisions that could yield higher returns, instead favouring conventional or “safe” alternatives to minimize anticipated regret.

Moreover, regret-averse investors may delay selling winning or losing positions, fearing that premature actions could result in missed gains or realized losses. Such patterns can reinforce market inefficiencies and influence trading behaviour over time (Pompian, 2011).

1.7.5.2 Definition of Regret Aversion Bias

1. Regret aversion is the tendency to avoid making decisions that could lead to regret, prioritizing emotional comfort over maximizing financial returns. (Bhatt & Chauhan, 2014)
2. It is a behavioural bias where investors anticipate regret from potential mistakes and adjust their choices to minimize the psychological impact of negative outcomes (Loomes & Sugden, 1982)

3. Regret aversion causes individuals to favour conventional or majority-backed decisions, even if higher-risk options could yield better results. (Mittal, 2022)
4. Investors exhibiting regret aversion often delay decisions, hold losing assets too long, or follow market trends to avoid anticipated regret. (Zeelenberg et al., 1996)

In conclusion, regret aversion represents a critical behavioural bias in finance, where the desire to avoid emotional discomfort often outweighs the pursuit of potential financial gain. Its foundation in Regret Theory, combined with evidence regarding errors of commission and omission, illustrates how anticipated regret can produce conservative decision-making, herding behaviour, and inefficient market outcomes. Understanding and accounting for this bias is essential for both behavioural finance research and the development of effective investment strategies.

1.7.6 Mental Accounting

1.7.6.1 Basics of Mental Accounting

Mental accounting emerged as a key concept in behavioural finance, challenging the traditional assumption that individuals make fully rational decisions aimed at maximizing overall wealth. Classical finance assumes that money is perfectly fungible, and economic agents evaluate decisions based on total wealth position. Behavioural research, however, demonstrates that individuals rarely process financial information in such an integrated manner (Upadhyay & Shah, 2019).

The development of mental accounting is closely linked to the rise of behavioural economics, particularly the work of Richard Thaler, who argued that individuals rely on simplified cognitive processes when managing financial resources (Thaler, 1999). Rather than continuously optimizing across all assets and liabilities, people divide wealth into subjective categories that help them manage complexity but often result in economically suboptimal outcomes.

The theoretical foundation of mental accounting is strongly tied to Prospect Theory by (Kahneman & Tversky, 1979). Prospect Theory introduced reference dependence and loss aversion, showing that individuals evaluate gains and losses relative to benchmarks rather than in absolute terms. Mental accounting extends this

logic by suggesting that people create separate mental accounts, each with its own evaluation rules.

1.7.6.2 Definitions of Mental Accounting

1. Mental accounting as the cognitive process through which individuals and households organize, track, and evaluate their financial activities. According to him, people mentally categorize and monitor money in ways that influence their spending and investment behaviour. (Thaler, 1999)

2. Mental accounting as a process in which individuals assign specific purposes to different groups of assets and apply personal classification systems when making financial decisions. This approach can lead to irrational choices and limited diversification. (Bhatt & Chauhan, 2014)

3. Diamond and Khemani define mental accounting as the subjective evaluation of financial transactions, where individuals treat money differently depending on its source or intended use, rather than applying a unified wealth-maximization principle. (Domian et al., 2007)

4. Pompian states that mental accounting involves creating mental budgets that guide financial behavior. While these mental accounts help individuals manage money, they may conflict with rational decision-making and optimal investment strategies. (Pompian, 2011)

1.7.6.3 Mental Accounting in Financial Decision-Making

(a) Household Financial Behaviour

At the household level, mental accounting is evident in budget compartmentalization. Families allocate funds to specific categories—such as food, entertainment, or savings—and adhere to these categories even when economic efficiency would dictate otherwise (Ritter, 2003). For example, households may spend more at restaurants while choosing cheaper options at home, despite the reverse being more economical.

Similarly, individuals may maintain “rainy-day” funds but simultaneously borrow at interest for small expenses, demonstrating rigid mental categories (Leković,

2020). Windfall gains like bonuses or gifts are often treated as psychologically separate from earned income and spent more freely (Mittal, 2022).

(b) Investment Behaviour

Investors also show a preference for dividends over capital gains, mentally assigning dividends to a “spending account” and capital gains to a “savings account” (Leković, 2020). Such compartmentalization can produce under-diversified portfolios and irrational exposure to employer stock (Pompian, 2011).

Empirical evidence from Indian investors confirms this bias: most treat gains and losses at the individual stock level rather than at the portfolio level (Chandra & Kumar, 2012).

In summary, mental accounting shows that people tend to divide money into separate mental categories, which affects how they spend, save, and invest. This compartmentalization can lead to decisions that are not economically optimal, such as sticking to strict budgets, holding concentrated portfolios, or reacting differently to gains and losses depending on their source. The way individuals engage in mental accounting is influenced by their cognitive skills, financial knowledge, experience, and personal characteristics. Understanding this tendency allows investors and households to make more thoughtful, holistic decisions, manage resources more effectively, and reduce the influence of psychological biases on financial behaviour.

1.7.7 Narrow Framing

1.7.7.1 Basics of Narrow Framing Bias

Narrow framing is a behavioural finance bias in which investors evaluate individual investments in isolation rather than considering the portfolio as a whole. Ideally, investment decisions should be made by assessing the impact of each asset on total wealth and overall portfolio risk. However, investors affected by narrow framing tend to focus excessively on the short-term performance or price fluctuations of individual securities, neglecting their broader financial context (Upadhyay & Shah, 2019).

This bias manifests in both a cross-sectional sense—where each investment is analyzed separately rather than as part of the portfolio—and a temporal sense, where

short-term performance is weighed more heavily than long-term outcomes (Mittal, 2022). As a result, narrow framing can lead to suboptimal decision-making, such as frequent trading in reaction to small price changes, overemphasis on recent gains or losses, and ignoring diversification benefits.

Psychologically, narrow framing is closely linked to mental accounting, a concept introduced by (Thaler, 1999), where individuals separate assets into distinct “mental accounts” instead of evaluating them collectively. This can cause investors to overreact to isolated gains or losses, make inconsistent investment choices, and misperceive risk at the portfolio level. (Benartzi & Thaler, 1995) also note that narrow framing can explain behaviours such as the disposition effect, where investors sell winning stocks too early while holding onto losing stocks, because they evaluate each asset independently rather than considering total wealth changes.

Recognizing narrow framing is crucial for both investors and financial advisors. By encouraging a holistic view of the portfolio, considering overall wealth, and evaluating risks and returns collectively, investors can reduce the adverse effects of this bias and make more rational, long-term investment decisions (Pompian, 2011; Upadhyay & Shah, 2019)

1.7.7.2 Conceptual Foundation of Narrow Framing

Narrow framing arises from cognitive limitations and the human tendency to simplify complex decisions. By focusing on individual investments rather than the portfolio as a whole, investors attempt to reduce cognitive load but often sacrifice rationality. The bias is grounded in prospect theory (Kahneman & Tversky, 1979), which highlights that individuals evaluate outcomes relative to reference points rather than final wealth, intensifying the focus on gains or losses of individual assets.

1.7.7.3. Definitions of Narrow Framing

1. Narrow framing refers to the tendency to separate assets into distinct mental accounts, causing investors to overweight short-term gains or losses of individual holdings. (Thaler, 1999)
2. Investors affected by narrow framing often ignore diversification benefits and focus excessively on price changes of individual securities. (Benartzi & Thaler, 1995)

In conclusion, narrow framing bias shows that investors often focus on individual investments in isolation rather than evaluating their portfolio as a whole. This tendency can lead to an overemphasis on short-term price movements, frequent trading, and misperceptions of risk, ultimately reducing overall portfolio performance. By concentrating on single assets instead of total wealth, investors may make inconsistent decisions, overlook diversification benefits, and amplify the effects of other biases such as loss aversion and overconfidence. Recognizing and addressing narrow framing encourages a broader perspective, helping investors assess risks and returns collectively, make more rational decisions, and improve long-term financial outcomes.

1.7.8 Shadow of the Past

1.7.8.1 Basics of Shadow of the Past

The Shadow of the Past is a behavioural finance bias that reflects how investors' prior experiences, particularly past gains and losses, shape their current risk-taking behaviour. This bias is closely associated with the house money effect and the snake bite effect, phenomena first studied in behavioural economics and gambling contexts. (Upadhyay & Shah, 2019) Describe the house money effect as the tendency for individuals to take higher risks with gains that they perceive as “extra” or not fully their own, such as winnings from prior investments or gambles. In contrast, the snake bite effect occurs after losses: individuals who have recently experienced negative outcomes become more risk-averse, treating the previous loss as a cautionary signal, much like a snake bite that discourages future risk-taking.

The Shadow of the Past bias is rooted in the emotional impact of previous outcomes on decision-making. Investors often fail to separate current opportunities from the emotional weight of past experiences, leading to inconsistent risk preferences. After a gain, people may irrationally treat the money as “house money” rather than part of their wealth, which encourages them to take excessive risks. Conversely, following a loss, fear and regret dominate the decision-making process, often causing overly conservative behaviour even when rational analysis indicates that risk-taking is justified (Odean, 1998)

This bias illustrates the temporal inconsistency in risk perception, where past outcomes disproportionately influence current behaviour. For instance, an investor who experienced a large profit in a particular stock may overestimate their skill and take unnecessary risks in subsequent trades, while an investor who suffered a loss may avoid similar opportunities altogether, even if the investment fundamentals remain strong. Such behavioural patterns can lead to suboptimal portfolio performance over time, as decisions are guided more by emotions linked to past events than by objective evaluation of present opportunities.

1.7.8.2 Conceptual Foundation of Shadow of the Past

The Shadow of the Past is conceptually linked to prospect theory (Kahneman & Tversky, 1979), which posits that individuals evaluate outcomes relative to reference points rather than final wealth levels. Gains and losses are not perceived symmetrically: a prior gain can be psychologically treated as “extra” wealth, encouraging risk-seeking behaviour, while a prior loss can trigger disproportionate fear, leading to risk aversion.

In financial markets, the shadow of the past can manifest in several ways:

1. **Post-Gain Risk-Taking:** Investors may take on riskier assets or increase exposure to volatile markets after experiencing gains, believing they are playing with “house money” rather than their own capital (Upadhyay & Shah, 2019)
2. **Post-Loss Conservatism:** Following losses, investors may overly restrict their portfolio choices, avoid risk altogether, or hold cash excessively, even when long-term strategies would benefit from calculated risk-taking (Odean, 1998).
3. **Performance Chasing:** Shadow of the Past can contribute to performance-chasing behaviour, where investors buy assets that have previously performed well, assuming past success predicts future gains, and avoid assets that have recently declined, potentially missing recovery opportunities.

1.7.8.3 Definitions of Shadow of the Past Bias

1. It occurs when investors fail to separate past investment outcomes from current decision-making, leading to inconsistent risk behaviour. (Odean, 1998)

2. Shadow of the Past bias is the tendency for investors' past gains and losses to influence their current risk preferences, leading to excessive risk-taking after gains and risk aversion after losses. (Upadhyay & Shah, 2019)

In conclusion, the Shadow of the Past bias highlights how prior gains and losses strongly influence investors' current risk-taking behaviour. Past successes may encourage excessive risk-taking through the house money effect, while previous losses often lead to heightened caution and risk aversion via the snake bite effect. This emotional carryover creates inconsistent decision-making, as investors react to past experiences rather than objectively assessing present opportunities. By understanding this bias, investors can recognize when prior outcomes are distorting their judgments, helping them maintain a consistent, rational approach to risk and improve long-term portfolio performance.

1.7.9 Loss Aversion

1.7.9.1 Basics of Loss Aversion

Loss aversion is a fundamental concept in behavioural finance that captures the disproportionate psychological impact of losses relative to gains of similar magnitude. Individuals tend to perceive losses as significantly more consequential than equivalent gains, with empirical research suggesting that the negative effect of a loss is nearly twice as strong as the satisfaction derived from an equal gain (Barberis & Huang, 2001; Tversky & Kahneman, 1992). This asymmetry implies that investors often prioritize the avoidance of losses over the pursuit of potential gains, a tendency that frequently leads to deviations from the rational decision-making assumed in traditional financial models (Benartzi & Thaler, 1995).

The theoretical underpinning of loss aversion is provided by Prospect Theory, developed by (Kahneman & Tversky, 1979). According to this framework, individuals evaluate outcomes in relation to a reference point rather than in absolute terms. In addition, the certainty effect demonstrates that individuals overweight certain outcomes relative to probabilistic ones, even when the expected values are equivalent, further reinforcing loss-averse behaviour (Dervishaj, 2018).

Ultimately, loss aversion provides a robust explanation for why investors often act contrary to normative financial predictions. By emphasizing the asymmetric evaluation of gains and losses, this bias sheds light on the psychological drivers of risk-taking, the persistence of suboptimal investment decisions, and the deviations from expected market behaviour. Understanding loss aversion is therefore essential for comprehensively analysing investor psychology and integrating behavioural insights into financial decision-making frameworks.

1.7.9.2 Conceptual Foundation of Loss Aversion

Loss aversion is a fundamental behavioural finance concept, describing the tendency of individuals to perceive losses as more psychologically significant than equivalent gains. Rooted in Prospect Theory (Kahneman & Tversky, 1979), it highlights that the value function is steeper for losses than gains, leading investors to prioritize avoiding losses over pursuing similar gains.

Psychologically, loss aversion is reinforced by the endowment effect, where individuals overvalue owned assets, and the disposition effect, where investors sell winners prematurely while holding onto losers to avoid realizing losses (Kahneman et al., 1991). Empirical studies confirm that losses generate stronger emotional responses than equivalent gains, influencing investor behaviour and contributing to market anomalies (Barberis & Huang, 2001; Benartzi & Thaler, 1995; Tversky & Kahneman, 1992).

Understanding loss aversion provides insight into why investors often act contrary to classical financial models and emphasizes the role of psychology in financial decision-making.

1.7.9.3 Definitions of Loss Aversion

1. Loss aversion is a behavioural bias in which losses are perceived as more psychologically significant than equivalent gains, leading individuals to avoid losses even at the expense of potential gains. (Barberis & Huang, 2001)

2. Loss aversion refers to the tendency for people to weigh potential losses more heavily than corresponding gains, influencing decision-making under risk. (Kahneman & Tversky, 1979)
3. Investors tend to prefer avoiding losses over acquiring equivalent gains, reflecting the asymmetry in human valuation of losses and gains. (Benartzi & Thaler, 1995)
4. Investors tend to prefer avoiding losses over acquiring equivalent gains, reflecting the asymmetry in human valuation of losses and gains. (Kahneman et al., 1991)

To conclude, loss aversion reflects the human tendency to give greater weight to losses than to equivalent gains, influencing both personal investment choices and broader market behaviour. Grounded in Prospect Theory, this bias can lead investors to alternate between caution and risk-taking, amplify phenomena such as the endowment and disposition effects, and result in decisions that may not maximize returns. Appreciating the role of loss aversion is key to understanding investor psychology and the ways market outcomes can diverge from classical financial predictions.

1.7.10 Herd Instincts

1.7.10.1 Basics of Herd Instincts Bias

Herding bias, also referred to as herd instinct or herd mentality, is a pervasive behavioural phenomenon in financial decision-making wherein individuals follow the actions of a majority rather than relying on their own independent analysis (Bhatt & Chauhan, 2014). It reflects a deep-seated human tendency to conform to social norms, seek approval from peers, and reduce perceived personal risk. In the context of financial markets, herding occurs when investors mimic the trades or strategies of others, often ignoring fundamental and technical analyses, leading to suboptimal investment outcomes (Upadhyay & Shah, 2019).

From a psychological perspective, herding is linked to the human desire for social acceptance, trust in collective wisdom, and the tendency to avoid social isolation (Leković, 2020). Neuroscientific studies indicate that the brain responds positively to conformity signals, activating reward pathways when individuals align with group

decisions, which may explain the unconscious tendency to imitate others (Cialdini & Goldstein, 2004).

Demographic factors also shape susceptibility to herding. Younger and less experienced investors tend to herd more, relying heavily on social and expert cues to guide decisions (Kumar & Goyal, 2016). Gender differences are context-dependent: in some markets, male investors demonstrate higher herding tendencies, while in others, female investors exhibit greater conformity to peer behaviour (Zainul & Suryani, 2021). Education, financial literacy, and cultural context further modulate the strength of herding behaviours, highlighting the interplay between individual characteristics and social influence in financial decision-making (Jetti & Bhaskar, 2021)

In summary, herding bias represents the intersection of psychology, sociology, and finance. It illustrates how social influence can override rational judgment, how uncertainty amplifies dependence on collective behaviour, and how demographic factors shape individual tendencies. Its widespread presence in financial markets underscores the importance of recognizing, mitigating, and educating investors about this bias to promote more rational and disciplined decision-making.

1.7.10.2 Definitions of Herd Instinct:

1. Herd bias describes the propensity of individuals to imitate the judgments and actions of others, particularly under uncertainty, which can override rational analysis and lead to suboptimal investment (Kumar & Goyal, 2016; Jetti & Bhaskar, 2021)
2. Herding is observed when investors, including professionals and institutions, replicate trades or portfolio strategies of others to protect their reputation, reduce perceived risk, or follow trends, rather than making decisions based on independent research (Grinblatt & Titman, 1994; Nofsinger, 2004).
3. Herding, or herd mentality, is the natural human inclination to conform to group behaviour in order to gain social acceptance or reduce perceived personal risk, even when such behaviour conflicts with one's own judgment (Festinger, 1957)

1.7.10.3 Herd Instinct Bias in Financial Decision-Making

The following mechanisms illustrate how herding manifests in financial decision-making:

1. Imitative Behaviour

Investors frequently engage in imitative behaviour, replicating trades or strategies of well-known market participants or peers to minimize reputational and social risks (Grinblatt & Titman, 1994). This behaviour is especially evident among less experienced or novice investors, who may lack confidence in their analytical abilities.

2. Loss Aversion Mitigation

Herding can serve a psychological function by reducing the anticipated regret of making individual errors. Investors may prefer to share losses collectively rather than bear the consequences of isolated poor decisions (Ahmad & Mahmood, 2020).

3. Demographic and Experience Influences

Research indicates that susceptibility to herding varies across demographic groups. Younger investors and those with limited financial knowledge are more prone to follow crowd behaviour (Kumar & Goyal, 2016). Gender differences also exist: some studies find that male investors tend to herd more in certain markets, while female investors may be more influenced by social conformity in others (Zainul & Suryani, 2021). Additionally, professional experience reduces the likelihood of herding, as seasoned investors rely more on personal analysis and risk assessment.

Table 1.3: Chronological Development of Key Theories and Contributions in Behavioural Finance

Researcher(s)	Year	Theory / Concept / Contribution
Herbert Simon	1955	Developed the concept of bounded rationality, highlighting limits to human decision-making.
Leon Festinger, Henry W. Riecken, Stanley Schachter	1956	Proposed the cognitive dissonance theory, explaining how people manage conflicting beliefs.
Amos Tversky & Daniel Kahneman	1973, 1974	Introduced heuristic-based biases such as availability, representativeness, and anchoring.
Daniel Kahneman & Amos Tversky	1979	Formulated prospect theory and highlighted the concept of loss aversion in decision-making.
Amos Tversky & Daniel Kahneman	1981	Presented framing bias, showing how context affects choices.
Richard Thaler	1985	Introduced mental accounting, explaining how people categorize and treat money differently.
Werner De Bondt & Richard Thaler	1985	Developed the theory of overreaction in financial markets.
Nicholas Barberis, Andrei Shleifer, Robert Vishny	1998	Proposed an investor sentiment model to explain overreaction and underreaction in stock prices.
Meir Statman	1999	Developed behavioural asset pricing theory and behavioural portfolio theory.
Andrei Shleifer	2000	Linked behavioural finance with the efficient market hypothesis, showing markets may be inefficient.
Nicholas Barberis, Ming Huang, Tano Santos	2001	Incorporated prospect theory into asset pricing models.
Mark Grinblatt & Matti Keloharju	2001	Studied the influence of behavioural factors on trading behavior.
Hubert Fromlet	2001	Highlighted the importance of behavioural finance, moving beyond the traditional 'homo economicus' model.
Nicholas Barberis & Richard Thaler	2003	Conducted a comprehensive survey of behavioural finance research.
Joshua Coval & Tyler Shumway	2006	Analyzed how biases affect stock prices and found that biased investors' price reversals occur faster.

Avanidhar Subrahmanyam	2008	Discussed normative implications of behavioural finance for investors and corporate decision-makers.
Richard Thaler	2008	Examined how mental accounting influences consumer choices.
Robert Bloomfield	2010	Compared traditional and behavioural finance approaches in explaining market inefficiencies.
Parag Parikh	2011	Explored practical applications of behavioural finance and investor sentiment in value investing.
Uzar & Akkaya	2013	Traced the development of behavioural finance from classical finance perspectives.

Source: From the Literature review of (Kapoor & Prosad, 2017)

1.8 Problem Statement

When people decide to invest in the equity market, their choices are influenced not only by logical analysis but also by psychological factors. Although investors may form optimistic views about certain opportunities, they may also experience doubt or uncertainty. Investment decisions are often shaped by subconscious behavioural tendencies rather than being based purely on financial data or market performance. Common behavioural biases such as overconfidence, misperception, representativeness, anchoring, cognitive dissonance, regret aversion, narrow framing, and mental accounting have been widely discussed in behavioural finance literature (Kahneman & Tversky, 1979). These biases can result in emotionally driven and irrational decisions, ultimately affecting investors' ability to reach their financial goals.

The present study aims to investigate how behavioural biases affect the decision-making patterns of equity investors in selected cities of the Saurashtra region, including Junagadh, Rajkot, and Jamnagar. By identifying and understanding these biases, the research intends to generate meaningful insights that can support investors in recognizing their own behavioural tendencies and improving their decision-making processes. Furthermore, the findings may assist financial advisors in offering more tailored guidance and help policymakers design investor awareness programs and regulatory measures that encourage disciplined and rational participation in equity markets. Ultimately, the study seeks to contribute to the broader understanding of

behavioural finance and its practical implications for strengthening investment outcomes in regional equity markets.

1.9 Research Questions

1. How are equity investors distributed across various demographic variables such as age, gender, education, income, occupation, and investment experience?
2. How do investment preferences toward equity vary across different demographic groups of investors?
3. To what extent do demographic factors such as age, gender, education, income, and investment experience affect the prevalence and intensity of behavioural biases among equity investors?
4. What are the levels and relative intensity of different behavioural biases among individual equity investors, and also the levels across the selected cities of the Saurashtra region, such as Junagadh, Rajkot, and Jamnagar?
5. How do different behavioural biases affect the investment decision-making of equity investors?

1.10 Objectives of the Study

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.

1.11 Significance of the Study

This study was undertaken to examine the behavioural biases that influence the investment decisions of equity investors in selected cities of the Saurashtra region, specifically Junagadh, Rajkot, and Jamnagar. A key focus of the research is to explore

how demographic factors shape these behavioural biases, thereby affecting investors' choices in the equity market. While extensive research has been conducted in the broader field of behavioural finance, particularly on the impact of biases on investment decisions, there is a notable gap in studies focusing on the Saurashtra region. In particular, no prior research has specifically investigated the interplay of demographic variables and behavioural biases among investors in these three cities.

By addressing this gap, the study offers several significant contributions. For individual investors, the findings can enhance awareness of cognitive and emotional biases, enabling them to make more rational and informed investment decisions. Financial advisors and wealth managers can use these insights to provide more personalized guidance, tailor investment strategies, and better understand the behavioural tendencies of their clients. Policymakers and regulatory authorities may benefit by designing targeted investor education programs and policies to promote disciplined, risk-aware participation in the equity market. Academic researchers and students of finance can also use this study as a foundation for further exploration into regional behavioural finance, expanding knowledge of how socio-demographic factors influence investment behaviour. Additionally, brokerage firms, mutual fund companies, and other financial institutions can leverage the insights to develop products and communication strategies that align with investor psychology and reduce decision-making errors.

Overall, this study not only fills a research gap in the context of the Saurashtra region but also provides practical, theoretical, and policy-oriented contributions that can improve investment behaviour, promote financial literacy, and support more efficient functioning of regional equity markets.

1.12 Limitations of the Study

- This research examines only eight behavioural biases, which may not encompass the full spectrum of cognitive and emotional factors influencing investor decisions. Future studies could explore additional biases to provide a more complete understanding of investor behaviour.

- The study is confined to three cities in the Saurashtra region—Junagadh, Rajkot, and Jamnagar, which limits the generalizability of the findings to other cities, regions, or national-level investors. Investor behaviour may vary in different economic, cultural, or social contexts.
- The study does not address the long-term effects of behavioural biases, focusing instead on immediate or current investment decision patterns.
- The study focuses on equity investors only and does not consider other investment instruments such as mutual funds, bonds, or derivatives, which might be subject to different behavioural patterns.

1.13 Scope of the Study

- Future research can investigate more behavioural biases beyond the eight examined here to gain a fuller picture of how investors make decisions.
- The study can be extended to other cities, states, or even nationwide, which would help understand regional or cultural differences in investor behaviour.
- Researchers could include different investment instruments such as mutual funds, bonds, derivatives, or commodities to see if behavioural patterns vary across asset types.

1.14 Organization of the Thesis

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 Literature

This chapter outlines 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 like overconfidence, herd behaviour, and loss aversion. 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 contribution 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 concerning study, the objectives, and the hypotheses. The chapter also presents the variables, conceptual model, research methodology, 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 an analysis of the gathered data employing a variety of statistical techniques and software. Reliability of the data was assessed using Cronbach's Alpha and also through PLS-SEM in Smart PLS, while the convergent and discriminant validity were examined through the help of PLS-SEM in Smart PLS. Descriptive statistics, cross-tabs, ANOVA, and multiple regression analysis was employed 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 (Findings and Conclusion)

In this chapter, the study's key findings on behavioural biases and their role in equity investment decisions are summarized. The discussion emphasizes the impact of biases—namely, overconfidence, loss aversion, and herd behaviour—on investor behaviour in the Saurashtra region. The chapter additionally outlines the conclusions reached 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 LITERATURE

CHAPTER- 2 REVIEW OF LITERATURE

2.1 Introduction:

The behavioural finance field has become an increasingly growing field, offering insights into how psychological and emotional components influence the financial decision-making of Investors.

Behavioural finance explains that investors do not always make logical decisions. Traditional finance, which assumes that people always think logically. Behavioural finance shows that emotions and psychological biases more or less affect investment decisions. These factors mean biases also help to explain many market situations that traditional theories cannot completely explain.

The Present chapter indicates important behavioural finance studies published between 2011 and 2025. For easy understanding, the review is divided into three Scenarios.

First Scenario (2011–2015) mainly focused on identifying common behavioural biases such as overconfidence, loss aversion, anchoring, herd behaviour, mental accounting, and regret aversion, etc. out of all these studies, most studies used questionnaire surveys and focused on developed financial markets.

Second Scenario (2016–2020) examined how different behavioural biases work together. It means with other variables. Researchers also studied the effects of demographic factors, such as age, gender, income, education, etc., culture, and technology on investor behaviour.

Third Scenario (2021–2025) showed fast growth in behavioural finance research studies. Many studies used artificial intelligence and machine learning to understand investor behaviour, especially in digital finance, FinTech, and cryptocurrency markets. Researchers also found that financial knowledge alone is not enough, as behavioural biases continue to influence investment decisions.

Overall, the literature shows that behavioural biases play an important role in equity investment decisions. It also identifies research gaps that support the need for the present study.

2.2 Scenario of Behavioural Finance from 2011 to 2015

Behavioural finance has emerged as an important area of research across the world, including in India. Behavioural finance became more famous through many research studies, especially after 2011.

(Raines & Leathers, 2011) explained that behavioural finance helps us understand how emotions and human psychology influence investors and markets. They also said that this approach does not explain everything because it gives less attention to economic and institutional factors. Authors discussed the idea of emotional finance, which explains some events such as market bubbles and manias. Lastly, they suggested that the Post-Keynesian institutionalist approach provides a more understanding of financial markets because it focuses both investor behaviour and wider economic conditions.

(Lin, 2011) studied how rational decision-making and behavioural biases affect investment decisions in the Taiwanese stock market. They collected data from 430 investors and used structural equation modelling (SEM) for testing. They got results that investors normally follow a logical decision process, but behavioural biases still influence their decisions. Overconfidence was found to increase both the disposition effect and herding behaviour. Herding behaviour was influenced more by market situations and other investors than by the rational decision-making. Overall, the study concluded that psychological factors affects investment decisions.

The research continued to grow in 2012 with (Muradoglu & Harvey, 2012) explained that behavioural finance helps us understand why investors do not always make logical decisions. The study showed that psychological biases, such as heuristics and overconfidence, can influence Investors. The authors recommended that understanding these behavioural factors can help improve both investment choices and financial policies.

In the same year, (Slowik, 2012) provided an important perspective on behavioural biases in consumer financial decisions in his article. In the Credit CARD Act of 2009 and found that it does not completely deal with the behavioural reasons behind excessive credit usage and debt. The study explained that biases like bounded rationality, hyperbolic discounting, optimistic, and overconfidence often affect user's

financial decisions. The author suggested that user must understand behavioural biases and also improve consumer protection and reduce excessive debt. (Slowik, 2012)

Another important contribution in 2012 was made by (Chaarlas & Lawrence, 2012), who examined the limitations of the Efficient Market Hypothesis and emphasized the growing relevance of behavioural finance in understanding investor decision-making. The study was conducted among equity investors in Tamil Nadu, India, where data were collected from 519 participants. The study found that investors possessed several behavioural biases, including anchoring bias, narrow framing bias, etc. with anchoring bias being the most common. The results showed that investors are not always rational because psychological biases influence their choices. Also, suggested that providing education to investor can help reduce these biases and support for making better investment decisions. (Chaarlas & Lawrence, 2012)

In 2012, Felicia Ramona Birău examined the role of behavioural finance in stock markets, providing a fresh perspective by incorporating psychological factors into investment decision-making. Unlike classical finance, which assumes that investors act rationally, behavioural finance recognizes that emotions, cognitive biases, heuristics, and social influences can strongly shape investment choices. The study highlighted that market anomalies, which are not adequately explained by traditional models such as the Efficient Market Hypothesis, can be better understood through the lens of behavioural finance. It also emphasized that irrational behaviour may contribute to market inefficiencies, and even when mispricing occurs due to irrational investors, rational participants may have limited ability to fully correct these distortions. In conclusion, while behavioural finance does not entirely replace classical financial theories, it offers important insights into the psychological determinants of investment decisions and their effects on overall market dynamics. (BIRĂU, 2012)

Building on the insights from 2012, which emphasized the role of psychological factors and behavioural biases in shaping investor decisions, (Bikas et al., 2013) further explored how behavioural finance challenges the traditional notion of fully rational markets. Their study highlighted key biases, including overconfidence, herding behaviour, and emotional decision-making, which frequently contribute to market inefficiencies. The authors also distinguished between micro- and macro-level behavioural finance, showing how individual biases can accumulate and influence broader market outcomes. These findings reinforced the idea that understanding

behavioural patterns can improve investment decisions and enhance market predictions. Overall, the study suggested that integrating psychological insights with classical financial theories provides a more comprehensive and practical framework for analysing market behaviour. (Bikas et al., 2013)

Continuing the exploration of behavioural influences on investment decisions, (Misal, 2013) The study found that behavioural biases such as overconfidence, regret aversion, and market overreaction affect people investment decisions. These biases can result in wrong decisions and reduce market efficiency.

Furthermore, in this year, Sahni, in his 2013 paper, studied how psychological factors such as loss aversion, anchoring, and risk perception affect investment decisions in India. Investors often keep losing stocks for a longer time and sell profitable stocks too early. (Sahni, 2013)

Extending the research on investor biases in India, (Bisen & Pandey, 2013) investigated behavioural patterns among investors in Lucknow, a rapidly growing economic and commercial centre. Based on a questionnaire survey method, the author analysed 195 responses from 200 investors and applied the Chi-square test. The results Chi-square showed that many investors held their losing shares for a longer time while selling profitable shares too early. This situation shows effect of loss aversion. One more thing they expressed that past market situations also affected their decisions, Which Showed the anchoring bias in investment behaviour.

Building upon the evidence from studies in 2013 on investor behaviour and psychological biases, (Bhatt & Chauhan, 2014) Study in Gujarat in the year 2014 reported that biases like overconfidence, herd mentality, anchoring, cognitive dissonance, regret aversion, and mental accounting influence investors' decisions. in result, decisions are emerged by emotions in place of logic, affected investment outcomes.

Extending the examination of investor behaviour beyond India, (Chaffai & Medhioub, 2014) Examine the effect of psychological and emotional factors on stock market investors in Tunisia. With the use of questionnaire and Multiple Correspondence Analysis, found that highly educated investors as well as the investors investing between 1,000 and 20,000 TND were more biased. Risk aversion, representativeness, availability, and anchoring were the major biases in this study, representativeness was common bias. Also suggested that behavioural factors should be studied for investor behaviour.

(Riaz & Iqbal., 2015) analysed investor behaviour in the Karachi Stock Exchange using responses from 50 investors and regression analysis. They considered investors from Karachi Stock Exchange for the study. Results showed that overconfidence, optimism, as well as self-control had a big effect Investors, while the illusion of control did not show any good impact.

A systematic review of anchoring bias in investment decisions with previous fifteen years was presented by (Kansal & Singh, 2015). It was Found that most investors relied on past stock values. also depend on market situations while making investment, whereas less experienced investors were more affected by anchoring bias. It was also described that most of the available studies were conducted in developed countries. So this kind of research needed in countries in India. (Kansal & Singh, 2015)

2.2.1 Conclusion Scenario of Behavioural Finance from 2011 to 2015

This was the first scenario of the review of the literature chapter, and it concluded that between 2011 to 2015, behavioural finance research grew quickly. Considering traditional way and method of research seen in this time period. Researchers conclude that investors do not always make logical decisions regarding investment. Emotions and behavioural biases often affect their choices. Studies from many countries, such as India, Pakistan, Tunisia, and Taiwan, describe that these biases are common. Biases may vary from country to country.

In this time period, behavioural finance became core area of research in emerging markets. Common biases seen in study were overconfidence, herding, loss aversion, anchoring, regret aversion, mental accounting, representativeness, and availability bias etc.

2.2.2 Research Gap (2011–2015)

The research gap between the years 2011 to 2015 showed that behavioural biases consider an important role in decisions. Most researchers focused on biases such as overconfidence, anchoring, loss aversion, herding, and regret aversion.

All the studies in this scenario give good knowledge, but some research gaps are also there. Lots of researchers studied only one or two biases in this time duration, while some studies showed the combined impact of different biases. Some research was also conducted in developed countries, with some limited work in emerging markets.

In addition, many studies were small-sampled and less focused in demographic and socio-economic variables.

Just because of these research gaps, more research was needed in emerging markets using broader data and different investor characteristics.

2.3 Scenario of Behavioural Finance from 2016 to 2020

After discussing the scenario of 2011 to 2015 as a part of the evolution of the Behavioural Finance field, the Discussion of the second scenarios in between the years 2016 and 2020. This scenario begins in 2016, (Deshmukh & Joseph, 2016) conducted a study in Raipur, India, examining how psychological biases affect mutual fund investment choices. Surveying 300 investors, they identified key factors such as perception, motivation, incentives, and external cues that shape investment behaviour. The study found that investors often rely on past performance, regulatory policies, and tax benefits, rather than making purely rational decisions, highlighting the role of heuristics, framing effects, and emotional influences in financial decision-making. These findings demonstrate that investor psychology plays a significant role in guiding investment choices, leading to systematic biases. Understanding these tendencies, the authors suggested, can help mutual fund companies design strategies that align with investor preferences, thereby improving investment decision-making and enhancing market efficiency. (Deshmukh & Joseph, 2016)

Continuing the exploration of behavioural finance in 2016, (Singh & Yadav, 2016) investigated the factors influencing equity investment decisions among investors in Jaipur (Rajasthan) and Moradabad (Uttar Pradesh). The study surveyed 100 participants (60 males and 40 females) using convenience sampling and collected data through structured questionnaires. Analysis using independent t-tests and mean scores revealed gender-based differences in investment behaviour: male investors tended to focus more on financial ratios and market trends, while female investors emphasized financial security and personal recommendations. The study highlighted the importance of financial literacy and suggested that investment decisions should consider thorough analysis, individual risk tolerance, age, and financial objectives. These findings complement earlier research in 2016, demonstrating that demographic factors,

alongside psychological biases, significantly shape investment behaviour and decision-making. (Singh & Yadav, 2016)

In 2016, (Charles & Kasilingam, 2016) examined the influence of behavioural biases on equity investors in Tamil Nadu, India, highlighting the critical role of psychological factors in investment decisions. The study identified six major biases—mood, emotions, heuristics, framing, personality, and gambling—and assessed their impact on investor behaviour. Using a structured questionnaire and multistage random sampling, data were collected from 742 retail investors. The findings demonstrated that these psychological biases significantly shape investor choices, often leading to irrational decisions. The study emphasized the importance of understanding such biases to promote more rational and informed investment strategies in the equity market. These results complement other 2016 research, reinforcing the idea that both psychological and demographic factors play a central role in guiding investor behaviour. (Charles & Kasilingam, 2016)

Following the 2016 studies on individual investors, 2017 research focused on biases among financial professionals. A study of behavioural biases among financial professionals was undertaken in the year 2017 with the help of surveys, interviews, and financial performance data of investors. It was found out in this research that more experienced professional persons showed less biases than retail investors. Overconfidence, herd behaviour, and loss aversion were observed. (Baker et al., 2017)

In 2017, (Rehan & Umer, 2017) investigated the impact of behavioural biases on investor decisions at the Pakistan Stock Exchange (PSX). A pre-tested questionnaire survey was used for collecting data from 385 regular investors. Who regularly investing only those can participate in this survey. After testing the collected data with statistical tools. The results cleared that anchoring, representativeness, risk aversion, overconfidence, and regret aversion biases affected decisions. But mental accounting and availability bias did not more affected.

In the year 2017, Behavioural finance and traditional financial theories were compared in this research. It was explained by the researchers that biases such as overconfidence, herd behaviour, loss aversion, and mental accounting can affect investor decisions and market situations. They used some examples of major financial

crises for examination, the study clearly showed that markets are not always efficient. (Kapoor & Prosad, 2017)

In 2017, Chopde and Kulkarni delved into the fascinating ways behavioural biases shape the investment decisions of individual investors in Mumbai. They argued that traditional finance models, which assume purely rational decision-making, often fail to capture the emotional and psychological forces influencing financial choices. The study identified 23 behavioural biases, highlighting four key factors—past experiences, incongruity, inducement, and dogmatism—that strongly affect investor decisions. While past experiences can serve as a guide, over-reliance without adapting to current market conditions may result in suboptimal outcomes. The research also emphasized how economic conditions and the broader investment environment influence financial goals, often mediated by these biases. Overall, the study illustrates how behavioural factors can hinder rational decision-making and impact the achievement of investors' financial objectives, complementing earlier 2017 research on both retail and professional investor behaviour. (Chopde & Kulkarni, 2017)

After reviewing the studies in the year 2017 in the year 2018, Mishra and Darshan examined the effects of self-attribution and overconfidence biases on investor behaviour using secondary data. In this study, the psychological factors affecting investor behaviour were discussed. It was observed that greed, fear, overconfidence, and self-attribution affect investors decisions. Also noted that overconfidence becomes down with age, while self-attribution keeps common. Investor behaviour was found affected by cultural and economic factors. (Mishra & Darshan, 2018)

In the same year, Kandpal and Mehrotra (2018) examined the influence of behavioural finance on investment decisions in India using primary data collected from 358 faculty members in Uttarakhand through structured questionnaires, supported by secondary sources such as financial research papers and market reports. Using descriptive and statistical analysis, the study identified key factors influencing investment choices, including assured returns, risk aversion, tax benefits, and capital gains. Conducted in Dehradun, the research indicates that investors tend to prefer low-risk and stable investment options due to prevailing economic conditions and varying levels of financial awareness. The findings also reveal that behavioural biases significantly affect decision-making, as many investors rely on past performance,

personal perceptions, and peer influence rather than detailed financial analysis. The study concludes that investors generally prioritise safety, liquidity, and long-term security over high-risk opportunities. It further suggests that improving financial literacy and investment awareness could help reduce behavioural biases and promote more rational investment decisions. (Kandpal & Mehrotra, 2018)

In the same year, the relationship between behavioural biases and life satisfaction, this concept was examined by Dickason-Koekemoer and Ferreira. Using data from 1,170 investors in South Africa. The results were that the life satisfaction level has changed with different behavioural biases. More satisfaction was reported by the gambler's fallacy, and lower satisfaction was regret aversion. Loss aversion and self-control were also some affected with life satisfaction. (Dickason & Ferreira, 2018)

Similarly, Ahmad, Ibrahim, and Tuyon (2018) investigated the presence of behavioural biases among fund managers in Malaysia. For this research surveys and the Delphi method were used to collect data from 30 fund managers. The results were confirmed by four industry experts. Behavioural biases were found to influence the decisions of fund managers. Existing governance systems gave little attention to these issues. Limited awareness of behavioural finance was also observed. It suggests the need for good policies and some education in the finance. (Ahmad et al., 2018)

Further extending this line of research, Aghazadeh, Sun, Wang, and Yang also in the year 2018 examined the effect of CEO overconfidence on the cost of equity capital in publicly traded firms in the United States. A total of 13,535 firm-year observations from 1996 to 2012 were considered by the researcher in the year of 2018. Results showed that a balanced level of CEO overconfidence supported new things and lessen the cost of equity. Excessive overconfidence increased business risk as well as the cost of equity. (Aghazadeh et al., 2018)

In another study, Trehan and Sinha in the same year 2018 examined the impact of overconfidence bias on investor decision-making. The study was conducted in Lucknow and collected primary data from 100 active investors using a structured questionnaire based on a five-point Likert scale. The analysis identified several factors contributing to overconfidence, including self-attribution, optimism, illusion of control, and trading frequency. The findings indicate that investors often overestimate their knowledge, their ability to manage portfolios, and their skill in selecting stocks. As a

result, overconfidence frequently leads to excessive trading and irrational investment decisions. The study concludes that recognising behavioural biases is essential for promoting more informed and rational investment behaviour among investors. (Trehan & Sinha, 2018)

Building on previous research, Raut, Das, and Kumar also in the year 2018 examined the influence of past behavioural biases on investment decisions among Indian investors, using the Theory of Planned Behaviour (TPB) as a conceptual framework. The study collected data from 396 individuals across financial institutions in Jharkhand, Bihar, Odisha, and West Bengal in Eastern India, and the findings reveal that factors such as attitude, subjective norms, and perceived behavioural control, shaped by past behavioural biases—including anchoring, representativeness, and availability—strongly affect investment behaviour. Investors were found to rely heavily on past experiences rather than objective financial analysis, which in turn influenced their investment attitudes and intentions, and they concluded that integrating cognitive biases into the TPB framework provides valuable insights into investor psychology and decision-making, particularly in emerging markets such as India. (Raut et al., 2018)

Further contributing to the understanding of investor behaviour in the year 2018, Mushinada and Veluri analysed the impact of overconfidence and self-attribution biases on traders at the Bombay Stock Exchange (BSE) in India. The study examined a sample of 1,290 stocks traded between April 2004 and March 2012 to investigate how behavioural biases influence market decisions. The findings indicate that overconfident investors tend to overreact to private information while underestimating publicly available information, often resulting in excessive trading, increased market volatility, and mispricing of stocks. Self-attribution bias was also observed, with investors crediting successes to personal skill and attributing failures to external factors, which can lead to riskier decision-making and also concludes that recognising these biases is essential for improving trading strategies, reducing market inefficiencies, and fostering a more stable and informed financial market. The research also provides practical insights for policymakers aiming to mitigate the effects of irrational investor behaviour. (Mushinada & Veluri, 2018)

Building on previous studies, Baker, Kumar, Goyal, and Gaur in the year 2018 investigated the relationship between financial literacy, demographic factors, and

behavioural biases among individual investors in India. The study collected survey data from 516 respondents across ten major cities, including Mumbai, Delhi, Bangalore, and Kolkata, and examined how biases such as overconfidence, self-attribution, the disposition effect, anchoring, representativeness, mental accounting, emotional biases, and herding influence investment decisions and their findings reveal that financial literacy is negatively associated with herding and the disposition effect, but has a limited impact on overconfidence or emotional biases. Demographic factors, including age, occupation, and investment experience, were found to significantly shape investor behaviour. Specifically, male investors exhibited higher overconfidence, while younger investors were more prone to herding. The study also concluded that understanding these behavioural biases can inform financial education programs and improve investment decision-making, particularly in emerging markets such as India. (Baker et al., 2018)

Continuing the exploration of investor behaviour, Mishra and Darshan in the year 2019 examined the investment patterns of financially literate individuals residing in Indore city. The study assessed how residents with substantial knowledge of investment options make financial decisions. The findings indicate that, despite their financial literacy, many investors prefer safer avenues such as fixed deposits, term deposits, insurance products, and mutual funds. This behaviour reflects a strong emphasis on security, which often takes precedence over higher-return or more diversified investment opportunities. The study concludes that even well-informed investors are influenced by risk aversion, highlighting the need to balance financial literacy with strategies that encourage more diversified and informed investment choices. (Mishra & Darshan, 2019)

Similarly, Upadhyay and Shah (2019) investigated the influence of behavioural finance on investment decisions among investors in Ahmedabad. The study collected primary data from 181 investors using a structured questionnaire and complemented this with secondary sources, including books, articles, and online materials. Convenience sampling was employed to include a diverse demographic of participants, and the data were analysed using bi-variate analysis and hypothesis testing to examine key biases such as overconfidence, confirmation bias, emotional bias, herding behaviour, and loss aversion and findings indicate that higher education levels were associated with greater overconfidence, while female investors relied more on intuition.

Investors tended to focus on positive news about their holdings, and business professionals and self-employed individuals were more likely to retain underperforming investments, reflecting higher risk tolerance. The study also found that investors showed a preference for familiar investments and frequently followed expert opinions and peer recommendations. Also, the study concludes that behavioural biases significantly shape investment decisions, demonstrating that investors are not entirely rational and that psychological factors play a critical role in financial decision-making. (Upadhyay & Shah, 2019)

In a similar investigation, Gupta and Saxena in the year 2019 explored the relationship between behavioural finance and investment preferences among employees of private equity firms in India. Data from 60 employees were collected with the help of a questionnaire. The data was analysed with statistical tests. The results confirmed that behavioural biases were common among the respondents. Males and Female affected by both behavioural biases and investment preferences. Income levels had some small impact. (Gupta & Saxena, 2019)

Further extending the research on investor psychology, Areiqat, Abu-Rumman, Al-Alani, and Alhorani in the year 2019 examined the influence of behavioural finance on stock investment decisions at the Amman Stock Exchange (ASE), focusing on four key psychological biases: overconfidence, loss aversion, risk perception, and herding behaviour. Primary data were collected from 165 active investors through a structured questionnaire, with 150 valid responses analysed. Multiple and hierarchical regression analyses were conducted using SPSS, and reliability and validity were confirmed through Cronbach's alpha and factor analysis. Normality and multicollinearity were also assessed to ensure robust results, and findings indicate that overconfidence, loss aversion, and herding behaviour significantly affect investment decisions, while risk perception showed no substantial impact. Overconfidence was identified as the most influential bias, reflecting investors' tendency to overestimate their knowledge and decision-making abilities. The study concludes that enhancing investor education and awareness programs is crucial for mitigating cognitive biases and promoting more informed investment decisions. (Areqat et al., 2019)

In a similar study, Bhoj (2019) investigated the behavioural biases affecting Indian investors and their financial decision-making, challenging the traditional finance

assumption of purely rational behaviour. A field study was applied to examine behavioural biases among investors. Urban and rural investors behave differently. Urban investors had better financial knowledge and they used different types of investment options. Rural investors used traditional saving options. Overconfidence and loss aversion behavioural biases affect both. (Bhoj, 2019)

Further expanding on the influence of psychological biases, Ritika and Himanshu in the year 2019 examined behavioural biases affecting investment decisions, challenging the traditional assumption that investors are fully rational. The secondary research method has been taken for this research using earlier research. Many investors rely on mental shortcuts in place of careful and deep analysis. Because of these poor investment decisions were taken. Loss aversion, familiarity bias, optimism bias, self-attribution bias, and regret aversion were more affect investors. (Ritika & Himanshu., 2019)

Similarly, Madaan and Singh in the year 2019 examined the impact of behavioural biases on investment decision-making at the National Stock Exchange (NSE) in India, focusing on overconfidence, anchoring, the disposition effect, and herding behaviour. Primary data were collected from 243 investors using a structured questionnaire and convenience sampling. Descriptive and inferential analyses were conducted using SPSS, with Cronbach's alpha confirming reliability and correlation and regression analyses assessing relationships between biases and investment decisions, and the study found that overconfidence and herding behaviour significantly influenced investment choices, while anchoring and the disposition effect had minimal impact. Overconfident investors tended to overestimate their knowledge, whereas those affected by herding behaviour often followed market trends rather than conducting independent research. The study concludes that psychological biases play a critical role in shaping investment decisions and recommends that financial advisors educate investors to mitigate these biases and promote more rational decision-making. (Madaan & Singh, 2019)

In a similar study, Kirera and Mburugu in the year 2019 examined the influence of heuristic biases on individual investor decision-making at the Nairobi Securities Exchange (NSE), focusing on Meru County, Kenya. Questionnaire data from 160 respondents across four brokerage firms were collected. Tested with factor analysis and

the PCA method. Availability bias have strongest impact on investment decisions. Overconfidence and anchoring also affected investor. But, the gambler's fallacy and representativeness had small effect, and some of them preferred local stocks because of the easier to information access. (Kirera & Mburugu, 2019)

Further extending research on behavioural finance, Audu and Abubakar (2019) examined the impact of behavioural finance theories on individual investment performance in the Nigerian stock market. The study used a survey design, collecting data from 400 investors through structured questionnaires, with a final sample of 204 respondents. Structural Equation Modeling (SEM) was employed to analyse the relationships between behavioural biases and investment outcomes, and findings indicate that heuristics theory negatively affected investment performance, suggesting that reliance on mental shortcuts and intuitive judgment often led to suboptimal financial decisions. In contrast, prospect theory, market factors, and herding behaviour showed positive but statistically insignificant effects. Overall, while behavioural biases were prevalent among investors, their direct influence on investment success was relatively limited, highlighting that stock market decisions are shaped by both rational and irrational factors. The study concludes that understanding behavioural biases can help investors and policymakers design strategies that balance psychological tendencies with rational decision-making to improve investment outcomes. (Audu & Abubakar, 2019)

Similarly, Peña and Mejía (2019) examined the impact of the anchoring and adjustment heuristic and optimism bias on financial forecasting through an experiment involving 670 students from Concepción (Chile), Cali (Colombia), and Lima (Peru). For this research predictions based on the S&P MILA Pacific Alliance Select Index were considered to know about investor behaviour. Many participants considering their forecasts of latest index value, affected with anchoring bias. Optimism bias was presented. Also some forecasting patterns were noted from students from given areas. (Peña & Mejía, 2019)

In a related study, Isidore and Christie in the year 2019 analyzed the influence of behavioural biases on investment returns among 436 equity investors in Chennai, India. Data were collected through structured questionnaires, and regression analysis was applied to assess the impact of various biases—including representativeness,

overconfidence, anchoring, gambler's fallacy, availability bias, loss aversion, regret aversion, mental accounting, and optimism—on actual annual returns and the results identified five significant biases—mental accounting, loss aversion, representativeness, overconfidence, and optimism—that affected returns. Most biases negatively influenced performance, while overconfidence, optimism, and anchoring showed positive effects. The model explained 59.2% of the variation in returns, confirming its robustness. The study concludes that recognising the role of behavioural biases is essential for investors and financial advisors. While detrimental biases can hinder performance, certain biases, such as overconfidence and optimism, may enhance returns, highlighting the need to manage harmful biases to improve investment strategies. (Isidore & Christie, 2019a)

Building on previous research, Isidore and Christie again in the year 2019 examined the influence of behavioural biases on investment decision-making in the secondary equity market among 436 investors in Chennai, Investment strategies of people and their behavioural biases were simply studied among investors in India. Nine behavioural biases were noted in this study. Mental accounting, anchoring, loss aversion, regret aversion, representativeness, and overconfidence. Conclusion suggests that all given biases had a big effect on investors. (Isidore & Christie, 2019b)

Building on prior research, Isidore and Christie (2019) examined the relationship between investors' annual income and eight behavioural biases, including mental accounting, anchoring, gambler's fallacy, availability bias, loss aversion, regret aversion, representativeness, and overconfidence. The study surveyed 436 secondary equity investors in Chennai, India, from the Tamil Nadu Investors Association and clients of a financial services firm, using a structured questionnaire. ANOVA tests, correlation analysis, and descriptive statistics were applied, with Cronbach's alpha confirming data reliability, and the findings indicate that higher-income investors were generally less influenced by most biases, though overconfidence tended to increase with income. In contrast, lower-income investors exhibited stronger biases such as loss aversion, availability bias, and mental accounting, likely due to limited financial knowledge and access to expert advice. The study concludes that income significantly affects susceptibility to behavioural biases, highlighting the importance of financial literacy in mitigating these effects. It suggests that financial advisors should tailor

guidance according to investors' income levels and promote education programs to reduce cognitive biases and improve decision-making. (Isidore & Christie , 2019c)

Similarly, Rashid, Fayyaz, and Karim in the year 2019 investigated the effects of investor sentiment and momentum on stock returns in the Pakistan Stock Exchange (PSX). Monthly stock returns of non-financial firms which were listed on the Pakistan Stock Exchange. All these firms were taken in to consideration for asset pricing models. Normally the Investor sentiment and momentum affect income on stock. It also impacted to market mispricing. Lastly it was confirmed that psychological factors affect stock price movements in Pakistan. (Abdul et al., 2019)

After reviewing the literature of 2019, the author studied the 2020 research. In a more recent study, Sharma and Firoz examined the impact of behavioural biases on financial decision-making, challenging the traditional assumption of fully rational investors. The research focused on biases such as overconfidence, herding, anchoring, and the disposition effect. Overconfidence was found to drive excessive trading, herding led investors to follow market trends blindly, anchoring caused reliance on initial information, and the disposition effect resulted in holding losing stocks for too long. Using a combination of surveys and regression analysis, the study revealed regional variations in investor behaviour, with urban investors taking higher risks due to greater financial awareness. The authors highlight the importance of financial literacy and structured investment strategies to mitigate irrational decision-making, demonstrating that behavioural finance provides a more accurate explanation of market anomalies than traditional theories. (Sharma & Firoz, 2020)

In the same year, Sharma highlighted how behavioural biases significantly influence individual equity investors, often leading to irrational decision-making. The study contrasts traditional finance, which assumes logical choices, with behavioural finance, demonstrating that cognitive and emotional biases distort investment behaviour. Key biases identified include overconfidence, herding, anchoring, availability bias, and the disposition effect, all of which contribute to repeated errors and suboptimal financial outcomes. The research emphasizes the importance of financial literacy and investor awareness in mitigating these biases and promoting more rational decision-making. By incorporating psychological factors into financial analysis, behavioural finance provides a more accurate understanding of investor

behaviour and underscores the need for continued research and education in this field. (Sharma B. , 2020)

In the same year, Kalbhor and Jagannathan investigated the impact of behavioural biases on investment decisions in the Indian capital market using the Bailard, Biehl, and Kaiser (BB&K) Five-Way Model. Various investor personalities were tested to know how behavioural biases influence investment decisions. For this, responses from 241 investors in Mumbai and Bengaluru taken. It noted that disposition effect, anchoring, and herding were linked with personalities. With this age, gender, and investment experience also affect behavioural biases. (Jagannathan & Kalbhor, 2020)

In the same year, Chidambaranathan and Guha (2020) employed an exploratory quantitative design to assess financial capability (FC) among households in Manipur and Tripura, focusing on individuals involved in microfinance organisations (MFOs). Using multistage sampling, data were collected through household surveys covering demographics, income, financial knowledge, attitudes, and behavioural economic factors. Financial Capability Index (FCI) scores were calculated using Principal Component Analysis (PCA), and multiple ordinary least squares (OLS) regression identified key determinants of financial capability. The results revealed that households participating in MFOs demonstrated higher financial capability (53%) than non-participants (44%). Loss aversion and mental accounting positively influenced financial decision-making, while present bias and impulsive spending produced mixed effects. The study concludes that behavioural factors play a critical role in financial capability and highlights the importance of financial literacy initiatives incorporating behavioural insights, particularly for underserved tribal regions. (Chidambaranathan & Guha , 2020)

Again in the same year, Leković conducted a qualitative study using existing literature, theoretical models, and case studies to explore the role of cognitive biases in financial decision-making. Some behavioural biases, like overconfidence, loss aversion, mental accounting, framing, herd behaviour, and confirmation bias, were considered in this research. It was described that all given biases influence the investors to trade. Hold on losing investments for long time, or follow present market situations. Such behaviour may affect both investors and financial markets. (Leković, 2020)

Satramani and Rupani also, in the year 2020, provided a comprehensive review of literature from 1979 to 2020, examining how behavioural biases influence investment choices. The study identified four key biases, including overconfidence and herding, that commonly affect both individual and institutional investors. It also highlighted that the impact of these biases often varies with demographic factors such as age and gender. The review emphasizes that understanding these psychological influences can help investors, companies, and policymakers make more rational financial decisions. While much research has focused on developed markets, the study notes significant opportunities for further investigation in developing economies. (Satramani & Rupani, 2020)

2.3.1 Conclusion of Scenario of Behavioural Finance from 2016 to 2020

The Conclusion of second scenario, the studies published between the year 2016 and 2020, described that normally investor decisions were strongly influenced by behavioural biases. It means they are not pure logical thinker. Overconfidence, loss aversion, herding, anchoring, and mental accounting were common biases in this scenario. Just because of given biases, many investors take emotional decisions. Some investors held losing investments for long duration. And some of them followed others without good analysis.

During this scenario, researchers and the authors or scholars also gave more priority some interesting factors such as age, gender, income, education, occupation, and residence. All given variables were found to influence investor behaviour in various ways. In this also advanced statistical methods were used. It also added that behavioural finance studies get boosted in many countries. Those countries were India, Pakistan, Kenya, and Nigeria. Overall, this scenario proved that psychology plays good role in investment. So investors should not ignore it.

From the Above Scenario of 2016 to 2020, the most dominant biases from the literature are: Overconfidence Bias, Loss Aversion Bias, Herding Behaviour Bias, Anchoring Bias, Mental Accounting Bias, Regret Aversion Bias, Availability Bias, Representativeness Bias, Disposition Effect Bias, Optimism Bias, Gambler's Fallacy Bias, Familiarity Bias, Self-Attribution Bias, Framing Effect Bias, Risk Perception Bias

2.3.2 Research Gap (2016 to 2020)

Between 2016 and 2020, research on behavioural finance consistently demonstrated that cognitive and emotional biases, such as overconfidence, loss aversion, herding, anchoring, and self-attribution, significantly influence investment decisions among both individual and professional investors.

As described in earlier sections, many studies were conducted in developed and developing countries India, Pakistan, Nigeria, and the United States, etc. But, less importance given to rural investors, women, and young investors. Also small business owners was not taken in to consideration. Some studies suggested that financial education can reduce behavioural biases. But overconfidence and some emotional factors still affects.

Another interesting gap is that in almost studies the researchers applied one-time questionnaire surveys but the investors' minds and thoughts changes time to time so changes in over a period of time were not considered. Only some researchers give importance to FinTech, AI, and other new technologies. So, these areas need more research work for exploring about investor behaviour.

2.4 Scenario of Behavioural Finance from 2021 to 2025

After discussing the scenario of 2016 to 2020 as a part of the evolution of the Behavioural Finance field, the discussion of the second scenario in between the years 2021 and 2025. This scenario starts from the year 2021, in this year Samal and Mohapatra (2021) examined the role of behavioural finance in shaping investor decision-making through a comprehensive review of existing literature on cognitive biases in financial markets. The study focused on psychological and emotional factors, identifying key biases such as overconfidence, loss aversion, mental accounting, framing, herd behaviour, and confirmation bias. The review highlighted that traditional financial models, which assume fully rational decision-making, fail to capture actual investor behaviour. Overconfidence was found to drive excessive trading, loss aversion led investors to hold underperforming assets, herd behaviour contributed to speculative bubbles, and framing effects influenced risk perception. The authors concluded that understanding these biases enables investors, financial advisors, and policymakers to develop strategies that mitigate irrational decision-making, enhance market efficiency,

and improve financial outcomes, demonstrating the practical significance of behavioural finance in modern investment practices. (Samal & Mohapatra, 2021)

In 2021, Ogunlusi and Obademi examined the influence of behavioural finance on investment decision-making in selected investment banks in Lagos, Nigeria. Data were collected from 180 clients of Afrinvest West Africa Limited, Meristem Securities, Vetiva Capital, and ARM Nigeria Limited using a structured questionnaire. Correlation analysis and multiple regression were employed to assess the effects of heuristics and prospect theory on investment choices and found out that investors relying on heuristics often made suboptimal financial decisions, while those guided by prospect theory tended to hold losing investments due to loss aversion. The study confirmed that psychological biases significantly shape investment behaviour, consistent with global behavioural finance research. It recommended improving investor awareness and implementing regulatory measures to enhance decision-making in the Nigerian stock market. (Ogunlusi & Obademi, 2021)

Building on earlier research, Financial literacy and behavioural biases in South India were studied by Suresh in the year 2021. For this research, he collected data from 250 investors. After testing data, he described that heuristic biases, in which mainly overconfidence and representativeness, had the strongest effect on investment. (Suresh, 2021)

In the same year 2021, Calzadilla, Bordonado-Bermejo, and González-Rodrigo conducted a systematic review to examine the impact of behavioural biases on financial decision-making among ordinary investors. The researchers reviewed 266 research papers published during the year 2009 to 2019. And they identified total 18 behavioural biases. The biases were overconfidence, confirmation bias, and the disposition effect were the most common. They also noted in research some biases changed with age, education, and location. Only some studies were visible from Africa. (Calzadilla et al., 2021)

Continuing the research in 2021, Gupta and Shrivastava examined the role of behavioural biases among retail investors in Chhattisgarh, India, applying Heuristic Theory and Prospect Theory. Behavioural biases influencing retail investors were studied using responses from 170 stock market investors. In this, representativeness bias had the more strong influence. Loss aversion and regret aversion both affected investment. But many investors relied on past experience. Some of them depended on easily available information. (Gupta & Shrivastava, 2021)

Also in 2021, Lasantha and Kumara highlighted the importance of data collection in research, particularly for ensuring the reliability and accuracy of findings. Their study examined investment behaviour across Colombo, Kandy, and Galle in Sri Lanka, using a structured questionnaire to gather data. Descriptive statistics and Structural Equation Modeling (SEM) were employed to analyse both direct and indirect relationships among variables, with fit indices such as CFI, RMSEA, and SRMR used to validate the model. The findings revealed that behavioural biases significantly influence investment decisions, though their impact varied across the cities. Overconfidence, anchoring bias, and herding behaviour were identified as the most influential, with effects shaped by demographic and regional factors. The study underscores the need to account for behavioural biases in investment research and encourages further exploration across diverse economic contexts. (Lasantha & Kumara, 2021)

Continuing research in 2021, Ravi Sankar Jeti and Dr. N. Udaya Bhaskar examined the role of behavioural biases in investment decisions across cash, futures, and options markets in Andhra Pradesh, India. The study focused on biases such as excessive optimism, directional trading, resistance to change, functional fixedness, risk-seeking tendencies, and social community influence. The findings revealed that investors frequently display overconfidence, follow short-term market trends, struggle to adapt to changing conditions, take higher risks after gains, and rely heavily on social media platforms like WhatsApp and Telegram for advice. Many also increase positions in losing trades rather than enforcing stop-loss measures, while aggressively reinvesting profits highlights emotional influences on behaviour. Despite growing financial literacy, these psychological biases continue to shape investment decisions, emphasizing the need for awareness programs and strategic measures to foster more rational decision-making. (Jeti & Bhaskar, 2021)

Also in the year 2021, Gamage, Wijekumara, and Sugathadasa examined the impact of behavioural biases on investment decisions among individual equity investors in Sri Lanka, focusing on the Colombo Stock Exchange (CSE) and the Kurunegala region. In this research, the availability, heuristic and herding behaviour were clearly seen. Which affects investors larger than other behavioural biases. They made comparison of representativeness and overconfidence and said that they only a smaller effect on decisions. lastly, Easy access to correct market information can help all the investors for making right decisions. (Gamage et al., 2021)

Following the growing research on behavioural finance in 2021, Talwar, S., Talwar, M., Tarjanne, V., and Dhir, A. investigated the influence of behavioural biases on millennial retail investors' trading behaviour and equity recommendation intentions during the COVID-19 pandemic in Finland. The study analyzed responses from 351 male millennial investors using an artificial neural network approach, complemented by a qualitative follow-up with 19 participants. The findings revealed that biases such as herding, hindsight, overconfidence, self-attribution, representativeness, and anchoring significantly shaped both trading activity and recommendation decisions, while loss aversion and mental accounting primarily affected recommendation intentions. Some biases exhibited nonlinear effects on trading behaviour, whereas others followed a linear pattern. The qualitative follow-up confirmed that these biases persisted throughout the pandemic, highlighting the strong role of psychological factors in shaping investment behaviour even during periods of market uncertainty. (Talwar et al., 2021)

Continuing the research in the year 2021, Sendilvelu and Shah investigated how cognitive biases influence the investment decisions of single parents in South Asian countries. The study emphasizes that single parents, often with limited resources and no financial backup, face unique challenges in making investment choices. The findings highlight that loss aversion is a dominant bias, with many single parents preferring low-risk investments to protect their children's future. Income level also affects risk tolerance, as higher earners are more willing to engage in moderate-risk investments. The study concludes that single parents tend to focus on short-term goals while neglecting long-term financial planning and recommends seeking professional advice to mitigate biases and make more informed investment decisions. (Sendilvelu & Shah, 2021)

Similarly in the year 2021, Wangzhou et al. investigated how regret aversion and information cascade influence investment decisions in the real estate sector of developing countries. The study also examined the moderating effect of financial literacy and the mediating role of risk perception. The findings reveal that regret aversion, where investors avoid decisions that might lead to regret, and information cascade, where individuals follow others without full information, negatively affect investment choices. Financial literacy was shown to mitigate these effects by enabling more informed decisions, while risk perception mediated the relationship between biases and investment behaviour, shaping how these biases influence choices. This

research highlights the critical role of financial knowledge and risk awareness in reducing the impact of cognitive biases, offering valuable insights for improving investment decision-making in real estate markets. (Wangzhou et al., 2021)

Building on the behavioural finance research of 2021, in 2022 Satish K. Mittal and Deepa Shrivastava conducted a study examining how behavioural biases influence investment decisions, particularly in the Indian market. Their research reveals that both individual and institutional investors are affected by psychological and social factors, which often lead to irrational decision-making. The study explores various biases, including overconfidence, herd mentality, and loss aversion, all of which significantly shape investment behaviour. By recognizing these biases, investors can make more rational and informed choices, enhancing the alignment of their portfolios with market efficiency. As financial markets move toward customer-centric and customised services, understanding investor psychology becomes crucial for both investors and financial service providers. (Mittal, 2022)

Following the insights from behavioural finance research in early 2022, Zahid Hasan, Vidya S. Athota, and co-authors proposed integrating Artificial Intelligence (AI) to manage cognitive biases in financial decision-making. They highlighted that biases such as confirmation and hindsight often result in suboptimal financial planning, limiting the effectiveness of financial advisors. The study suggests that AI can mitigate these biases by leveraging supervised and unsupervised learning techniques, with deep neural networks and deep reinforcement learning proving particularly effective. These AI methods process information through multiple layers, reducing the influence of prior data on decision outcomes. By incorporating AI, financial planners can make more objective and rational investment decisions, improving strategies and outcomes while addressing cognitive limitations in the financial sector. (Hasan et al., 2022)

Building on the 2022 research exploring behavioural biases in investment decisions, Pulgam, Magar, and Agrawal analyzed how such biases influence investor choices in Mumbai, challenging the traditional assumption of fully rational decision-making. Their study, grounded in behavioural finance theories, highlights key biases including Representativeness Bias, Hindsight Bias, and Regret Aversion Bias, all showing significant correlations with investment behaviour. Representativeness Bias was found to have the strongest effect, prompting investors to base decisions on

perceived patterns rather than objective analysis. While Self-Attribution Bias displayed a negative correlation with investment choices, it became relevant primarily in combination with other biases. The findings underscore the importance of integrating psychological insights into financial products and strategies, enabling investors to mitigate cognitive biases and make more informed decisions. (Pulgam et al., 2022)

Building on recent research on behavioural finance, Bose and Shah in the year 2022 investigated how cognitive biases affect investment decisions, often leading to suboptimal financial outcomes. Their study identified key biases, including loss aversion, anchoring, availability bias, mental accounting, gambler's fallacy, and herd behaviour, which impair rational judgment and create a behavioural gap affecting portfolio performance. The research emphasizes that enhancing investor awareness and financial literacy can mitigate the influence of these biases. Additionally, factors such as financial literacy, investment experience, and demographics were found to significantly affect an investor's susceptibility to psychological biases. The findings highlight the importance of addressing these cognitive tendencies to improve decision-making and achieve better financial outcomes. (Bose & Shah, 2022)

Also in 2022, Isik Akin highlighted that behavioural finance demonstrates how individuals often deviate from rational decision-making due to cognitive biases and emotions. Unlike traditional finance, which assumes rationality, behavioural finance identifies systematic errors that influence financial choices. Common biases include anchoring, conservatism, overconfidence, and framing, often resulting in suboptimal decisions. Cultural and economic contexts also shape these biases: young adults in Bristol tend to exhibit over-optimism, anchoring, and conservatism, whereas those in Istanbul are more affected by framing, cognitive dissonance, and the illusion of knowledge. Financial literacy plays a crucial role, as individuals with limited knowledge are more susceptible to biases. Understanding these differences is vital for designing targeted financial education programs, and mitigating biases requires awareness, critical thinking, and data-driven decision-making. (Akin, 2022)

Investor risk perception reflects an individual's evaluation of uncertainty in financial returns, influenced by both psychological and demographic factors. In 2022, Rangapriya Saivasan and Madhavi Lokhande examined this complex relationship, identifying risk propensity—encompassing return expectation, time horizon, and loss

aversion—and behavioural biases as central determinants. Their study highlights the significant role of biases such as familiarity, overconfidence, anchoring, and experiential biases in shaping investment decisions. Familiarity bias drives investors toward known assets, overconfidence bias prompts excessive risk-taking, anchoring bias encourages reliance on past reference points, and experiential bias affects choices based on previous market experiences. Using exploratory factor analysis, multiple regression, and the Kruskal–Wallis test, the research demonstrates that demographic characteristics significantly influence these biases and risk attitudes. The findings emphasize the importance of incorporating behavioural factors into investment risk assessment and asset pricing models for a more accurate representation of market behaviour. (Saivasan & Lokhande, 2022)

In 2022, Aniruddha S. Rao and Dr. Savitha G. Lakkol examined the relationship between personality traits, as described by the HEXACO model, and overconfidence levels among retail investors in equities, mutual funds, and bonds. The study surveyed 208 investors using the 24-item Brief HEXACO Inventory (BHI) developed by De Vries. The findings reveal a strong positive association between Openness to Experience and heightened overconfidence, while Honesty-Humility, Emotionality, Agreeableness, and Conscientiousness showed significant negative correlations with overconfidence. Extraversion, however, had no notable impact on overconfidence levels. This research provides valuable insights for behavioural finance by demonstrating how investor personalities, as measured through the HEXACO model, influence overconfidence—a cognitive bias that can affect financial decision-making. (Rao & Lakkol, 2022)

Behavioural biases significantly shape investor decisions, particularly during periods of market uncertainty. In 2022, Deepak Kumar and Devendra Jarwal investigated herding behaviour in equity markets, highlighting its short-term nature, especially in developing economies and during financial crises. The study emphasizes that herding disrupts market efficiency, increases volatility, and causes asset prices to deviate from fundamental values. Both individual and institutional investors exhibit herding tendencies, with younger analysts being particularly susceptible. In emerging markets, factors such as reliance on informal information sources, lack of transparency, and weak financial infrastructure amplify this behaviour. The research also identifies gaps in current literature, particularly in Southeast Asia and Africa, and notes limited

studies on alternative financial sectors, including derivatives, mutual funds, and cryptocurrencies. (Kumar & Jarwal , 2022)

Herding behaviour has become a critical area of study in understanding investor psychology, especially during periods of market turbulence. In the time period of COVID-19 situation, lots of investors in Saudi Arabia did not take their investment decisions on their own. They copied other people in investment. In this study male investors blindly go through the crowd more than female. But older investors are more likely to make their own investment decisions. (Alnori & Ahmad, 2022)

Gender-based biases have increasingly been recognized as influential factors in investment decision-making. Investment choices in equity crowdfunding was a research conducted by Cicchiello and Kazemikhasragh in the year 2022 in Latin America. It was seen that many investors interested to invest in businesses. Especially those run by people of the same gender. Both the gender investors also preferred safe investment. They like more set businesses rather than taking higher risks. (Cicchiello & Kazemikhasragh, 2022)

Overconfidence is widely recognized as a critical factor influencing investor behaviour and financial performance. Overconfidence and investment performance were studied by Abdin et al. in the year 2022. They prove that illusion of control, optimism, and self-attribution biases create more overconfidence. Investors with higher earnings showed overconfidence. That affected the level of risk. (Abdin et al., 2022)

Overconfidence bias has been shown to fluctuate with changing market conditions, affecting investor decisions across different economic cycles. Jitender Kumar and Neha Prince in 2022 investigated how market conditions influence overconfidence bias among investors in the Indian stock market. Analysing data from the BSE 100 index, the study assessed investor behaviour across different market phases, including pre-crash, crash, and post-crash periods. The results showed that investors were highly overconfident before major downturns, such as the 2008 financial crisis and the period leading up to the COVID-19 pandemic. However, this overconfidence subsided in post-crash periods (2008–2010, 2010–2015, and 2020–2021). Utilising econometric techniques like Vector Auto Regression (VAR) and Impulse Response Function (IRF), the research highlights the impact of market

volatility on investor sentiment and decision-making, offering valuable insights into behavioural biases in financial markets. (Kumar & Prince, 2022)

Similarly, the study by Shahani and Ahmed in 2022 examines how behavioural biases affect stock purchasing decisions among investors in the Pakistan Stock Exchange. Their research finds that anchoring and adjustment bias negatively impact stock buying choices, whereas herd mentality and availability biases contribute positively. The study also highlights that while investors demonstrate strong basic financial literacy, their advanced financial literacy remains moderate. Furthermore, basic financial literacy moderates the relationship between herd mentality bias and stock purchasing decisions, whereas advanced financial literacy influences the effect of mental accounting bias on investment behaviour. (Shahani & Ahmed, 2022)

Similarly the research conducted in 2022, Goel, Dash, Brooks, and Subramaniam explore how FEARS sentiment asymmetrically impacts stock returns, particularly under conditions of short-selling restrictions, arbitrage limitations, and behavioural biases. Their research identifies a strong negative relationship between FEARS sentiment and stock returns, indicating that heightened market pessimism significantly influences investor decisions. The study further shows that short-sale and arbitrage constraints reduce the impact of sentiment on return patterns, limiting price adjustments. Additionally, FEARS sentiment amplifies behavioural biases such as herding and anchoring, resulting in irrational trading behaviour. Using quantile regression analysis, the authors demonstrate that the negative effects of pessimistic sentiment are more pronounced in stocks with greater short-selling and arbitrage limitations, underscoring the role of market frictions and investor biases in sentiment-driven mispricing within the Indian stock market. (Goel et al., 2022)

In line with previous research, Jain, Walia, Kaur, and Singh in the year 2022 highlighted the significant role of behavioural biases in shaping investors' decision-making across multiple dimensions. Their study developed and validated a comprehensive scale to measure these biases, identifying ten key factors: Availability Bias, Representativeness Bias, Overconfidence Bias, Market Factors, Herding, Anchoring, Mental Accounting, Regret Aversion, Gambler's Fallacy, and Loss Aversion. Using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), the researchers confirmed the scale's reliability and validity. The findings

underscore the importance of examining multiple biases collectively, rather than in isolation, as they jointly influence investment choices. By introducing a structured and empirically validated measurement tool, this study contributes to behavioural finance in the Indian context, offering valuable insights for investors, policymakers, and scholars to better understand and manage these biases. (Jain et al., 2022)

Building on recent behavioural finance research, Pursiainen in the year 2022 examines how cultural biases influence equity analysis, showing that analysts tend to give more optimistic stock recommendations and higher target prices for firms from countries they perceive more favourably. This trust bias is especially pronounced for eponymous firms and intensifies during periods of economic instability, such as the European debt crisis and Brexit, when regional biases were stronger. While greater trust bias is associated with lower earnings forecast errors—suggesting a potential informational advantage—the study also finds that these biased recommendations are less reliable in predicting actual stock performance. Moreover, the market appears to recognize these biases, as stock price reactions to recommendations from more biased analysts are muted. These findings enrich behavioural finance literature by demonstrating how both long-term cultural biases and short-term perceptual shifts influence investment decisions, equity analysis, and market efficiency. (Pursiainen, 2022)

Extending insights from recent studies on behavioural finance, Wang and Nuangjamnong in the year 2022 examine how herding behaviour, investor sentiment, overconfidence, and risk tolerance shape investment decisions among individual investors in China. Using both surveys and secondary data, the research finds that herding behaviour amplifies investor sentiment, leading to more favourable investment choices, while overconfidence increases risk tolerance, which subsequently influences decisions. Among these factors, risk tolerance emerges as the most significant determinant of investment behaviour. The authors stress the importance of rational decision-making, especially in volatile markets, and highlight how cognitive biases like herding and overconfidence can result in suboptimal financial choices. They also recommend further investigation into additional behavioural and contextual factors that influence investment decisions across diverse economic environments. (Wang & Nuangjamnong, 2022)

Following the growing body of research on behavioural finance, Rosyidah and Pratikto in the year 2022 conducted a systematic literature review and bibliometric analysis to explore how behavioural biases influence financial decision-making. Analyzing 51 articles published between 2018 and 2022 using VOSviewer for bibliometric mapping and PRISMA for article selection, they identify seven key biases—overconfidence, self-attribution, heuristic, herding, aversion, disposition effect, and framing—that significantly shape investment behaviour. The study also highlights current research trends, including leading journals, influential articles, and prominent contributing countries, while noting a significant gap in studies conducted in developing economies. By synthesizing these insights, the paper provides a theoretical framework for understanding behavioural biases and underscores the need for future research to address underexplored contexts and emerging patterns in investor behaviour. (Rosyidah & Pratikto, 2022)

Building on the behavioural finance research of 2022, in 2023 Extending the research on behavioural finance, Tahira Iram, Ahmad Raza Bilal, Zeshan Ahmad, and Shahid Latif investigated how financial mindfulness moderates the relationship between financial literacy and behavioural biases among women entrepreneurs. Their study, involving 346 participants in Pakistan, revealed that financial literacy helped reduce anchoring and herding biases but did not significantly affect mental accounting biases. Importantly, financial mindfulness strengthened the positive effects of financial literacy, particularly in mitigating herding and mental accounting biases, though it showed no influence on anchoring bias. These findings underscore that combining financial literacy with mindfulness can support women entrepreneurs in making more rational and informed financial decisions, thereby improving business outcomes and addressing cognitive biases in entrepreneurial finance. (Iram et al., 2023)

Building on contemporary behavioural finance research, Jinesh Jain and co-authors in the year 2023 examined how heuristic biases influence investment decision-making, with a focus on the mediating role of risk perception. Their study, based on data from 432 individual investors trading on India's National Stock Exchange, revealed that risk perception partially mediates the effects of biases such as overconfidence, availability, gambler's fallacy, and anchoring on investment decisions, while it fully mediates the impact of representativeness bias. The findings indicate that these biases often lead investors to underestimate risk, highlighting the need for

interventions to improve decision-making. The study offers actionable insights for investors, financial advisors, and policymakers and suggests that future research could expand sample sizes, explore additional behavioural factors, and leverage advanced methods like machine learning to better predict investor behaviour. (Jain et al., 2023)

Similarly, in 2023, Mohan Prasad Sapkota examined the impact of emotional biases on the equity investment decisions of individual investors in Chitwan. The study, involving 385 investors with a 79% response rate, identified biases such as loss aversion, overconfidence, self-control, regret aversion, endowment, and status quo biases. The results showed that loss aversion, overconfidence, self-control, and regret aversion significantly influenced investors' decisions, whereas endowment and status quo biases had no meaningful effect. The research found that investors often relied on easily accessible information and personal emotions rather than performing detailed market analysis, leading to overtrading, overreaction, and irrational investment choices, which contributed to market inefficiency. Sapkota concluded that emotional biases play a crucial role in investment decisions and advised investors to manage their emotions, seek expert guidance, and adopt more rational strategies to avoid biased judgments. (Sapkota, 2023)

Similarly, Tejashwini and Dr. Cirappa, in the year 2023, explored the influence of behavioural finance on the derivatives market, a complex and intricate financial sector. The study begins by presenting traditional financial theories before introducing key concepts from behavioural finance, focusing on cognitive biases that can affect traders' decisions in derivatives markets. Although derivatives require careful analysis of factors such as market conditions and risk management, investors are often influenced by biases like overconfidence and loss aversion. The authors suggest that applying principles from behavioural finance can improve decision-making, enhance risk management, and increase market efficiency. While it may not resolve all challenges, behavioural finance provides useful tools for better understanding market behaviour and making more informed investment choices, emphasizing the importance of ongoing education for investors in the derivatives market. (K C & Cirappa, 2023)

Similarly, Yin Wang in 2023 investigates the psychological and behavioural tendencies of young investors in China, particularly college students. Despite having a solid understanding of finance, these investors are still influenced by biases such as

emotional heuristics, loss aversion, confirmation bias, and the tendency to sell stocks prematurely. Unlike the general population, they do not exhibit strong overconfidence or herd behaviour but often struggle with balancing self-confidence and self-doubt in their investment choices. To address these challenges and improve investment decisions, the research suggests adopting strategies like contrarian investing, momentum-based approaches, focused investments, small-cap stock selection, dollar-cost averaging, and spreading investments over time. These methods help counter cognitive biases and enhance investment effectiveness. (Wang Y. , 2023)

Similarly, in 2023, Chiau conducted a systematic review of mental accounting and its impact on financial decision-making. One of the behavioural biases, mental accounting, was reviewed with the help of old research papers during the time period of 1900 to 2015. It showed that mental accounting creates a big effect on consumers as well as investors. Loss aversion bias was also closely connected with mental accounting. It affecting the people when they think about gains and losses. (Cruz et al., 2023)

Likewise, Schulz also in 2023 examines how behavioural biases like overconfidence, herding, and anchoring influence investment decisions among German investors. Surveying 342 participants, the study finds that men are more prone to overconfidence and anchoring biases, while women are more susceptible to herding bias. These biases, driven by cognitive shortcuts and emotional influences, often lead to irrational decisions. The study highlights how market conditions and external factors can intensify these biases and stresses the importance of awareness in helping investors avoid costly mistakes. (SCHULZ, 2023)

Similarly, Rzesutek, Szyszka, and Okoń (2023) investigate the influence of behavioural biases on corporate risk management and investment decisions during the COVID-19 pandemic in Poland. The study examines whether managers of companies listed on the Warsaw Stock Exchange are affected by irrational risk preferences and how these biases shape their decision-making. The findings reveal that biases such as overconfidence and loss aversion led to poor decisions during the pandemic. By conducting interviews and utilizing Agent-Based Modeling (ABM), the study connects individual biases with broader macroeconomic effects, such as changes in investment and employment. The authors emphasize the need for incorporating behavioural finance

into corporate finance research to enhance decision-making during crises. (Rzeszutek et al., 2023)

Similarly, Guan and co-researchers (2023) explore how trauma influences investment behaviour among Chinese equity investors. Their findings show that individuals who have recently experienced events like illness, natural disasters, or family loss tend to favor short-term trading over long-term investment. This behaviour is linked to heightened impulsivity, immediate gratification, trend-following, and risk-taking. However, the effect is weaker among older and married investors. The study notes limitations in analyzing the timing and type of trauma and cautions against generalizing the results beyond China, suggesting future research in different cultural contexts. (Guan et al., 2023)

Similarly, Altaf and Jan also in 2023 examined how millennial investors are influenced by generational-specific psychological tendencies. The study identifies four key biases—fear of missing out, ethical investment preferences, overconfidence, and a tendency to follow peer behaviour—as major factors shaping their investment decisions. Millennials are especially inclined to follow trends and make group-based investment choices, often driven by social media influence. Their high digital engagement contributes to overconfidence in their financial decision-making. Additionally, they favor companies that demonstrate strong social and environmental responsibility. The authors highlight the need for financial institutions to adopt strategies such as digital engagement, financial education, and socially responsible branding to effectively reach and support millennial investors. (Altaf & Jan, 2023)

Building on more advancements, Agarwal and Natarajan in the year 2023 presented a novel method for addressing human behavioural biases in joint human-AI decision-making through active learning systems. Their framework conceptualizes human-AI interaction as a dynamic process and introduces the ESIS strategy to detect and adjust for biases during learning. Applied to a pancreatic cancer dataset across varying expertise levels, the results demonstrate that bias-adaptive adjustments significantly improve AI decision accuracy, outperforming standard models by up to 16%. This study underscores the potential of incorporating bias-aware approaches to enhance reliability and effectiveness in complex decision-making tasks. (Agarwal & Natarajan, 2023)

Another significant study by Harisha and Muralidhara (2023) investigates how behavioural biases influence investment decisions among young individuals aged 20 to

30. Their study focuses on common psychological patterns such as loss aversion, confirmation bias, overconfidence, and herding, which shape investor behaviour. Using a mixed-methods approach, they find a moderate positive relationship between these biases and investment outcomes. While the quantitative results highlight this connection, the qualitative insights reveal how these biases manifest in real-life decisions. The study emphasises the importance of recognising these influences to improve decision-making, manage risk effectively, and achieve long-term financial goals. It also highlights the need for continued research across different groups and market environments.. (Harisha & Muralidhara, 2023)

Building on the behavioural finance research of 2023, in the year 2024, Parsaei, Molanazari, Mashayekhi, and Jalali Aliabadi have examined how instruction can help reduce mental accounting bias in capital investment decisions. The research explores how mental accounting was described as a behavioural bias. This bias can direct people to make poor decisions. Managers considered debt and equity investments differently just because of mental accounting. They suggested that training and some education is required to handle mental accounting and making good (Parsaei et al., 2024)

Consistent with studies in 2024 Mahmood and fellow researchers explore how behavioural biases affect investment decisions in the Pakistan Stock Exchange, finding that overconfidence, herding, and anchoring significantly drive irrational investment choices. While biases such as risk aversion, disposition effect, and representativeness bias showed no significant impact on decision-making, the study highlights the role of financial literacy in shaping these biases. However, the researchers also discovered that financial literacy had a negative and statistically insignificant effect on investment decisions and did not effectively moderate the relationship between behavioural biases and decision-making. These findings suggest that in countries like Pakistan, where financial education is often limited, improving financial literacy alone may not be sufficient to counteract behavioural biases. (Mahmood et al., 2024)

In the same year 2024, Shunmugasundaram and Sinha explore how behavioural biases affect investment decisions among life insurance policyholders in India. The study emphasises the role of overconfidence and the disposition effect in mediating the impact of these biases on investment choices. Overconfidence leads investors to overestimate their abilities, often resulting in greater risk-taking, while the disposition

effect causes them to sell winning investments too early and hold losing ones for longer periods. The findings show that these biases significantly shape investment decisions, with overconfidence strengthening the disposition effect, which in turn positively influences investment outcomes. By integrating these two biases into a serial mediation model, the research provides valuable insights into how behavioural factors influence investment behaviour, particularly in emerging markets, and contributes to the broader field of behavioural finance. (Shunmugasundaram & Sinha, 2024)

Also in 2024, Yadav examines the impact of behavioural biases on cryptocurrency returns through the lens of Prospect Theory (PT). By analysing a sample of 1,629 cryptocurrencies, the study uncovers an inverse relationship between Prospect Theory Value (PTV) and returns, with the strength of this connection varying according to market conditions. The research highlights the significance of Probability Weighting (PW), indicating that investors tend to prefer cryptocurrencies with lottery-like characteristics. The findings suggest that PTV is a stronger predictor for smaller, more volatile, and illiquid cryptocurrencies. Cryptocurrencies with high PTV are generally overvalued, leading to lower future returns, while those with low PTV are undervalued, resulting in higher returns. This study contributes to behavioural finance by providing insights into trading strategies based on PTV and recommending that policymakers consider investor biases when managing market volatility. Future research may further refine decision-making models under risk to expand on these findings. (Yadav, 2024)

Further, in 2024, Shukla and co-researchers explore the influence of behavioural biases—Overconfidence Bias, Representativeness Bias, and Herding Bias—on stock trading decisions of investors in North India. Utilising primary data from Uttar Pradesh, Delhi, Haryana, and Punjab, the study employs structural equation modelling to assess how these biases impact investor behaviour. The results show that Overconfidence Bias leads investors to overestimate their capabilities and engage in riskier trading, while Representativeness Bias prompts decisions based on incomplete or misleading patterns, often resulting in poor choices. Additionally, Herding Bias was found to have a significant effect, with investors frequently following the crowd instead of making independent and rational decisions, contrary to initial expectations of its weaker influence. These findings underline the significant role of behavioural biases in shaping stock trading decisions, challenge traditional financial theories, and highlight the

importance for financial advisors to consider these psychological factors in their strategies. (Shukla et al., 2024)

Continuing in 2024, El Ghmari and co-authors investigate how behavioural finance challenges traditional financial theories by integrating psychological elements to explain anomalies in financial markets. The paper emphasises key biases such as loss aversion, overconfidence, and cultural influences, exploring how these psychological factors shape the investment choices of Moroccan investors. Using empirical data and behavioural experiments, the authors demonstrate how these biases lead to deviations from efficient market theory predictions, showing that psychological behaviour significantly affects risk perception, market confidence, and overall market performance. Additionally, the study suggests strategies to mitigate these biases and improve the application of behavioural finance in decision-making. The results offer valuable insights into the unique financial behaviours of Moroccan investors, providing a context-specific model that could enhance financial decision-making in the region. (Ghmari et al., 2024)

Also in 2024, Rosid and co-authors investigate how cognitive biases, including overconfidence, herd behaviour, and loss aversion, affect investment decisions in the Indonesian capital market. Through an experimental study with 100 individual investors, the research demonstrates that overconfidence leads to more frequent transactions and higher risk-taking, increasing market volatility. Herd behaviour, particularly during high-volatility periods, causes investors to follow the crowd, contributing to price bubbles and sharp declines. Loss aversion drives investors to hold onto losing stocks for too long and sell profitable ones prematurely, limiting long-term gains. The study also identifies market anomalies in Indonesia, such as the momentum effect, January effect, and day-of-week effect, showing how these biases distort market behaviour. The findings underscore the importance of understanding and addressing these biases to improve investment outcomes and market stability, recommending strategies like investor education and enhanced market transparency. (Rosid et al., 2024)

In the year 2024, Behavioural finance was discussed by Padmavathy in their research, they examine why investors do not always make rational decisions. also revealed that anchoring, overconfidence, and loss aversion affected investment

decisions. Emotions like fear and greed, clearly influence investment behaviour. These factors were linked price bubbles and other market changes. (Padmavathy, 2024)

Following in 2024, Podile and co-researchers examine how behavioural biases, such as overconfidence, loss aversion, and herding behaviour, influence investment decisions and market dynamics. Using the PMBAC framework, they find that overconfidence leads to a -25% return impact and market overvaluation, while loss aversion results in a -5% return and 10% market overvaluation. Herding behaviour, associated with short-term gains but long-term risks, causes 40% market overvaluation. Other biases, including mental accounting and anchoring, contribute to poor investment choices and reduced returns. The study underscores the importance of addressing these biases for better risk management and more effective investment strategies. (Podile et al., 2024)

Following in 2024, Rehman and co-researchers explore how behavioural biases affect global investors' decisions, with a particular focus on regional differences between India and China. Based on data from 467 global investors and using SEM and Multi-Group Analysis, the study reveals that behavioural biases have a significant impact on investment decisions, with a stronger influence on Indian investors compared to their Chinese counterparts. In India, biases like Confirmation Bias, Herding Bias, Loss Aversion, Mental Accounting, and Status Quo Bias were more prominent, whereas in China, Herding Bias, Loss Aversion, and Mental Accounting had a greater impact. The findings emphasise how regional diversity influences the extent of these biases, providing important insights for investment firms to customise strategies and products based on cultural factors. (Rehman et al., 2024)

Also in 2024, Baulkaran and Jain examine how behavioural biases influence financial planners' advice on using home equity for retirement income. The study highlights that factors such as gender, education, and employment setting affect biases like mental accounting, loss aversion, and herding behaviour. Planners displaying mental accounting bias tend to avoid recommending home equity utilisation, while those with loss aversion and overconfidence are more likely to suggest selling investments or using home equity. The findings emphasise the need to recognise these biases to improve advisory practices, better guide clients, and refine planner training to minimise the influence of these biases in retirement planning. (Baulkaran & Jain, 2024)

In the year 2024, Isik Akin and Meryem Akin examine the impact of behavioural finance on stock market volatility, focusing on the S&P 500 index over a 10-year period. They explore factors like real interest rates (RR), consumer confidence (CCI), market volatility (VIX), and credit default swaps (CDS), analyzing how biases such as loss aversion, sentiment, and herding behaviour influence market fluctuations. The study finds that rising interest rates negatively affect stock prices, while higher consumer confidence boosts the market due to optimism and herding behaviour. It also shows that market volatility negatively correlates with the S&P 500, and higher CDS rates lead to declines in stock prices. The regression analysis reveals that RR, CCI, VIX, and CDS significantly impact the S&P 500, highlighting the role of psychological factors in market behaviour and volatility. (Akin & Akin, 2024)

In the year 2024, Werner Ria Murhadi, Devina Frederica, and Deddy Marciano investigate how financial literacy and demographic factors affect investor biases, including overconfidence, disposition effect, and herding behaviour. Using structural equation modeling on data from 170 Indonesian stock investors, they find that financial literacy significantly increases both overconfidence and herding biases, while higher income reduces these biases. The disposition effect, however, is unaffected by financial literacy or demographic factors. The study also shows that investment experience is positively related to herding bias. These findings suggest that while financially literate investors tend to make more informed decisions, they may still participate in herding behaviour, particularly in markets influenced by external parties like "bookies." High-income investors are less prone to herding and more likely to trust professional financial management. The authors recommend further research to explore additional demographic factors and a wider age range for a deeper understanding of these dynamics. (Murhadi et al., 2024)

Also, in the year 2024, Rahul Chauhan and Neerav Patel investigate how behavioural biases and psychological factors influence investment decisions in Baroda City. The findings reveal that awareness of financial products and innovation significantly shape investment choices, with purchasing power being a key determinant. The study also highlights that group biases and herding behaviour play a major role, whereas mental accounting and overconfidence have a smaller impact in this context. The authors emphasise that recognising these biases can help investors make more rational decisions and improve market efficiency. They further suggest that

interventions such as financial education and decision support tools can mitigate the negative effects of these biases, ultimately leading to better investment outcomes. (Chauhan & Patel, 2024)

In the year 2024, Chidimma Maria-Gorretti Umeaduma also investigates how cognitive and emotional biases shape individual investment choices, particularly in volatile markets and shifting economic conditions. The study argues that traditional finance theories, such as the Efficient Market Hypothesis, often fail to explain investor behaviour during periods of instability, whereas behavioural finance highlights biases like overconfidence, loss aversion, herding, and the recency effect. These biases manifest differently across economic cycles, with optimism dominating in bull markets and fear in bear markets. The research also examines how media, demographics, and psychological factors, including financial knowledge, influence these biases, often leading to suboptimal investment decisions and market distortions. The study suggests that interventions such as financial education, robo-advisors, and regulatory measures can mitigate these biases, improve portfolio performance, and contribute to more resilient financial systems. (Umeaduma, 2024)

Building on recent research in behavioural finance, Asep Risman in the year 2024 investigates the impact of digital finance, managerial biases, and financial literacy on the financial behaviour of MSMEs in DKI Jakarta. The study finds that both digital finance and financial literacy positively influence financial behaviour, resulting in improved financial management, enhanced performance, and greater efficiency. The adoption of digital finance, driven by its benefits and ease of use, supports better financial decision-making. In contrast, managerial biases were found to have no significant effect, likely because micro and small enterprises are typically managed by individuals or families, with major financial decisions occurring infrequently. Furthermore, MSMEs with higher financial literacy demonstrate more responsible financial practices, including improved financial planning and decision-making. (Risman, 2024)

A comprehensive bibliometric analysis by Poonam Das, Amit Kumar Das, and Sourav Charjee in the year 2024 examines the evolution of research on behavioural biases and investment decision-making from 1991 to 2022. The review showed that the number of studies increased speedily between 2008 and 2022. In this, United States was

big contributor. Also pointed out that more research is required on financial literacy, personality traits, and optimism bias. (Das et al., 2024)

Building on the behavioural finance research of 2024, in the year 2025, Santha Ganesh Iyer et al. investigated how demographic factors and behavioural biases influence mutual fund investment decisions among academicians. The study revealed that gender and professional experience did not significantly affect investment choices, whereas biases such as risk perception and financial market conditions had a stronger influence. Of these, financial market conditions emerged as the most important determinant, followed by risk perception and economic growth. Despite their academic expertise, academicians were still susceptible to biases that could impair rational decision-making. The authors suggest that a deeper understanding of these dynamics can inform more targeted financial education programs, enhance financial literacy, reduce biases, and support the development of personalised investment strategies for both academicians and the wider investor population. (Iyer et al., 2025)

Expanding on contemporary insights, Ranjan in the year of 2025 highlights that behavioural finance incorporates psychological factors, including cognitive biases and social influences, to deepen the understanding of financial decision-making in banking and management. The study shows how biases such as overconfidence, loss aversion, and herd behaviour affect risk assessment, lending practices, and investment strategies. This approach facilitates the creation of customer-centric financial products, strengthens financial literacy, and enhances risk management through technologies like artificial intelligence and big data. In the management context, it also helps mitigate biased thinking in strategic decisions and organizational processes. While cultural and ethical considerations persist, behavioural finance offers practical tools to drive innovation, improve customer satisfaction, and build organizational resilience. (Ranjan, 2025)

Building on recent developments, Abdeldayem in 2025 investigates the integration of behavioural finance and Fintech in shaping investor decision-making across GCC capital markets, including Saudi Arabia, Bahrain, UAE, Kuwait, Qatar, and Oman. The study finds that Fintech adoption helps mitigate behavioural biases, increases investor satisfaction, enhances participation, and fosters trust in financial systems, while behavioural finance remains critical in managing investment factors

such as diversification and returns. Socio-cultural influences are also shown to affect investor behaviour, evolving alongside Fintech growth. Key determinants of investment outcomes include returns, sensitivity to market sentiment, and trading activity. While Fintech improves accessibility and market efficiency, it may also introduce new behavioural challenges, with poor diversification linked to lower returns and higher trading frequency associated with improved. (Abdeldayem & Aldulaimi, 2025)

Building on recent evidence, Pitthan and De Witte in the year 2025 investigate the effectiveness of financial education programs that integrate behavioural biases—particularly myopia—compared to traditional approaches. Using a randomized controlled trial with Belgian secondary school students, they found that lessons explicitly addressing short-term thinking improved financial knowledge while reducing myopic tendencies, which in turn enhanced overall financial literacy. Behavioural-focused interventions were especially effective for students with initially low financial literacy, older participants, and females, highlighting the value of tailored educational strategies. Although traditional financial education reduced myopia to some extent, only behaviour-based courses showed a significant mediating effect on financial literacy. The authors advocate for brief, computer-assisted programs that incorporate bias awareness and recommend expanding curricula to cover multiple cognitive biases. Limitations include the focus on myopia alone, a localized sample, and a short-term evaluation period, suggesting the need for further research on long-term impacts and additional biases. (Pitthan & De Witte, 2025)

2.4.1 Conclusion of Scenario of Behavioural Finance from 2021 to 2025

In the Scenario of the years 2021 to 2025, Behavioural finance has developed from a largely academic and research context theory into a great extent of a practical and real-world focused field.

The third scenario consists of studies during the years 2021 to 2025. This describes that behavioural finance is not conventional. It became more practical and technology-oriented. In this time period, researchers show that behavioural biases do not work separately, but it affects each other internally. Some variables like age, gender, income, culture, and residence also influenced investor behaviour. In addition, in the pandemic of COVID-19, lots of investors made more emotional decisions.

This scenario also expressed the increasing use of AI and FinTech in behavioural finance research. Studies suggested that only financial education is not enough to lessen behavioural biases. If investors want to get good results, then they have to combine financial knowledge with technology and behavioural awareness. Overall, behavioural finance became a crucial field for investment decisions.

The most same behavioural biases noted during 2021–2025 were as under:

Overconfidence, herding, loss aversion, anchoring, mental accounting, disposition effect, confirmation bias, availability bias, representativeness, optimism bias, regret aversion, self-attribution bias, status quo bias, myopia (present bias), endowment effect, and emotional biases such as fear and greed.

2.4.2 Research Gap (2021-2025)

Despite significant research from 2021 to 2025 on behavioural biases and investment decision-making, several gaps persist. In this scenario, most studies during 2021 and 2025 described only specific groups of investors or a single country. So that the comparisons among different regions and people were not possible. Also several studies are there which only considered some behavioural biases. Instead of studying different biases also can work together. Almost all research depended on the survey method. Some of them using long-term or real-time market samples. It is correct that financial literacy and AI platforms received focused, but their real impact on reducing behavioural biases is still not clear. So that, more research is needed.

2.5 Conclusion of 2011 to 2025:

The research concepts and methods in the field of behavioural finance have changed over time. In the time period of 2011–2015, lots of research studies contributed on understanding behavioural biases with the help of questionnaires, surveys, and simple statistical tools. The scenario basically covered traditional financial markets.

In Second scenario 2016–2020, researchers take one step ahead and started advanced methods like Structural Equation Modeling (SEM) and other statistical tools. large attention was given to understanding different behavioural biases.

In third scenario 2021–2025, the behavioural finance field became more practical and technology based. In this time period AI and machine learning also used

for investor behaviour. New concepts as FinTech, cryptocurrencies, and digital investment became core parts of behavioural finance research.

The research studies were also much more interdisciplinary, mixing insights from psychological biases, finance, data science, and education, etc. This scenario of year 2021 to 2025 clearly indicates a clear change from just understanding Behavioural Finance biases to actively developing tools, mechanisms, and strategies that can be used by investors and make more than a good investment decision.

Table 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(ML), digital tools, and big data analytics

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, Myopia (Present Bias), Regret Aversion, Self-Attribution Bias, Availability Bias, Endowment Effect, Status Quo Bias, 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	Overconfidence Bias, Loss Aversion, Herding Behaviour,	Overconfidence Bias, Herding Bias, Loss Aversion, Anchoring Bias,

	Bias, Mental Accounting,	Anchoring Bias, Mental Accounting, Regret Aversion,	Mental Accounting, Regret Aversion
Availability of Study Regarding Equity Investors	Yes	Yes	Yes

(Source: Literature Review)

2.6 Research Gap

Over the past decade (2011–2025), studies in behavioural finance have consistently shown that cognitive and emotional biases—such as overconfidence, loss aversion, herding, anchoring, self-attribution, and regret aversion—strongly influence investment decisions among both individual and professional investors. The main Research gap from the earlier studies mainly considered the investors at the national level or on specific groups only. Very few studies examined investor behaviour at the regional or city level, especially in the Saurashtra region of Gujarat.

Most studies also used survey-based data, which provides only limited information. But did not examine that investor's behaviour changes time to time. Although recent research has discussed AI, FinTech, and financial literacy but, these fields received very small attention in regional studies.

Very limited research has been conducted on equity investors in Junagadh, Rajkot, and Jamnagar. So that, the present study tries to fill this gap by examining different behavioural biases and their impact on investment decisions in given three cities. The findings will provide some useful insights for researchers, investors, and financial planners in the Saurashtra region.

CHAPTER- 3
MATERIAL AND
METHODS/METHODOLOGY

CHAPTER- 3 MATERIAL AND METHODS/METHODOLOGY

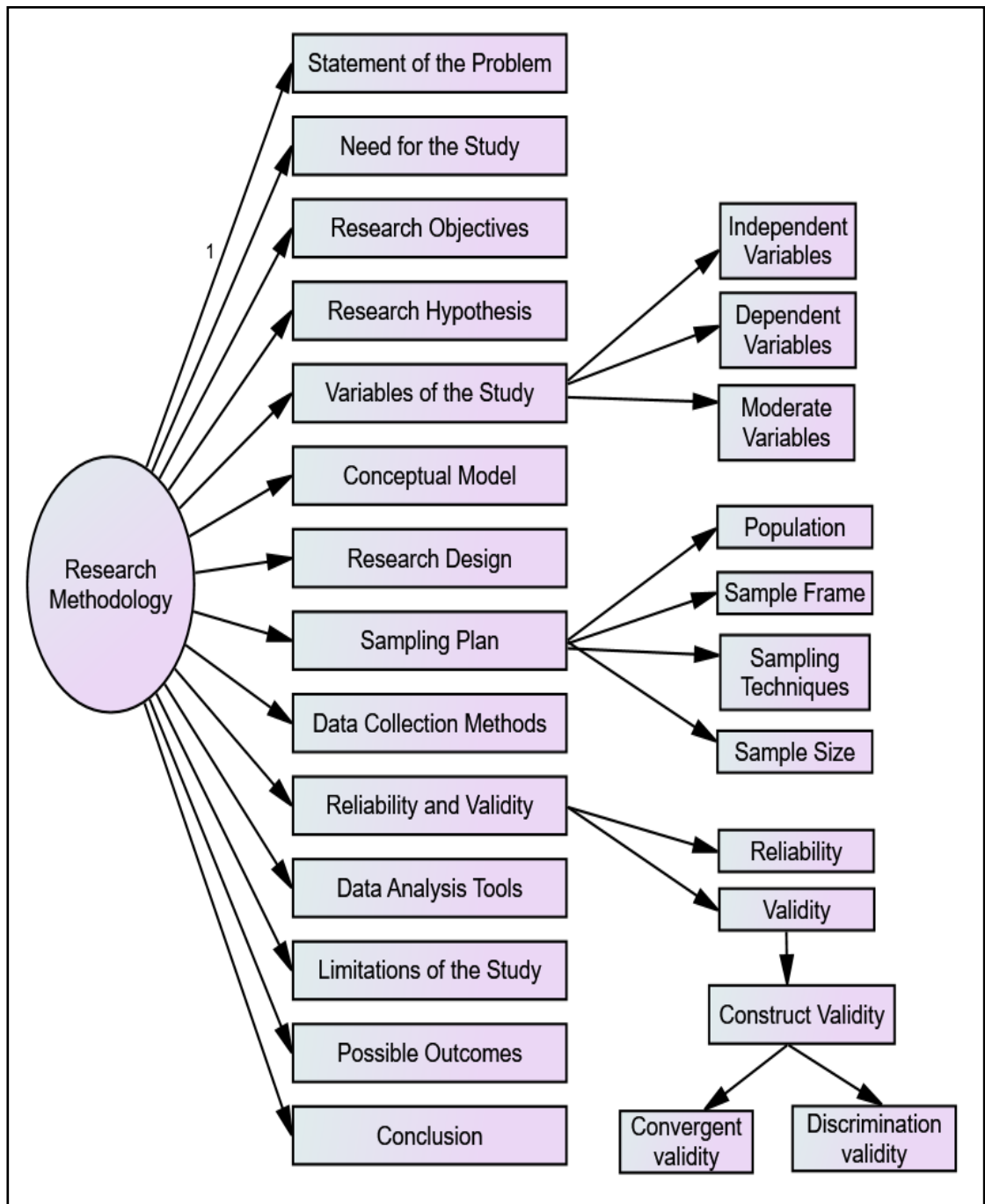
3.1 Introduction:

This chapter describes the methods and processes that were utilized to conduct the research. It elaborates the overall research design of the present study, the approach taken, and the steps followed to collect and analyze the data. The main goal of this chapter is to present a clear and organized framework that ensures the research process is rational or logical, trustworthy, and easy to apply.

To begin with, the chapter outlines the chosen research design and explains all the contexts that why it is appropriate for achieving the study's objectives. It also indicates the target population, the sampling methods used to select participants for collecting data, and the tools and techniques utilized in collecting the data. Moreover, it showcases how the collected data was analyzed to justify the research questions as well as the research objectives and create meaningful conclusions of the present study.

In addition, the chapter also discusses ethical considerations and the measures taken to ensure the study remains reliable and valid. For this purpose, the reliability and validity methods and their discussion are also covered in this chapter. By presenting the methodology and procedures in this manner, readers can easily understand how the research study was conducted, thereby strengthening the credibility of the study. This chapter also offers a foundation for other authors, researchers, and scholars who may want to replicate or present the results. In short, this chapter provides a logical guide to the systematic steps towards ensuring the results are accurate, consistent, and relevant to the objectives or not.

To describe the Whole Research methodology, the researcher prepared a Research Methodology Framework to understand the whole process in one vision with the help of IBM Amos 2023. The following diagram indicates the RM Framework.

Figure 3.1: Research Methodology Framework

(Source: Researcher's Compilation with the help of IBM Amos-2023)

The above given Research Methodology Diagram was created by the researcher with the help of IBM Amos 2023. This diagram shows the clear understanding of the whole research method which was used in this research. In short this research methodology frame work is the Bird View of whole research process of the present study.

3.2 Problem Statement

When individuals consider investing in equity markets, their decisions are often shaped by a combination of rational evaluation and psychological influences. While some thoughts about investment opportunities may be positive, others create hesitation or uncertainty. In many cases, investors do not make decisions based solely on financial information or market trends but are unconsciously affected by different behavioural biases. These include overconfidence, perception errors, representativeness, anchoring, cognitive dissonance, regret aversion, narrow framing, and mental accounting. (Kahneman & Tversky, 1979) Such biases can lead to emotional and irrational decision-making, which may prevent investors from achieving their desired financial outcomes. Traditional finance theories assume that investors act rationally, but real-world scenarios show that psychological factors strongly impact how investment decisions are made. (Barberis & Thaler, 2003) Given this situation, it becomes crucial to explore how behavioural finance influences the decision-making of equity investors. This study focused on examining the role of behavioural biases in the investment decisions of equity investors in selected cities of the Saurashtra region, like Junagadh, Rajkot, and Jamnagar. Understanding these biases can help equity investors, financial advisors, and policymakers develop strategies to minimize the effects of Behavioural biases and promote more informed and rational investment behaviour regarding equity investment.

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 Research Objectives

OBJECTIVE: 1

To study the Demographic variables of equity investors.

OBJECTIVE 2:

To know the preference of people towards equity Investment.

OBJECTIVE 3:

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

OBJECTIVE 4:

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

OBJECTIVE 5:

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

3.5 Research Hypothesis

OBJECTIVE 3:

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

Hypothesis:1

- 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

Hypothesis:2

- 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

Hypothesis:3

- 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

Hypothesis:4

- 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

Hypothesis:5

- 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

Hypothesis:6

- 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

Hypothesis:7

- H0: Different Number of Family Members of respondents assign the same mean towards behavioural biases

- H1: Different Number of Family Members of respondents do not assign the same mean towards behavioural biases

Hypothesis:8

- H0: Different Number of Earning Members of respondents assign the same mean towards behavioural biases
- H1: Different Number of Earning Members of respondents do not assign the same mean towards behavioural biases

OBJECTIVE 5:

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

Hypothesis:9

- H0: Different Behavioural Biases do not significantly affect the Investment Experience of equity investors of the selected cities of the Saurashtra Region
- H1: Different Behavioural Biases significantly affect the Investment Experience of equity investors of the selected cities of the Saurashtra Region

Hypothesis:10

- H0: Different Behavioural Biases do not significantly affect the Trading Frequency of equity investors of the selected cities of the Saurashtra Region
- H1: Different Behavioural Biases significantly affect the Trading Frequency of equity investors of the selected cities of the Saurashtra Region

Hypothesis:11

- H0: Different Behavioural Biases do not significantly affect the Amount of Single trade invested by equity investors of the selected cities of the Saurashtra Region
- H1: Different Behavioural Biases significantly affect the Amount of Single trade invested by equity investors of the selected cities of the Saurashtra Region

Hypothesis:12

- H0: Different Behavioural Biases do not significantly affect the Number of Companies in which investments are made by equity investors of the selected cities of the Saurashtra Region
- H1: Different Behavioural Biases significantly affect the Number of Companies in which investments are made by equity investors by equity investors of the selected cities of the Saurashtra Region

Hypothesis:13

- H0: Different Behavioural Biases do not significantly affect the Objective of the Regular Return of equity investors of the selected cities of the Saurashtra Region
- H1: Different Behavioural Biases significantly affect the Objective of the Regular Return of equity investors of the selected cities of the Saurashtra Region

Hypothesis:14

- H0: Different Behavioural Biases do not significantly affect the Objective of the Safety of the Principal Amount of equity investors of the selected cities of the Saurashtra Region
- H1: Different Behavioural Biases significantly affect the Objective of the Safety of the Principal Amount of equity investors of the selected cities of the Saurashtra Region

Hypothesis:15

- H0: Different Behavioural Biases do not significantly affect the Broking Apps as a source of information for equity investors of the selected cities of the Saurashtra Region
- H1: Different Behavioural Biases significantly affect the Broking Apps as a source of information for equity investors of the selected cities of the Saurashtra Region

3.6 Variables of the Study

Mainly, there are Two Types of Variables considered by the researcher in this study:

3.6.1 Independent Variables

In this study Researcher considered Behavioural biases and Demographic Variables as independent variables

3.6.1.1 Behavioural biases

- Overconfidence
- Familiarity
- Confirmation
- Regret aversion
- Narrow framing
- Shadow of the past
- Loss aversion
- Heed instincts

3.6.1.2 Demographic Variables

- Location (City)
- Gender
- Age
- Education
- Occupation
- Individual Annual Income
- Marital Status
- Family Type
- No. of Family Members
- No. of Earning Members in the Family

3.6.2 Dependent Variables

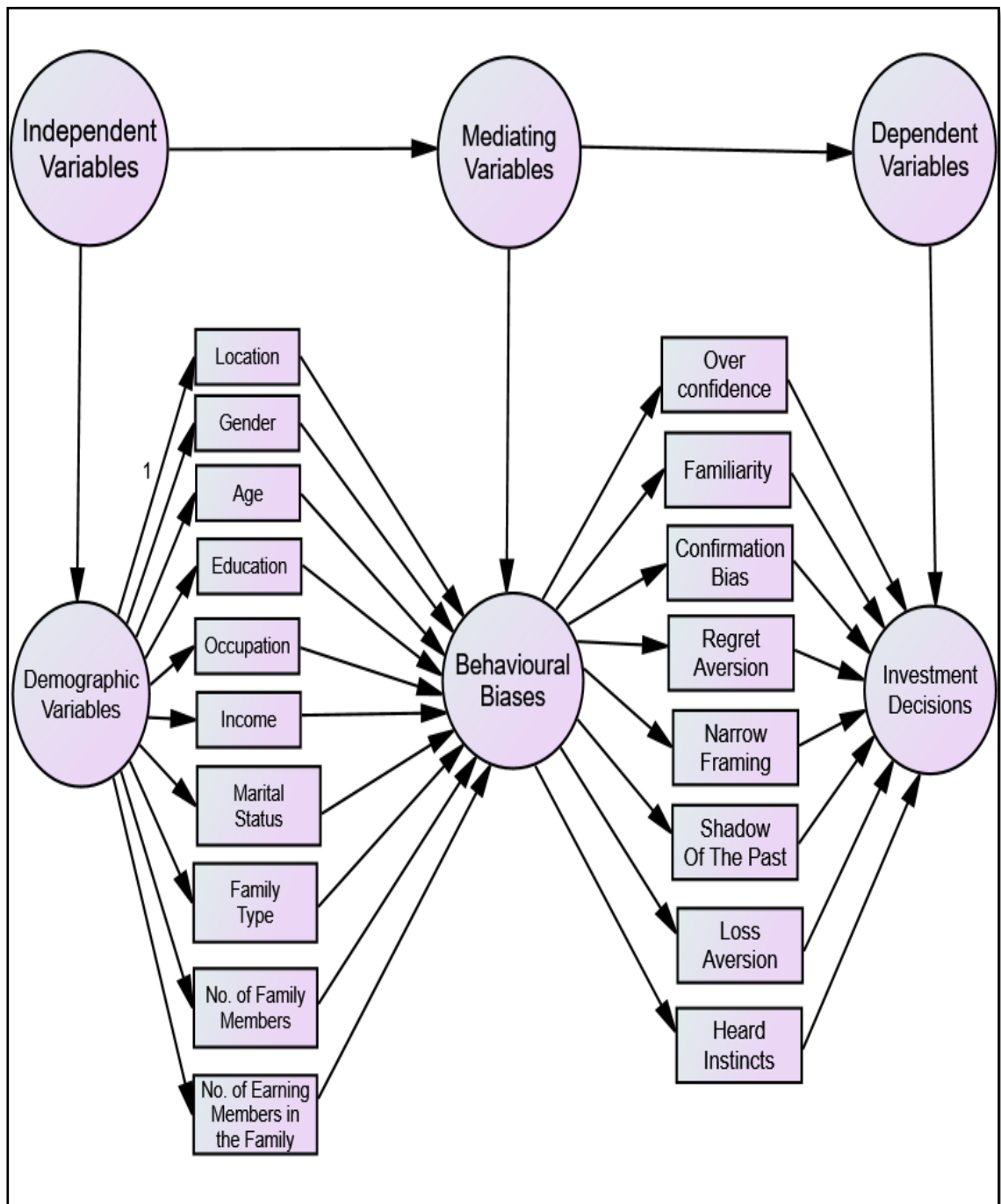
In this Study, the Investment Decision is considered as the Dependent variable.

3.6.3 Moderate Variables

Demographic variables can also play a role as moderating variables for the investment decision-making process (Jaiswal & Kamil, 2012)

3.7 Conceptual Model / Conceptual Framework

Figure 3.2: Conceptual Model /Conceptual Framework



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

The present Conceptual Framework was Developed by the researcher based on Literature review and graphics was prepared with the help of IBM Amos-2023. This conceptual frame works describes How Demographic Variable like Age, Gender, Education, occupation, income, etc. affects Equity investment decisions and as well as

how these eight Behavioural Biases Influences Equity investment decision. It also indicates the variables of the study.

3.8 Research Design of the Study

The Present Research was done as per the following Phases:

Phase 1: In the first phase, the researcher conducted an Extensive literature review of research papers and articles. The researcher also got a library membership at the Vikram Sarabhai Library in the IIMA (Indian Institute of Management Ahmedabad), and with the help of library materials and papers, the researcher identified the Behavioural Biases that influence an Investor's Investment decisions. With this, the base of the present study has been built up.

Phase 2: After building up a base for the study, the researcher has conducted an in-depth literature review to find out the research gap. With the help of the research gap, further aspects of the research were identified, such as Location, Demographic Contexts, Equity investors' profiles, and Behavioural biases, which affect Equity Investors while making investment decisions.

Phase 3: After completing Phase 1, Identifying Behavioural Biases and Phase 2, gathering information regarding Equity Investment Decisions and influencing Behavioural Biases, the researcher developed a structured questionnaire and collected Primary data from the Equity Investors of Junagadh, Rajkot, and Jamnagar cities of the Saurashtra Region.

Phase 4: After Phase 3, Primary data collection with the help of various statistical techniques, all the data was analyzed the results were gathered, which showed that behavioural bias influences the investment decisions of equity investors while making investment decisions.

3.9 Sampling Plan

The sampling plan is the basic plan for deciding the samples from the entire Big amount of population of the present study

3.9.1 Population

In the present study, People of three selected cities, viz. Junagadh, Rajkot, and Jamnagar of the Saurashtra region were considered for the population.

3.9.2 Sample Frame

In the present study, the people who invest in equity are the sample frame.

3.9.3 Sampling Techniques

With the help of the population: People of Junagadh, Rajkot, and Jamnagar of the Saurashtra region, and the sample frame: People who invest in equity only in these three cities, the non-probability convenience sampling technique was selected for deciding the sampling technique.

In this study, the equity investor came from any gender, age group, education level, income level, or marital status, considered as a convenience sample, which means respondents of this study were selected by the researcher.

3.9.4 Sample Size

In the Present study, the Sample Size is calculated as per the given formula (Cochran, 1977)

$$n = \frac{Z^2 pq}{e^2} \dots\dots\dots \text{Equation 3.1}$$

$$n = \frac{(1.96)^2 \times (0.8) \times (1-0.8)}{(0.05)^2}$$

$$n = \frac{3.8416 \times 0.8 \times 0.2}{0.0025} = \frac{0.614656}{0.0025}$$

$$n = 246$$

In this formula:

n stands for Sample size = 246

Z represents the statistical parameters that depend on the Confidence level (95%) = 1.96

p is the percentage of the population (80%) = 0.8

q is the numerical probability of failure, i.e., (1-p)

e is the desired level of precision (margin of error)

As per the above given Formula researcher calculated the sample size for the present study. With the (Cochran, 1977) formula, each city must consist minimum of 246 responses. It was decided to collect 300 samples from each city. The researcher collected 306 samples from Junagadh, 372 responses from Rajkot, and 383 Samples from Jamnagar city, for the sum total of 1061 samples collected. The collected data from Junagadh, Rajkot, and Jamnagar cities as per the following table:

Table 3.1: Decided sample size and the data collected

City	Cochran Estimate	Target	Collected (Actual)
Junagadh	246	300	306
Rajkot	246	300	372
Jamnagar	246	300	383
Total	738	900	1061

(Source: Primary Data Collection)

3.10 Data Collection Method

For the Collection of accurate data, a structured questionnaire was designed by the researcher, and the survey was conducted to collect data by distributing Physical Questionnaires as well as a Google form in Junagadh, Rajkot, and Jamnagar cities.

As mentioned above, the structured questionnaire was designed for collecting data from the respondents. This questionnaire was divided into three parts as below.

Part 1 - Demographic Profile of Respondents

The Demographic Profile part consists of questions like Location (City), Gender, Age, Education, Occupation, Individual Annual Income, Marital Status, Family Type, No. of Family Members, and No. of Earning Members in the Family of respondents of Junagadh, Rajkot, and Jamnagar cities.

Part 2 - Equity Information Profile of Respondents

The Equity Information Profile consists of questions like experience in equity investment, the purpose of the investment, trading frequencies, Source of information, amount invested in a single trade, number of companies in which investments are made, Mode of trading, preferred sectors, and objectives of equity investments of respondents.

Part 3 - Behavioural biases in equity investment decisions.

The Behavioural Biases in Equity Investment Decision Part consists of 5 Point Likert scale questions in which various statements were given, and also selecting the appropriate answer, 5 points were given, in which 1 point suggested Strongly Disagree, 2 Points Suggested Disagree, 3 points suggested Neutral, 4 points suggested Agree, and 5 points suggested Strongly Agree.

For the present study, 850 Physical questionnaires were distributed, and a Google form link was sent via WhatsApp app. For collecting data, the researcher personally visited around 100 plus respondents in Junagadh, 100 plus in Rajkot, and 100 plus in Jamnagar, and also clicked Google location photographs with the respondents and collected data from them.

With the help of a physical questionnaire and a Google form, the data was collected by the researcher. Total data collection for the present study was 1061 responses out of 600 responses collected from physical questionnaires and 461 collected from Google Form.

The table given below indicates information regarding the total response as well as city-wise data collected from the physical questionnaire and Google form.

Table 3.2: City-wise data collection from questionnaire and google form

City	Total Data Collected	Questionnaire	Google Form
Junagadh	306	146	160
Rajkot	372	274	98
Jamnagar	383	180	203
Total Data Collected	1061	600	461

(Source: Primary Data Collection)

3.11 Reliability and Validity of the Questionnaire

The present study consists of the Reliability and Validity of the questionnaire. Though the questionnaire was well structured but it is necessary to check its reliability and validity of the constructs of the questionnaire. This process made the researcher clear about the language as well as the understanding of the given contexts.

3.11.1 Reliability

Reliability testing is important because it refers to the consistency across the parts of a measuring whole data collection instrument. (Huck, 2012) Also, the reliability includes the extent to which a measurement of a content provides stable and consistent results every time, and also, it can be considered that reliability is also related to repeatability, i.e., a test is reliable if repeated measurements made by it under constant conditions will give the same results (Taherdoost, 2016)

In the present study, the researcher used the coefficient alpha, which is famous with the name as Cronbach's Alpha. For testing the reliability of the data collection instruments, the pilot study was conducted, and 120 responses were collected from the respondents, and then the data was tested with the help of Cronbach's Alpha in IBM SPSS 2022. The Details of Cronbach's Alpha results and scales are described in Chapter 4, Data Analysis.

3.11.2 Validity

Validity means "measure what is intended to be measured." (Field., 2009) There were different types of validity, like face validity, content validity, construct validity, and criterion validity (Taherdoost, 2016)

Construct Validity

Construct validity found that when the relationship is causal, then to determine the specific cause and effect behaviours or constructs connected in the relationship, the construct validity is used. And also, construct validity is considered how well it translates or transforms a concept, idea, or behaviour that is a construct into a functioning and operating reality. For this study, the construct validity was used. The Construct validity has two Elements: convergent validity and discriminant validity. (Taherdoost, 2016)

Convergent validity and Discriminant validity

The Present study examined both the Convergent validity and the Discriminant validity. Convergent validity shows the degree to which two measures of constructs that theoretically should be related, meaning it describes the relatedness of constructs (Taherdoost, 2016), and Discriminant validity shows that measures whether constructs that theoretically should not be related to each other. (Taherdoost, 2016) So, in simple terms, Convergent validity refers to relatedness, and Discriminant (Divergent) Validity refers to unrelatedness of constructs.

Convergent and discriminant validity were examined using Pearson correlation analysis in IBM SPSS Statistics 22. The relationships among the study constructs were reviewed to understand how they are associated with one another, while also checking whether each construct remained sufficiently distinct and represented its own underlying concept within the research model.

The measurement model was further analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4. Reliability of the constructs was determined through Composite Reliability (CR) values and factor loadings, which indicated the consistency of the latent variables. Convergent validity was evaluated using the Average Variance Extracted (AVE), whereas discriminant validity was assessed through the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. These analyses followed widely accepted PLS-SEM procedures, and the complete results are provided in Chapter 4: Data Analysis.

3.12 Data Analysis Tools

The data was analyzed by various statistical tools based on objective proven as given below.

Table 3.3: Statistical tools for data analysis

Analysis Statistical Technique	Purpose of the Test	Software Used
Cronbach's Alpha	For measuring the Reliability of the Data	IBM- SPSS 2022
Pearson Correlation	For measuring the Convergent Validity of the Data	IBM- SPSS 2022
Pearson Correlation	For measuring the Discriminant Validity of the Data	IBM- SPSS 2022
Descriptive Statistics	For procuring Mean, median, Percentage, standard deviation, and Frequencies for understanding the Data	IBM- SPSS 2022
Cross Tabs	For examining the Relationship between two variables (Demographic variables and Equity investment Decisions in this study)	IBM- SPSS 2022
ANOVA	For examining whether the average (Mean) results of three or more groups are significantly different from each other. (Demographic Variables and Equity Investment Decisions in this study)	IBM- SPSS 2022
Multiple Regression	For examining the effect of two or more factors on one outcome at the same time. (Behavioural Biases and Equity Investment Decisions)	IBM- SPSS 2022
BBII	For Measuring Levels of Behavioural Biases	BBII Calculation Method
PLS-SEM (Structural Equation Modeling)	For examining how different factors are linked with each other and how they affect each other within one overall model. (Behavioural Biases)	Smart-PLS-4

(Source: Researcher's Own Compilation)

3.13 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.

3.14 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.

3.15 Conclusion

This chapter gives a small glance at the Research Methodology of the whole study and explains the statement of the problem, the Objectives of the study, the Hypothesis, the variables of the study, the Data collection tools, the Sampling plan, reliability, as well as validity, and data analysis tools.

CHAPTER - 4

RESULTS AND DISCUSSION

CHAPTER - 4 RESULTS AND DISCUSSION

4.1 Introduction

The present Chapter provides detailed information about the statistical tools and data analysis techniques used to analyze the data collected by the Researcher, along with the results of the analysis and their 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 begins with the reliability and validity of the measurement instruments being tested. Reliability is assessed through Cronbach's Alpha, which helps to check the internal consistency of the scales used in the structured questionnaire. Convergent and discriminant validity were examined using Pearson correlation analysis in IBM SPSS Statistics 22. For checking correlations among the study constructs were inspected to see how they relate to each other, while also checking that each construct represents a separate and clearly defined concept within the overall research model.

Then, after, the normality of the data is tested using several statistical tools. The Skewness and Kurtosis values are analyzed to identify if any deviation from normal distribution exists. Moreover, two formal tests—the Shapiro–Wilk test and the Kolmogorov–Smirnov test—are applied to further confirm whether the collected dataset follows a normal distribution, which is essential before applying parametric statistical tests.

Afterwards, it presents a detailed demographic profile of the Equity investors with separate cities, Junagadh, Rajkot, and Jamnagar. Moreover, the researcher includes a city-wise comparison to find out the background characteristics of different cities from the collected sample population. This is followed by an examination of the investors' profile, also organized city-wise, to explore variations in investment behaviour, preferences, and financial awareness among respondents from Junagadh, Rajkot, and Jamnagar cities of the Saurashtra Region.

After completing the Demographic study and Investors Profile study, the next sections focus on hypothesis testing. In this study, Analysis of Variance (ANOVA) is used to determine whether there are significant differences between groups, like demographic variables and Behavioural biases, while Multiple Regression Analysis helps to identify the influence of independent variables (Behavioural Biases) on the dependent variables (Equity Investment Decisions). With this, the Weighted Average Mean Method is also applied to measure the overall level of behavioural biases among investors.

Lastly, the modern statistical tool the Structural Equation Modeling (SEM), is performed using SmartPLS software to test the proposed model and establish the causal relationships among all variables. The Present chapter concludes with a discussion on the implications of the findings, highlighting their relevance for investors and future researchers in the area of behavioural finance and investment decision-making.

4.2 Reliability Analysis

Before testing the reliability of the questionnaire and collected data, it is essential to first understand what reliability is. Reliability is considered how consistently a method measures something, and getting the same outcome every time means consistently using the same method and getting the same result in the same situations, that it can believe that the method or measurement is reliable. Reliability testing is important because it refers to the consistency across the parts of a measuring whole instrument (Huck, 2012) Also, the reliability includes the extent in which a measurement of a content provides stable and consist result every time and also, it can be considered that reliability is also related with repeatability i.e. a test is reliable if repeat measurement made by it under constant conditions will give the same result (Taherdoost, 2016)

In present study Behavioural Biases are consider for reliability test and Likert scale is used for getting responses from the respondents and collected data from 1061 respondents and inserted in the SPSS-22 and applied Cronbach's Alpha test and got reliability of Junagadh 0.864 Rajkot 0.832and Jamnagar 0.864 and Overall all cities 0.867 and this reliability is accepted because Cronbach's alpha Internal consistency $\alpha \geq 0.9$ Excellent, $0.8 > \alpha \geq 0.9$ Good, $0.8 > \alpha \geq 0.7$ Acceptable, $0.7 > \alpha \geq 0.6$ Questionable, $0.6 > \alpha \geq 0.5$ Poor, $0.5 > \alpha$ Unacceptable (Cortina, 1993) according to the range given

in his papers about coefficient alpha the Present study consist reliability ranges between $0.8 > \alpha \geq 0.9$ means it is acceptable. Table 4.1, given below, shows the output of SPSS of the Cronbach's Alpha test.

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)

4.3 Validity Analysis

After testing reliability, the Researcher has conducted the validity test because it is most important for this study. After all, Reliability is about the consistency of a measure, and validity is about the accuracy of a measure, so, first of all, what validity is the biggest question. For getting an answer researcher had reviewed some articles about validity and books and found out that validity means “measure what is intended to be measured” (Field., 2009) and also the different types of validity like face validity, content validity, construct validity, criterion validity (Taherdoost, 2016) but for this study the construct validity was used and after studying construct validity found that, When the relationship is causal than to know the specific cause and effect behaviours or constructs connected in the relationship the construct validity is used. Construct validity considers how well a concept, idea, or behaviour that is a construct is translated or transformed into a functioning and operating reality. The Construct validity has two Elements: convergent and discriminant validity. (Taherdoost, 2016)

In this study, both the Convergent validity and Discriminant validity both sub-elements of construct validity, were used. Convergent validity shows the degree to which two measures of constructs that theoretically should be related, meaning it

describes the relatedness of constructs (Taherdoost, 2016) and Discriminant validity shows that measures whether constructs that theoretically should not be related to each other. (Taherdoost, 2016) So, in simple Convergent validity refers to relatedness, and Discriminant (Divergent) Validity refers to unrelatedness of constructs. In the present study, the validity test was conducted of all 27 Items of the eight behavioural biases with a Likert scale response from 1061 respondents from Junagadh, Rajkot, and Jamnagar of the Saurashtra region.

In the present study to examine the relationships among the eight behavioral bias variables—Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts—were analyzed using Pearson's correlation coefficient (r) with the help of IBM SPSS- 2022. This analysis was performed to check both convergent and discriminant validity of the constructs. The results of the correlation are displayed in Table 4.2 below.

4.3.1 Convergent Validity

The table, 4.2, shows that Moderate correlations were observed between constructs that are conceptually related. For example, Familiarity and Confirmation Bias ($r = 0.391$), Confirmation Bias and Regret Aversion ($r = 0.403$), Regret Aversion and Loss Aversion ($r = 0.549$), and Shadow of the Past and Loss Aversion ($r = 0.457$) showed meaningful associations. These results indicate that measures of theoretically connected biases move together, supporting convergent validity and showing that the scales capture similar underlying tendencies (Cohen et al., 2003; Field., 2009)

4.3.2 Discriminant Validity

Table 4.2 below indicates that Discriminant validity was conducted to determine whether each construct is distinct from the others. All correlations were below 0.60, with the weakest links between Overconfidence and Regret Aversion ($r = .122$) and Overconfidence and Shadow of the Past ($r = .120$). These low-to-moderate correlations suggest that each bias measures a unique aspect of equity investor behavior, with little risk of redundancy. According to (Field., 2009) correlations below 0.85 indicate that constructs are empirically separate, confirming discriminant validity

So in the present study, both the Convergent validity and the Discriminant validity of the Construct were established.

Table 4.2: Pearson correlation matrix of behavioural biases

		Over confidence	Familiarity	Confirmation Bias	Regret Aversion	Narrow Framing	Shadow Of The Past	Loss Aversion	Heard Instincts
Over confidence	Pearson Correlation	1	.174**	.240**	.122**	.280**	.120**	.151**	.149**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.000
	N	1061	1061	1061	1061	1061	1061	1061	1061
Familiarity	Pearson Correlation	.174**	1	.391**	.317**	.276**	.359**	.309**	.212**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000	.000
	N	1061	1061	1061	1061	1061	1061	1061	1061
Confirmation Bias	Pearson Correlation	.240**	.391**	1	.403**	.402**	.313**	.419**	.314**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000	.000
	N	1061	1061	1061	1061	1061	1061	1061	1061
Regret Aversion	Pearson Correlation	.122**	.317**	.403**	1	.340**	.417**	.549**	.426**
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000	.000
	N	1061	1061	1061	1061	1061	1061	1061	1061
Narrow Framing	Pearson Correlation	.280**	.276**	.402**	.340**	1	.300**	.282**	.237**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000
	N	1061	1061	1061	1061	1061	1061	1061	1061
Shadow Of The Past	Pearson Correlation	.120**	.359**	.313**	.417**	.300**	1	.457**	.246**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.000

	N	1061	1061	1061	1061	1061	1061	1061	1061
Loss Aversion	Pearson Correlation	.151**	.309**	.419**	.549**	.282**	.457**	1	.457**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000
	N	1061	1061	1061	1061	1061	1061	1061	1061
Heard Instincts	Pearson Correlation	.149**	.212**	.314**	.426**	.237**	.246**	.457**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	.000	
	N	1061	1061	1061	1061	1061	1061	1061	1061

(Source: IBM SPSS-22 Bivariate Pearson Correlation Out Put)

4.4 Normality Test for Data

For statistical analysis of data, various methods and tools rely on the assumption that data follow a normal distribution, which creates a shape like a bell curve. The Normal distribution tests are tools and techniques used to check if the collected data is normally distributed or not. These tests, such as the Shapiro-Wilk test, Kolmogorov-Smirnov test, and graphical methods like Q-Q plots, etc., are used to check normality. If data is normally distributed, then Parametric statistical techniques are appropriate. If the data are not normally distributed, non-parametric methods are appropriate. So, performing a normality test is an essential step in ensuring accurate statistical analysis for the data.

In the present study, the sample size was very large (N=1061), so the researcher had to decide whether the collected data were normally distributed or not. For deciding this, Descriptive test, Skewness & Kurtosis, and Formal tests, Shapiro-Wilk and Kolmogorov-Smirnov tests were used. The results are given in the following tables.

Table 4.3: Shapiro-wilk and kolmogorov-smirnov

Variable	Shapiro-Wilk Statistic	Shapiro -Wilk Sig.	Kolmogorov-Smirnov Statistic	Kolmogorov-Smirnov Sig.	Acceptable Range (p)
Overconfidence	0.966	0.000	0.101	0.000	> 0.05
Familiarity	0.909	0.000	0.204	0.000	> 0.05
Confirmation Bias	0.964	0.000	0.104	0.000	> 0.05
Regret Aversion	0.957	0.000	0.133	0.000	> 0.05
Narrow Framing	0.927	0.000	0.179	0.000	> 0.05
Shadow of the Past	0.924	0.000	0.197	0.000	> 0.05
Loss Aversion	0.970	0.000	0.095	0.000	> 0.05
Herd Instincts	0.959	0.000	0.130	0.000	> 0.05

(Source: IBM SPSS-22 Normality test Shapiro-Wilk and Kolmogorov-Smirnov Output)

The normality of the dataset was evaluated using the Shapiro–Wilk and Kolmogorov–Smirnov tests, as summarized in Table 4.3. The findings revealed that all variables yielded significant p-values ($p < 0.05$), indicating departures from perfect normality. Nevertheless, given the relatively large sample size ($n = 1061$), these tests can be overly sensitive, detecting even minor deviations from normality (Field., 2009)

To gain further insight into the data distribution, skewness, and kurtosis values for all measured Behavioural Biases. All values fall within the commonly accepted range of **-1 to +1**, as recommended by (George & Mallery, 2010). This range suggests that the distributions are sufficiently symmetrical and not excessively peaked or flat. Based on these results, the data can be considered to follow an approximately normal distribution. Table 4.4, given below, shows the results of the skewness and kurtosis test.

Table 4.4: Normality test of data skewness & kurtosis

Variable	Skewness	Kurtosis	Interpretation	Within ± 1 Range?
Overconfidence	-0.559	-0.059	Normal	Yes
Familiarity	-0.870	0.496	Normal	Yes
Confirmation Bias	-0.631	0.331	Normal	Yes
Regret Aversion	-0.466	-0.456	Normal	Yes
Narrow Framing	-0.885	0.525	Normal	Yes
Shadow of the Past	-0.677	-0.141	Normal	Yes
Loss Aversion	-0.472	-0.081	Normal	Yes
Herd Instincts	-0.308	-0.840	Normal	Yes

(Source: IBM SPSS-22 Normality test Skewness & Kurtosis Output)

In short, in the present study, taking into account both the descriptive measures and the large sample size, the data were considered to sufficiently meet the assumption of normality (Field., 2009). Consequently, the use of parametric statistical tools, such as Pearson correlation, ANOVA, and multiple regression, was appropriate for further analyses.

4.5 Data Analysis for Various Objectives

4.5.1 Objective 1: To study the Demographic variables of equity investors.

Table 4.5: Demographic profile of investors of Junagadh city

Demo-graphic Profile	Category	Frequency	Percentage (%)	Remarks
Gender	Male	250	81.7	The majority of respondents are male (81.7%), while females make up only 18.3%.
	Female	56	18.3	
	Total	306	100	
Age	18-25	182	59.5	Most participants fall in the 18-25 age group (59.5%), with very few aged 56 and above (1.3%).
	26-35	84	27.5	
	36-45	24	7.8	
	46-55	12	3.9	
	56 and above	4	1.3	
	Total	306	100	
Education	Below HSC	16	5.2	The highest education level among respondents is Post Graduate (29.7%), whereas those below HSC are the smallest group (5.2%).
	12th/HSC	32	10.5	
	Under Graduate	73	23.9	
	Graduate	80	26.1	
	Post Graduate	91	29.7	
	Professional	14	4.6	
	Total	306	100	
Occupation	Salaried	104	34	Occupations are mainly Salaried (34.0%) and Students (33.7%), with very few Retired (0.7%) or House Wives (1.3%).
	Businessman	60	19.6	
	Professional	15	4.9	
	Retired	2	0.7	
	House Wife	4	1.3	
	Student	103	33.7	
	Equity Trader	9	2.9	
	Others	9	2.9	
	Total	306	100	
Individual Annual Income	Up to 2,50,000	159	52	Over half of the respondents earn up to ₹2,50,000 annually (52.0%), and only a small percentage earn ₹10,00,000 or more (3.9%).
	2,50,000 to 5,00,000	94	30.7	
	5,00,000 to 10,00,000	41	13.4	
	10,00,000 and Above	12	3.9	
	Total	306	100	
Marital Status	Married	93	30.4	Most respondents are unmarried (69.0%), while married individuals account for 30.4%.
	Unmarried	211	69	
	Others	2	0.7	
	Total	306	100	

Family Type	Nuclear Family	110	35.9	Majority live in joint families (64.1%), with nuclear families representing 35.9%.
	Joint Family	196	64.1	
	Total	306	100	
No. of Family Members	Two	9	2.9	Families with more than four members are the largest group (46.4%), and very few families have only two members (2.9%).
	Three	54	17.6	
	Four	101	33	
	More than Four	142	46.4	
	Total	306	100	
No. of Earning Members in the Family	One	77	25.2	Most families have two earning members (45.4%), while families with more than four earners are rare (2.6%).
	Two	139	45.4	
	Three	64	20.9	
	Four	18	5.9	
	More than Four	8	2.6	
	Total	306	100	

(Source: Author's Compilation.)

Table 4.6: Demographic Profile of Investors of Rajkot City

Demo-graphic Profile	Category	Frequency	Percentage (%)	Remarks
Gender	Male	231	62.1	The survey is predominantly male, with 62.1% of participants identifying as men, while females make up a smaller but significant 37.9%.
	Female	141	37.9	
	Total	372	100	
Age	18-25	232	62.4	Young adults dominate the sample, as 62.4% are between 18 and 25 years old. Conversely, the smallest segment falls in the 46-55 years category, representing just 2.2% of respondents.
	26-35	89	23.9	
	36-45	43	11.6	
	46-55	8	2.2	
	Total	372	100	
Education	Below HSC	3	0.8	Nearly half the group (44.4%) are undergraduates, highlighting a strong base of higher education. The least represented education levels are those with schooling below or just completing high school (each at 0.8%),
	12th/HSC	3	0.8	
	Under Graduate	165	44.4	
	Graduate	71	19.1	
	Post Graduate	57	15.3	
	Professional	68	18.3	
	Others	5	1.3	
	Total	372	100	

				indicating fewer participants with lower academic qualifications.
Occupation	Salaried	123	33.1	The two largest occupational groups, both holding equal shares of 33.1%, are salaried professionals and students, showcasing a blend of working individuals and learners. On the other end, Equity Traders are the smallest group, comprising only 1.9%.
	Businessman	51	13.7	
	Professional	28	7.5	
	House Wife	9	2.4	
	Student	123	33.1	
	Equity Trader	7	1.9	
	Others	31	8.3	
	Total	372	100	
Individual Annual Income	Up to 2,50,000	228	61.3	Most respondents earn a modest income, with 61.3% making up to ₹2,50,000 annually. The high earners, those bringing in ₹10,00,000 or more, form the smallest bracket at just 6.2%.
	2,50,000 to 5,00,000	38	10.2	
	5,00,000 to 10,00,000	83	22.3	
	10,00,000 and Above	23	6.2	
	Total	372	100	
Marital Status	Married	104	28	A majority are single, with 70.7% unmarried, while those married account for less than a third (28.0%).
	Unmarried	263	70.7	
	Separated	4	1.1	
	Others	1	0.3	
	Total	372	100	
Family Type	Nuclear Family	131	35.2	Joint family living is clearly more common, with 64.8% residing in joint households, compared to 35.2% living in nuclear families.
	Joint Family	241	64.8	
	Total	372	100	
No. of Family Members	Two	14	3.8	Larger families dominate the landscape, as over half (50.8%) have more than four members, while small two-member families are rare, only 3.8%.
	Three	49	13.2	
	Four	120	32.3	
	More than Four	189	50.8	
	Total	372	100	
No. of Earning Members in Family	One	142	38.2	Most families have two earners (44.1%), suggesting shared financial responsibility, whereas households with four or more
	Two	164	44.1	
	Three	43	11.6	
	Four	11	3	
	More than Four	12	3.2	
	Total	372	100	

				earners are quite uncommon, collectively making up just about 6.2%.
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(Source: Author's Compilation.)

Table 4.7: Demographic Profile of Investors of Jamnagar City

Demo-graphic Profile	Category	Frequency	Percentage (%)	Remarks
Gender	Male	276	72.1	The Jamnagar investor base is mostly male (72.1%), with women representing just 27.9%, highlighting a clear gender gap.
	Female	107	27.9	
	Total	383	100	
Age	18-25	121	31.6	Young investors dominate, as over 61% are aged between 18 and 35 years. Those aged 56 and above form a very small group (1.8%), indicating limited senior participation.
	26-35	115	30	
	36-45	104	27.2	
	46-55	36	9.4	
	56 and above	7	1.8	
	Total	383	100	
Education	Below HSC	6	1.6	A majority (50.9%) of investors hold professional qualifications, while only 1.6% have education below high school, reflecting a highly educated investor population.
	12th/HSC	13	3.4	
	Under Graduate	86	22.5	
	Graduate	44	11.5	
	Post Graduate	39	10.2	
	Professional	195	50.9	
	Total	383	100	
Occupation	Salaried	129	33.7	Salaried employees (33.7%) and professionals (30%) lead investor occupations. Retirees represent just 0.5%, showing minimal engagement from the retired demographic.
	Businessman	19	5	
	Professional	115	30	
	Retired	2	0.5	
	House Wife	3	0.8	
	Student	107	27.9	
	Equity Trader	6	1.6	
	Others	2	0.5	
	Total	383	100	
Individual Annual Income	Up to ₹2,50,000	132	34.5	Most investors earn between ₹5,00,000 and ₹10,00,000 (35.8%), followed closely by those earning up to
	₹2,50,000 to 5,00,000	37	9.7	
	₹5,00,000 to 10,00,000	137	35.8	

	₹10,00,000 and Above	77	20.1	₹2,50,000 (34.5%). The ₹2,50,000 to ₹5,00,000 bracket is the smallest (9.7%).
	Total	383	100	
Marital Status	Married	218	56.9	Over half (56.9%) are married, with unmarried investors making up 42.6%. Separated and other statuses are negligible.
	Unmarried	163	42.6	
	Separated	1	0.3	
	Others	1	0.3	
	Total	383	100	
Family Type	Nuclear Family	115	30	Joint families dominate at 70%, while nuclear families make up 30%, highlighting the cultural preference for extended family living.
	Joint Family	268	70	
	Total	383	100	
No. of Family Members	Two	16	4.2	Large households prevail, with 64.5% having more than four members. Small families of two members are rare (4.2%).
	Three	50	13.1	
	Four	70	18.3	
	More than Four	247	64.5	
	Total	383	100	
No. of Earning Members	One	104	27.2	Dual-earner families are most common at 54%. Families with more than four earners are minimal (2.6%), indicating fewer multi-earner households.
	Two	207	54	
	Three	51	13.3	
	Four	11	2.9	
	More than Four	10	2.6	
	Total	383	100	

(Source: Author's Compilation.)

Table 4.8: 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

		12th/HSC	32 (10.5%)	3 (0.8%)	13 (3.4%)	Moderate education is more in Junagadh	Junagadh shows a spread — Postgraduates (29.7%), Graduates (26.1%), and Undergraduates (23.9%).
		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 $\leq$ ₹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 (50.8%), Junagadh (46.4%). Shows a stronger joint family culture.
		Three	54 (17.6%)	49 (13.2%)	50 (13.1%)	Slightly more in Junagadh	
		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	

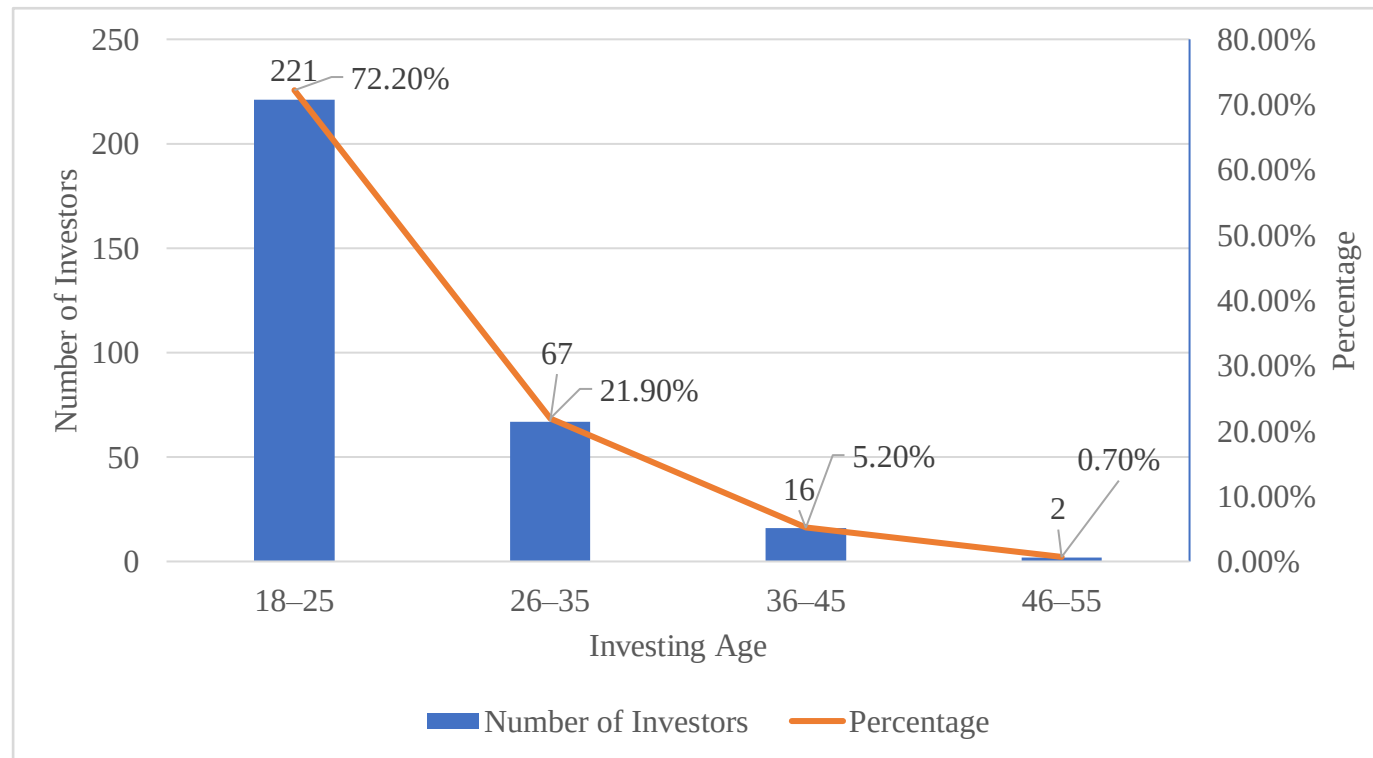
10	Earning Members	One	77 (25.2%)	142 (38.2%)	104 (27.2%)	More single earners in Rajkot	Dual-income families dominate — Jamnagar (54.0%), Rajkot (44.1%), Junagadh (45.4%). Rajkot also has the highest single-earner families (38.2%).
		Two	139 (45.4%)	164 (44.1%)	207 (54.0%)	Dual earners are the most in 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: Author's Compilation.)

4.5.2 Equity Investors' Profile

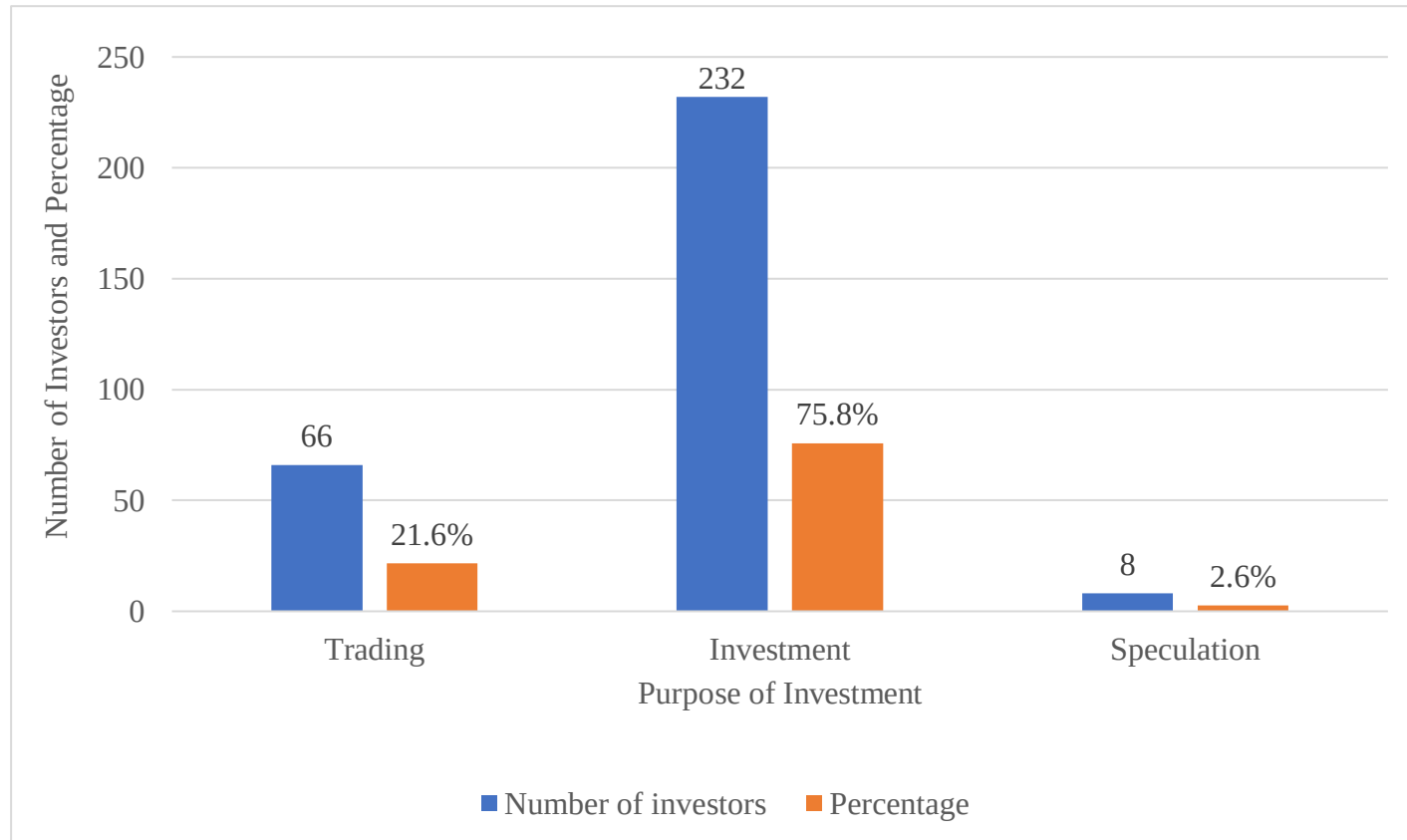
4.5.2.1 Equity Investors' Profile of Junagadh City

Figure 4.1: At Which Age Have You Started Investing in Equity?



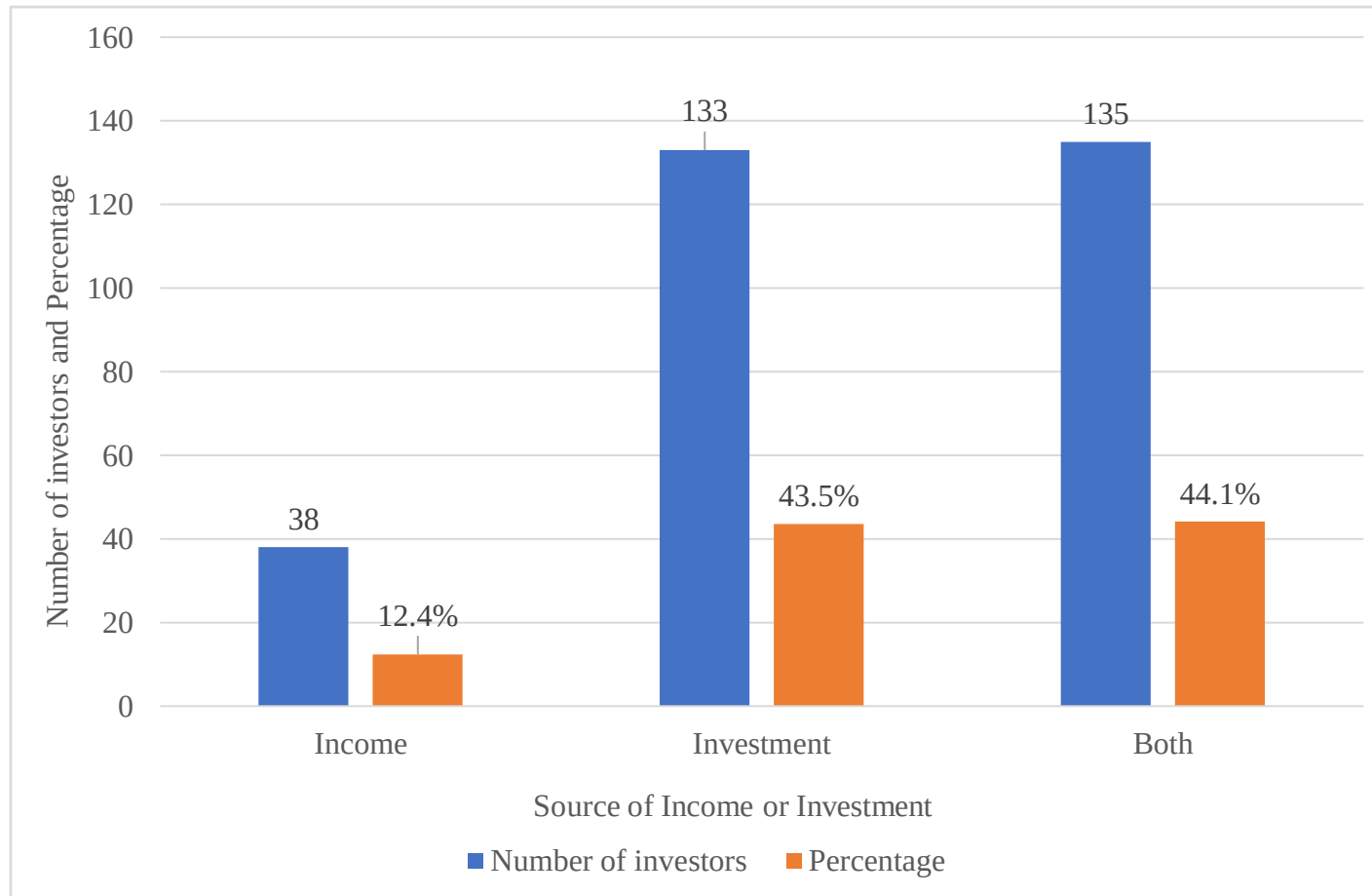
The graph shows that in Junagadh, most people start investing in equity at a young age. The majority, around (72.20%), begin between 18 and 25 years old. On the other hand, very few—just (0.7%) start as late as 46 to 55 years. This shows that equity investing is more common among younger individuals, with much less interest developing later in life.

(Source: Author's Compilation.)

Figure 4.2: Purpose of Investment of Equity Investors of Junagadh City

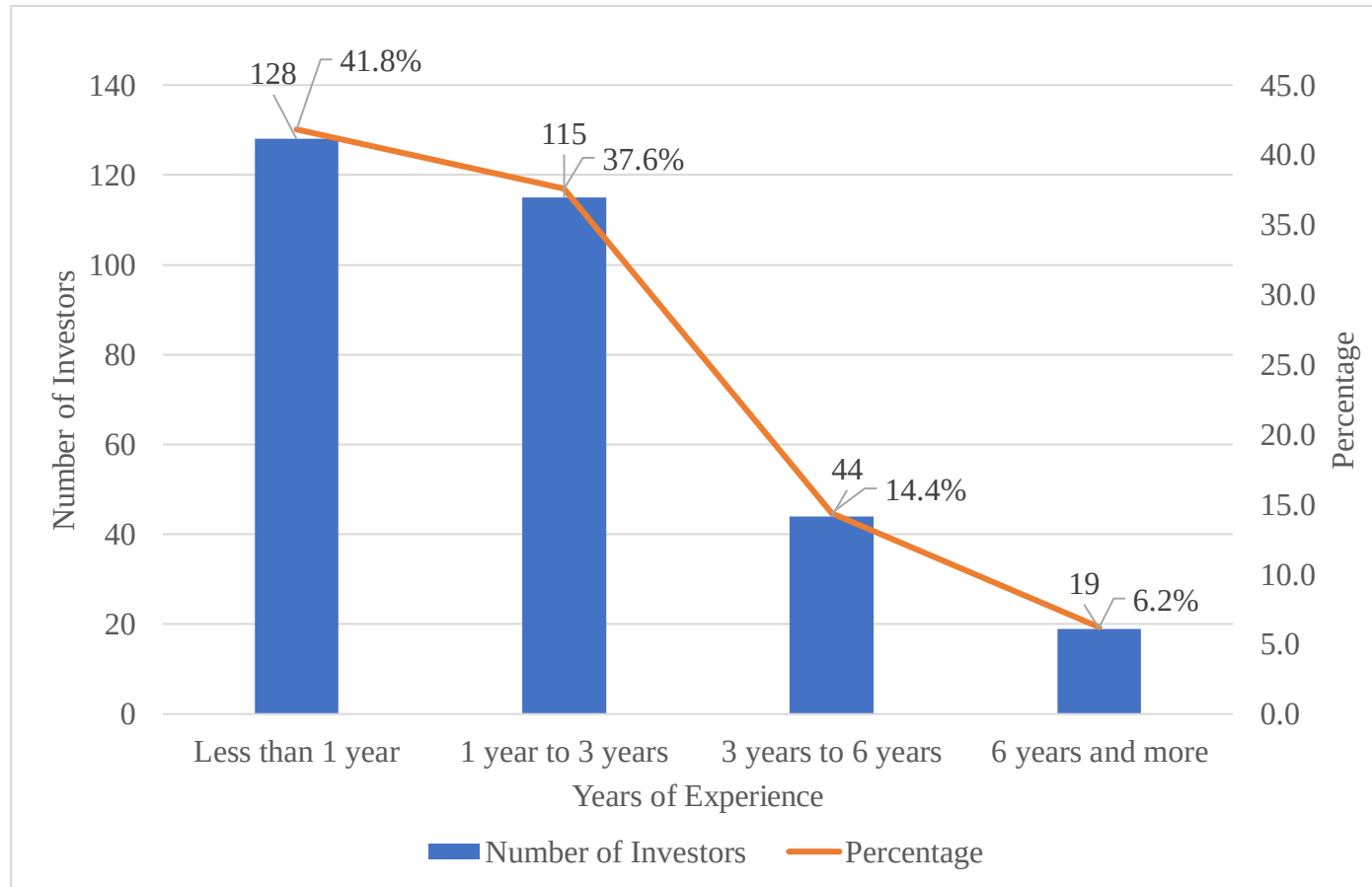
The graph shows that in Junagadh city, most people are in the market to invest, with (75.8%) focusing on long-term growth. About (21.6%) are involved in trading, likely aiming for shorter-term gains. Only a small group, (2.6%), are into speculation, suggesting that high-risk strategies aren't very common in the area.

(Source: Author's Compilation.)

Figure 4.3: Is It Your Source of Income or Investment?

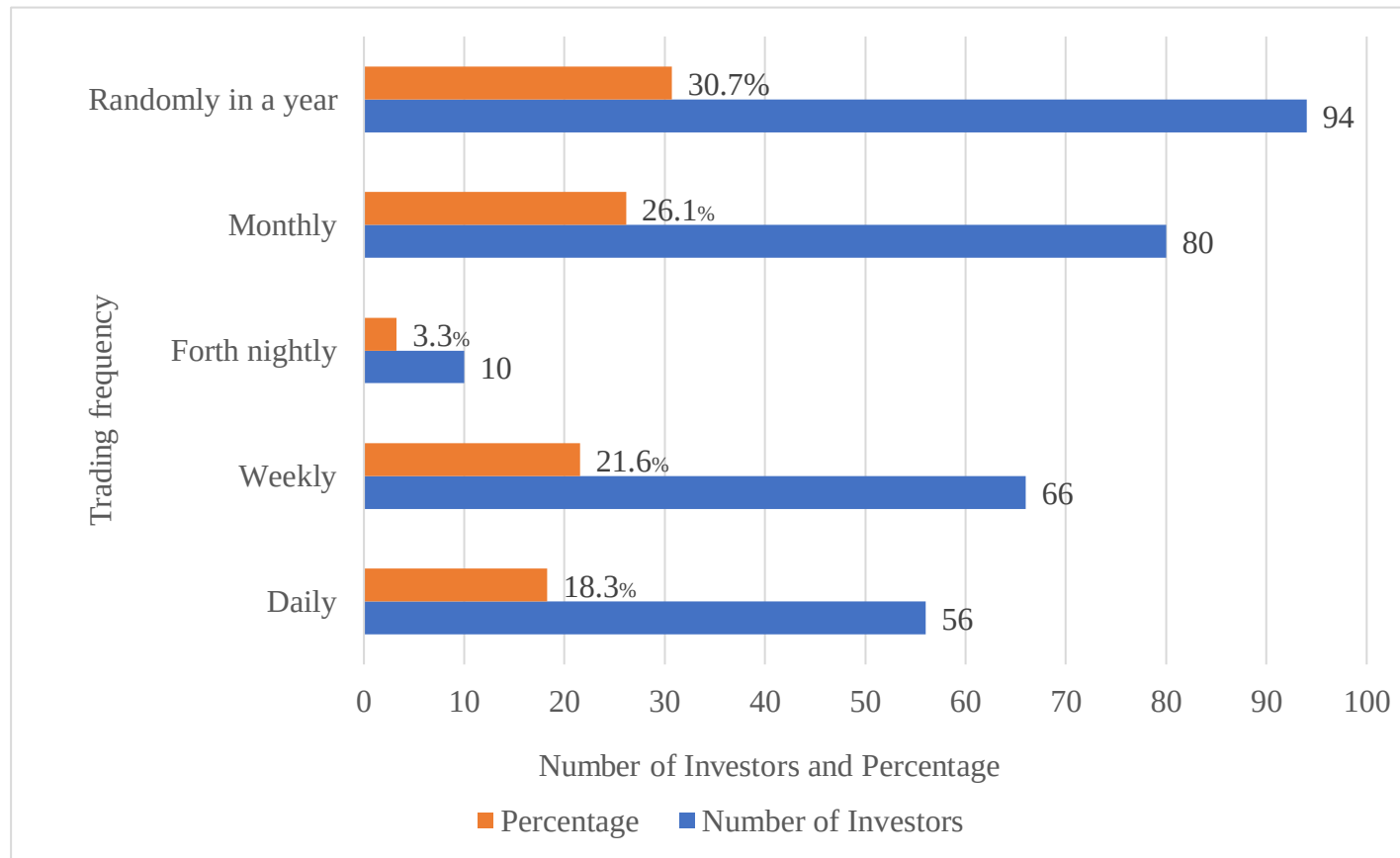
The graph shows that in Junagadh city, many individuals use the market both to earn income and to build long-term wealth, with (44.1%) falling into this group. Another (43.5%) see it mainly as a tool for investment, while only (12.4%) rely on it solely for income. This shows that most people prefer a balanced or future-focused approach to their financial activities.

(Source: Author's Compilation.)

Figure 4.4: Years of Experience in equity investors of Junagadh city

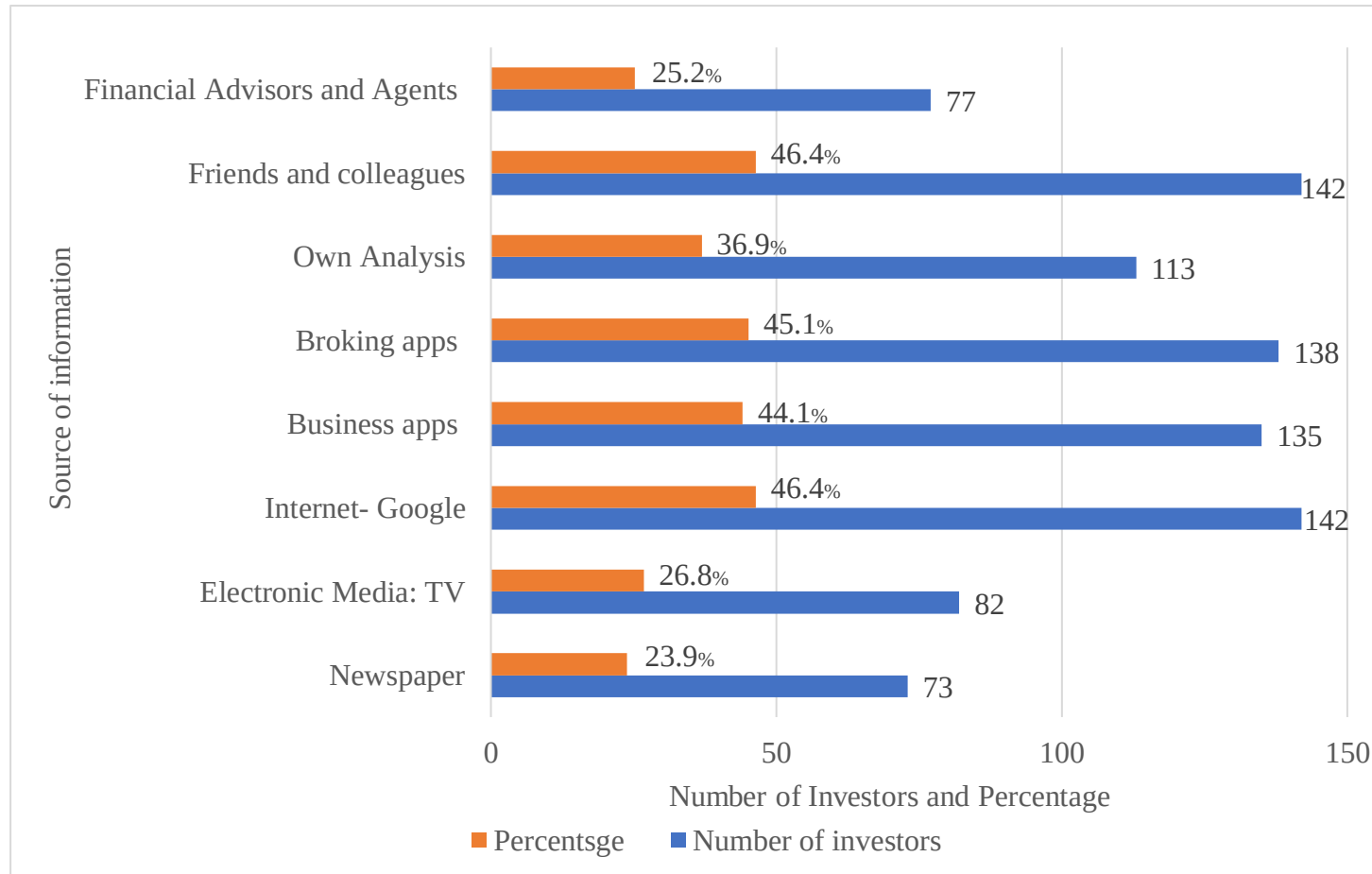
The graph shows that the majority of equity investors are relatively new, with (41.8%) having less than 1 year of experience and (37.6%) between 1 to 3 years. Only a small portion, (20.6%), have more than 3 years of experience, showing that the investor base is largely made up of newcomers.

(Source: Author's Compilation.)

Figure 4.5: Trading frequency of equity investors of Junagadh city

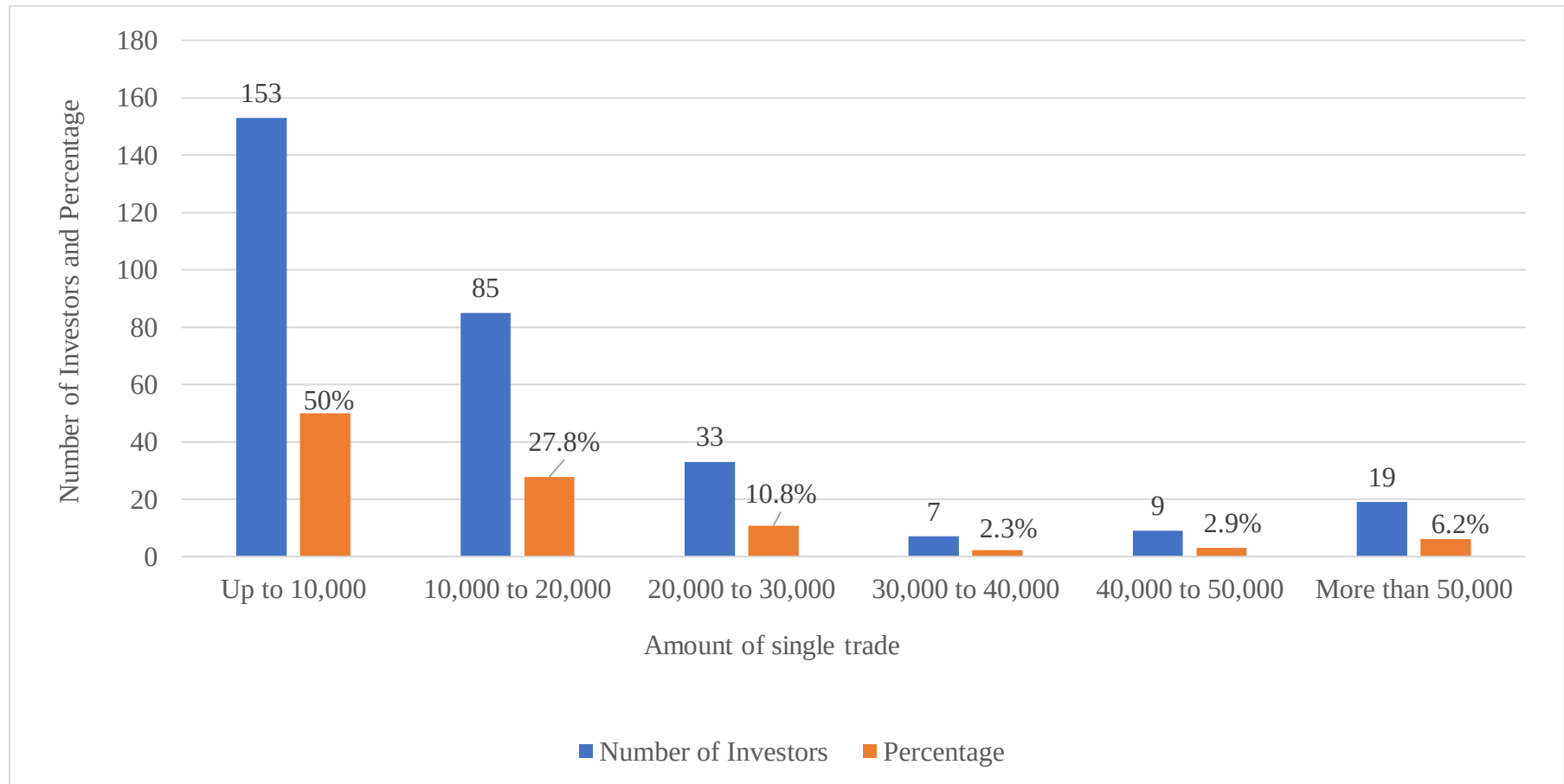
The graph shows that the largest group of equity investors (30.7%) trade randomly, while only (3.3%) trade fortnightly, indicating most trade infrequently, preferring random or monthly trading.

(Source: Author's Compilation.)

Figure 4.6: The source of information for equity investment.

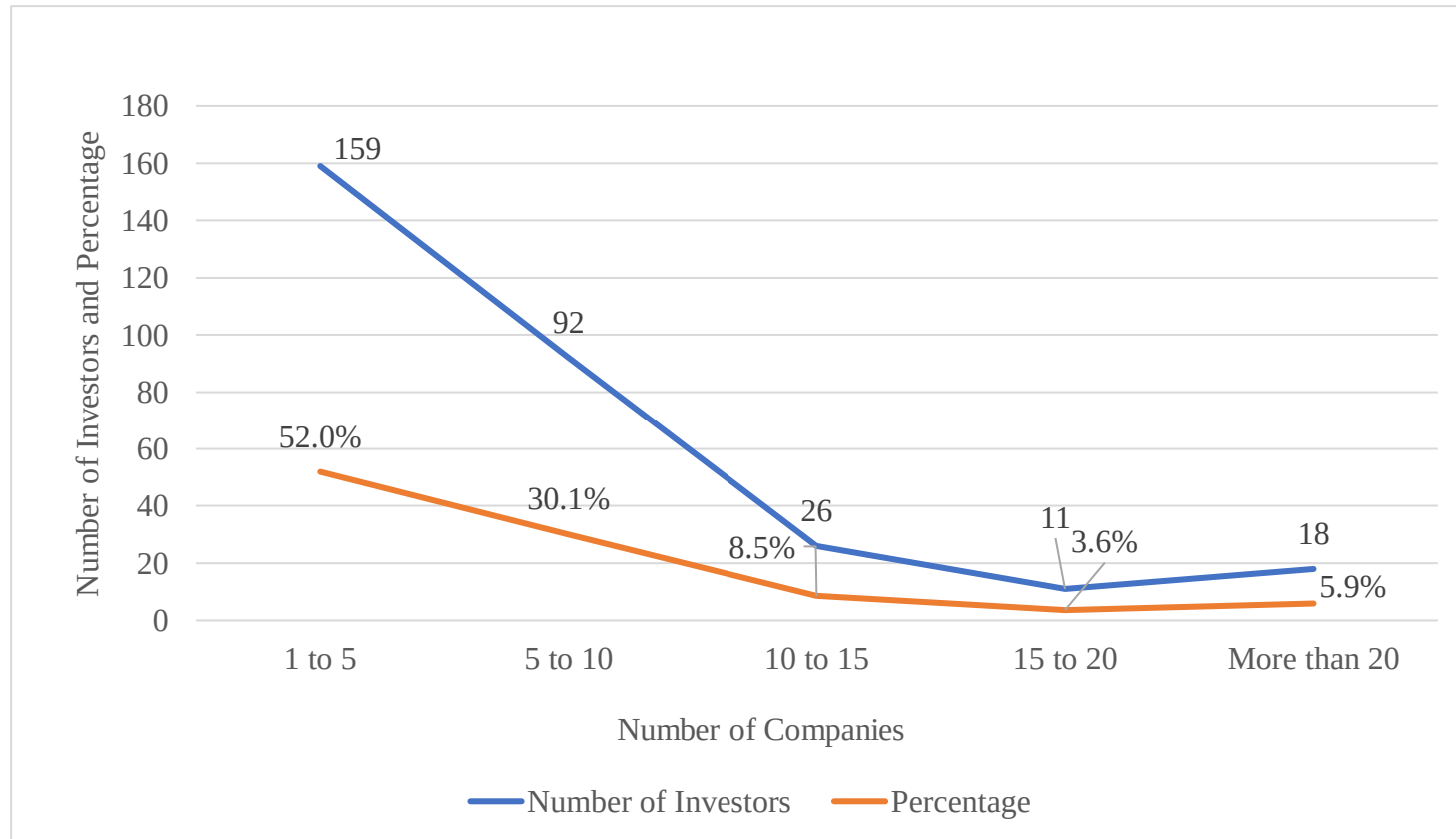
The graph shows that in Junagadh, the most common sources of information for equity investment are the internet (Google) and friends and colleagues, both at (46.4%). The least used source is the newspaper, with only (23.9%) relying on it.

(Source: Author's Compilation.)

Figure 4.7: How much amount of single trade do you execute?

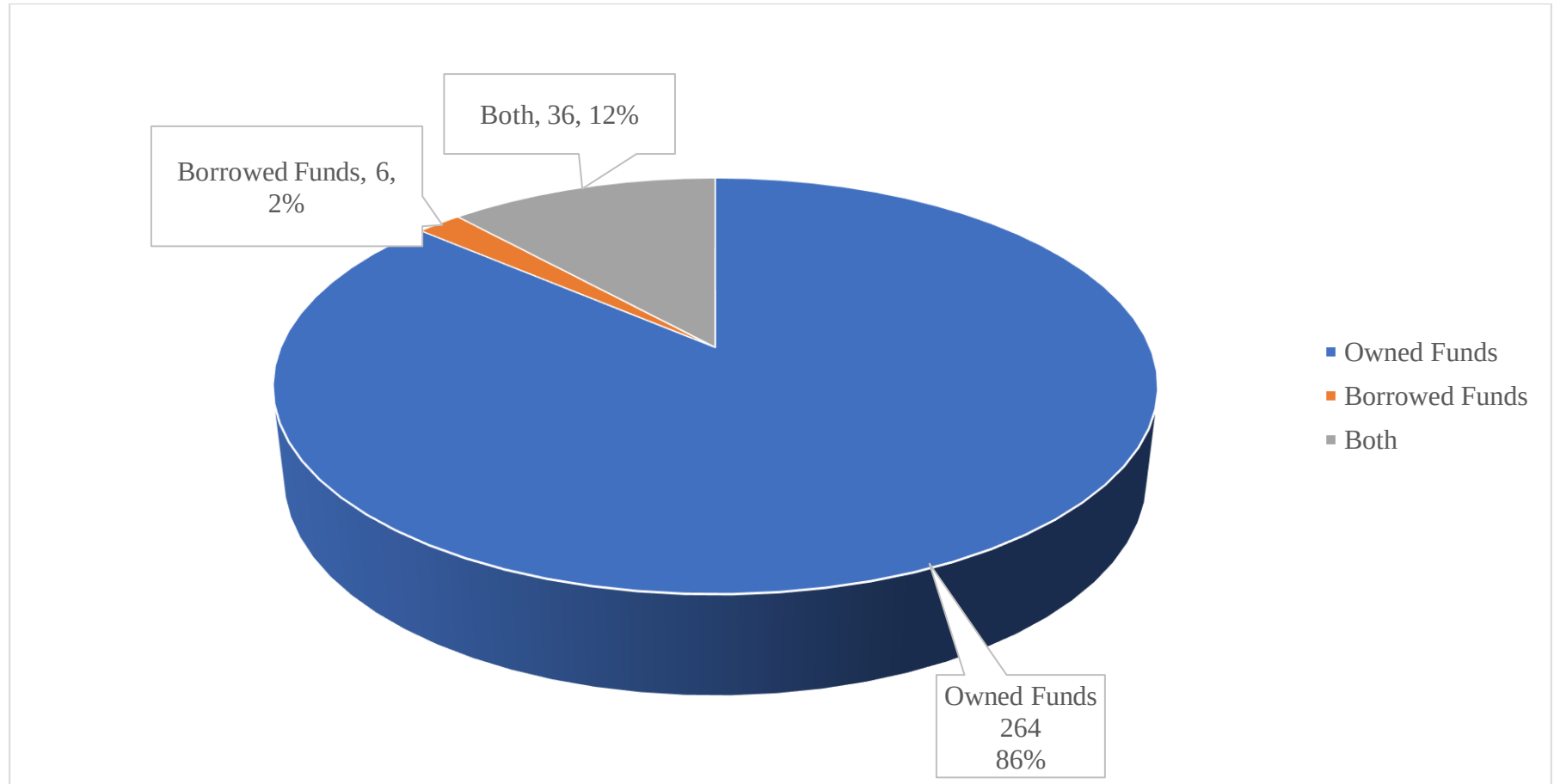
(Source: Author's Compilation.)

The Graph Shows that in Junagadh city, the highest number of investors (50%) execute trades up to ₹10,000, while the lowest (2.3%) trade between ₹30,000 to ₹40,000.

Figure 4.8: Number of companies in which investments are made by investors

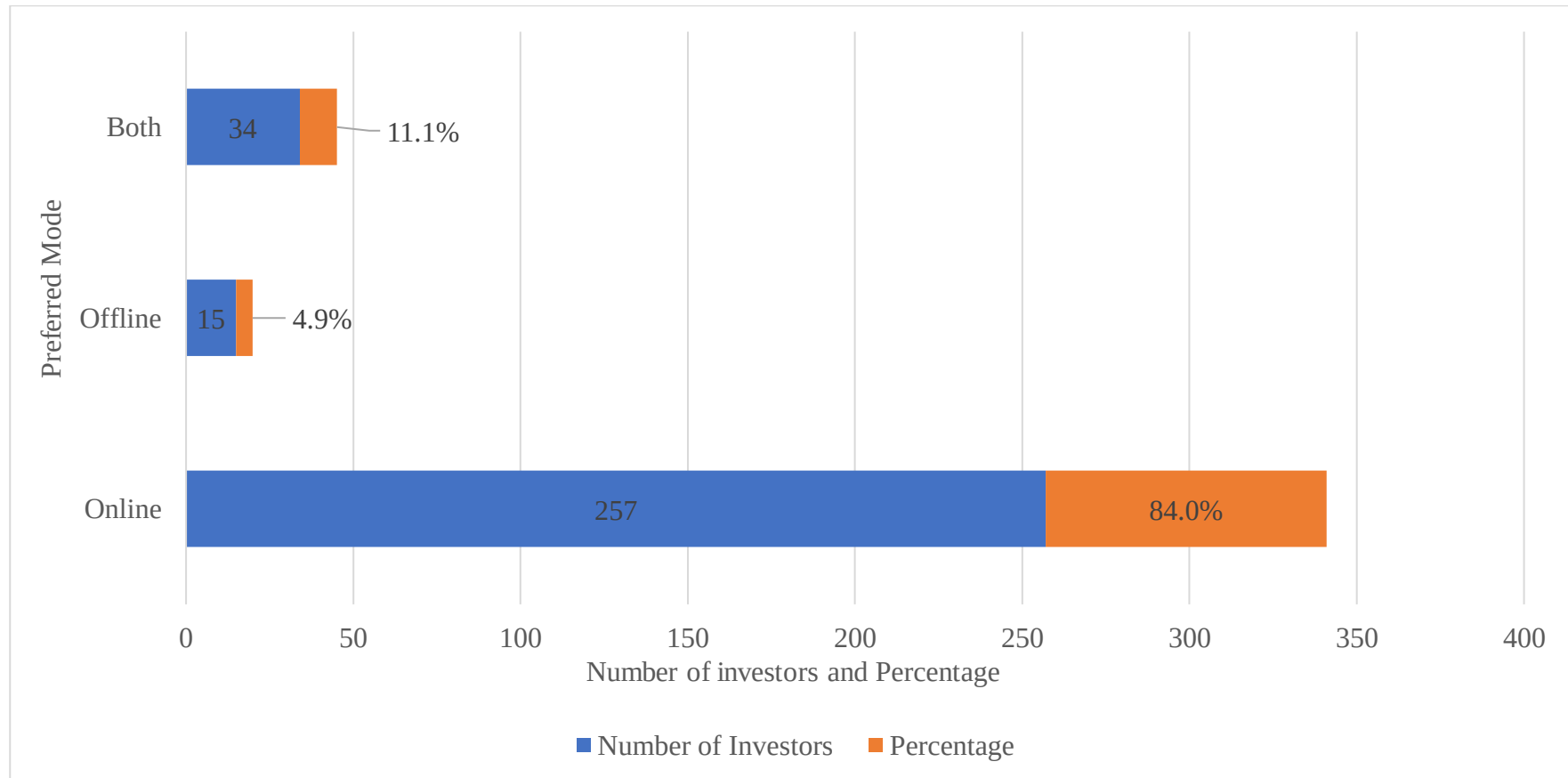
The graph shows that the majority of equity investors (52.0%) invest in 1 to 5 companies, while the smallest group (3.6%) invests in 15 to 20 companies, indicating a preference for more focused portfolios.

(Source: Author's Compilation.)

Figure 4.9: Source of Investment of equity investors of Junagadh city

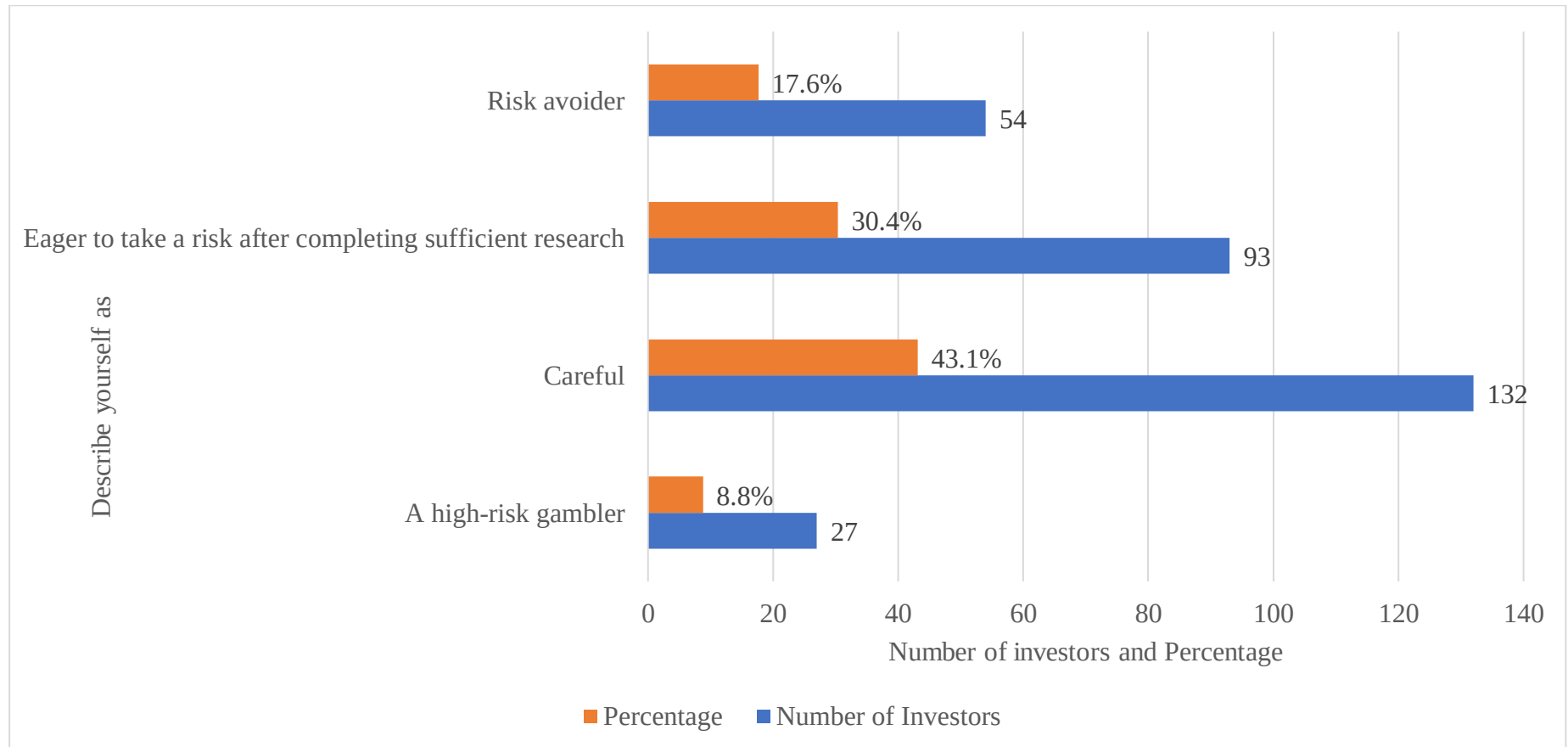
(Source: Author's Compilation.)

The Pie chart shows that in Junagadh city, 86% of equity investors use owned funds, while 2% rely on borrowed funds.

Figure 4.10: Preferred Mode of trading of equity investors of Junagadh city

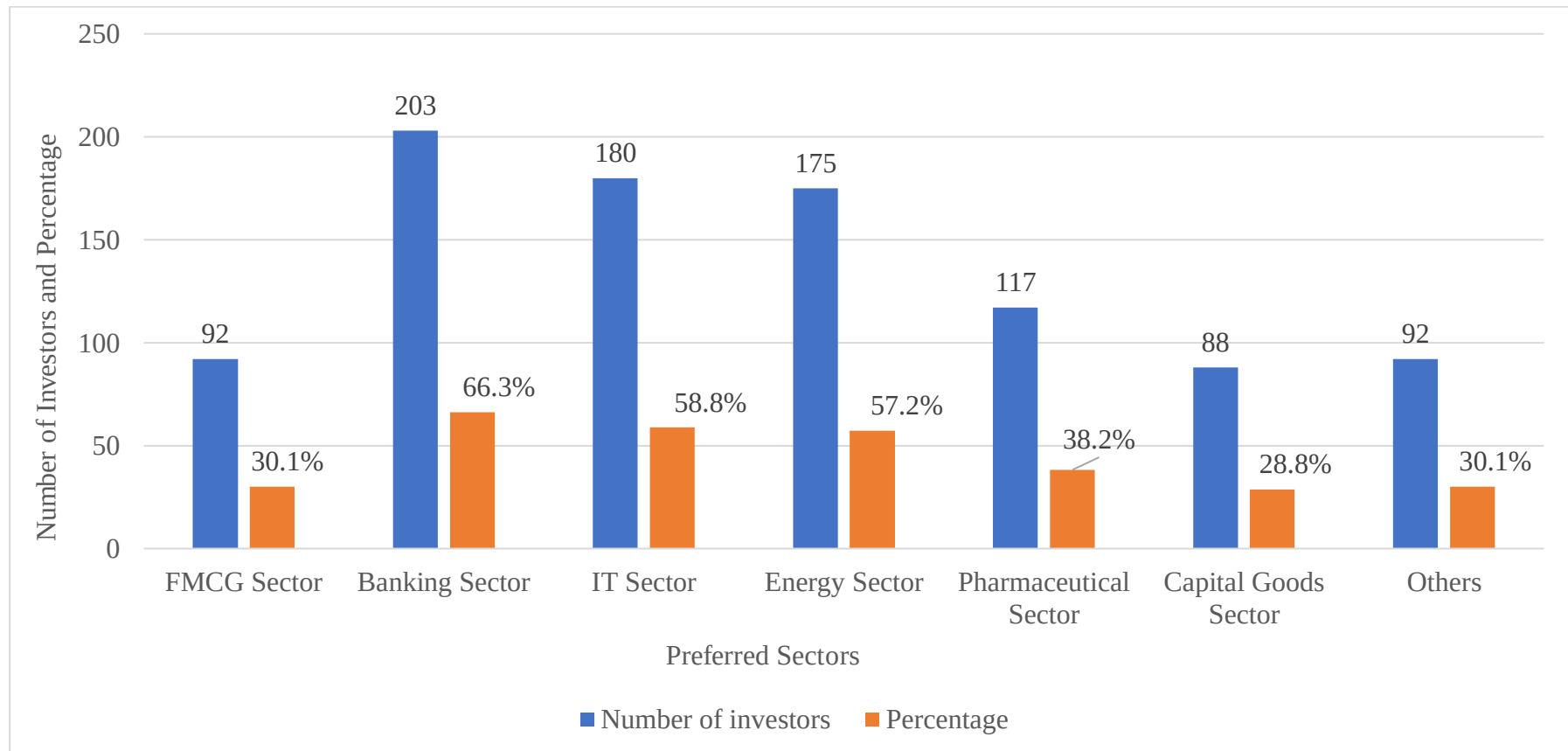
(Source: Author's Compilation.)

The graph indicates that 84% of equity investors in Junagadh City prefer online trading, while only 4.9% engage with offline trading.

Figure 4.11: You Describe yourself as

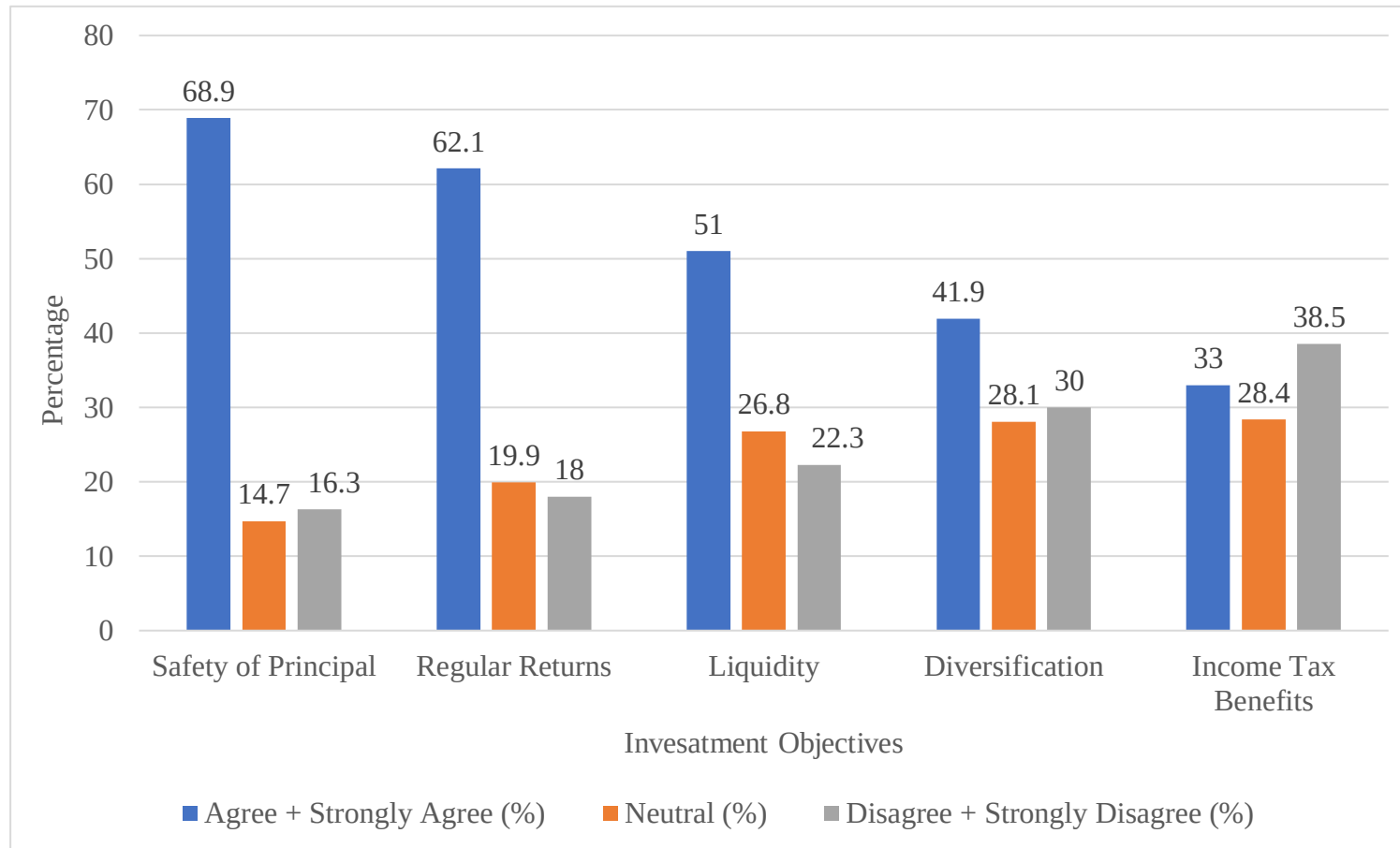
(Source: Author's Compilation.)

The Graph Shows in Junagadh city, the majority of investors (43.1%) describe themselves as careful, while the smallest group (8.8%) identify as high-risk gamblers.

Figure 4.12: Preferred sectors of equity investors of Junagadh city

(Source: Author's Compilation.)

The graph indicates in Junagadh city, the banking sector is the most preferred among equity investors, with (66.3%) showing interest. The capital goods sector is the least preferred, with only (28.8%) investing in it.

Figure 4.13: What are your investment objectives?

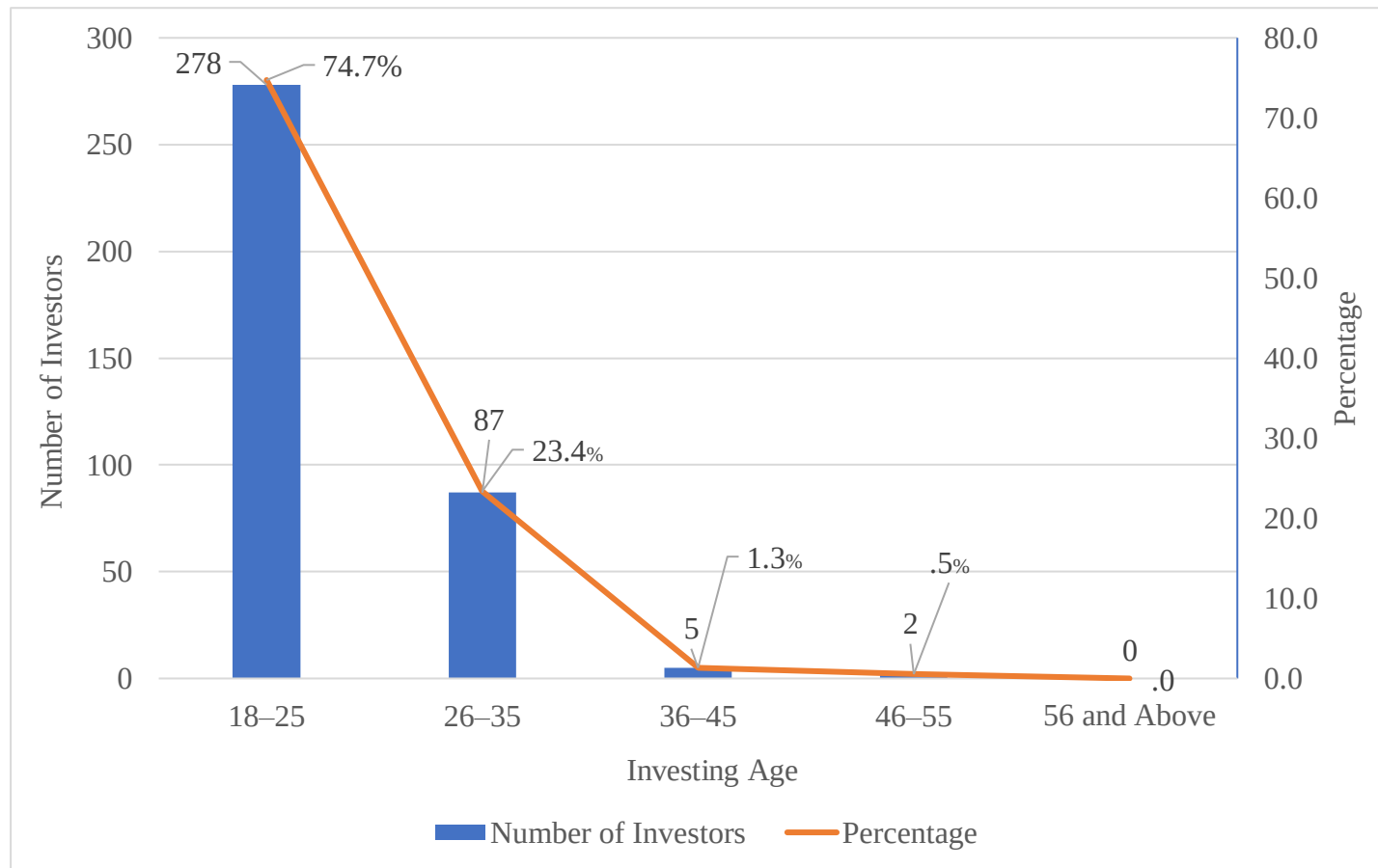
The Graph shows in Junagadh, many equity investors place the highest value on keeping their investment safe, with about (68.9%) feeling their principal is well-protected. In contrast, only (33%) consider income tax benefits an important reason to invest. This

suggests that for most people, the peace of mind that comes from security matters more than potential tax savings.

(Source: Author's Compilation.)

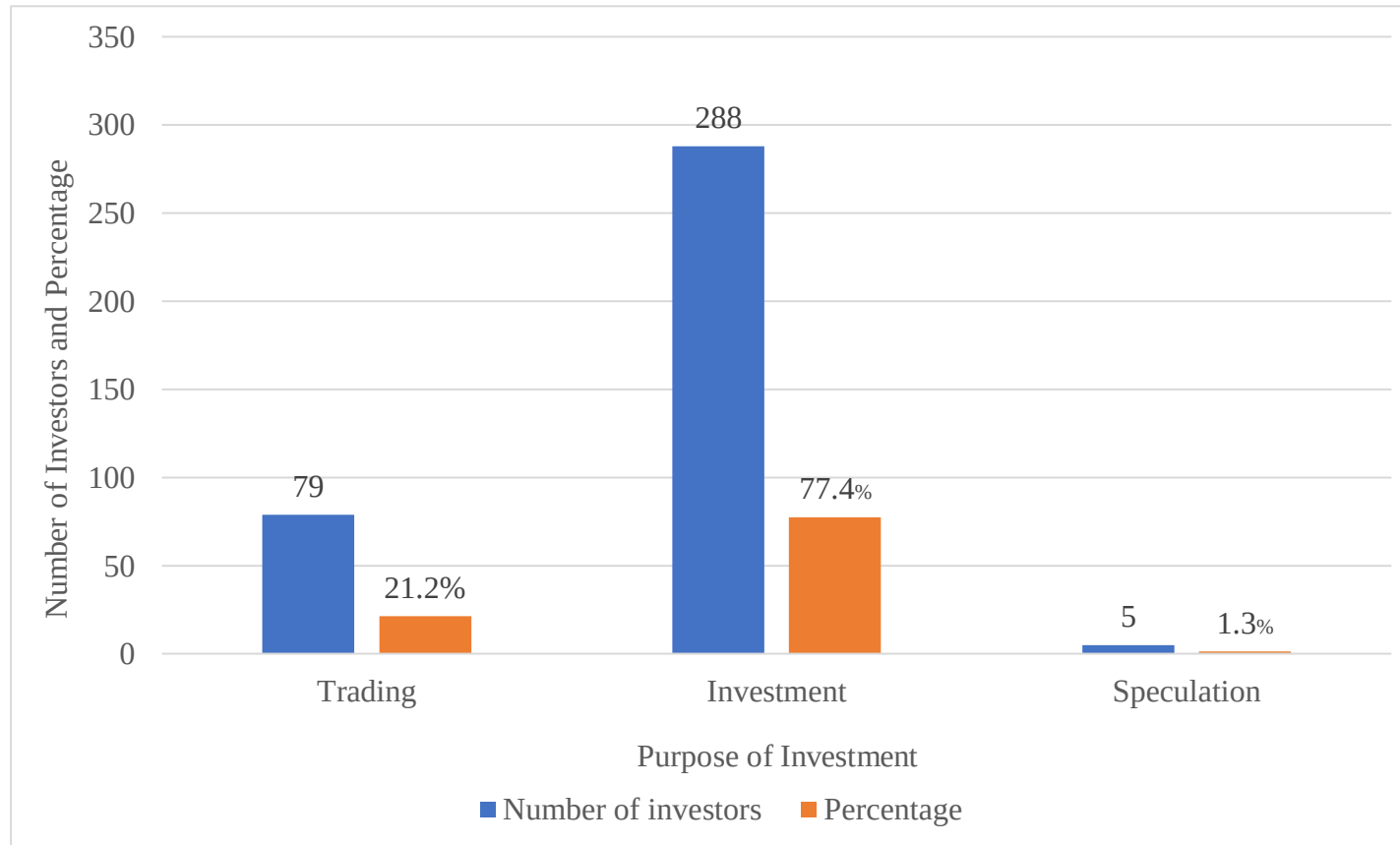
4.4.2.2 Equity Investors Profile of Rajkot City

Figure 4.14: At Which Age Have You Started Investing in Equity?



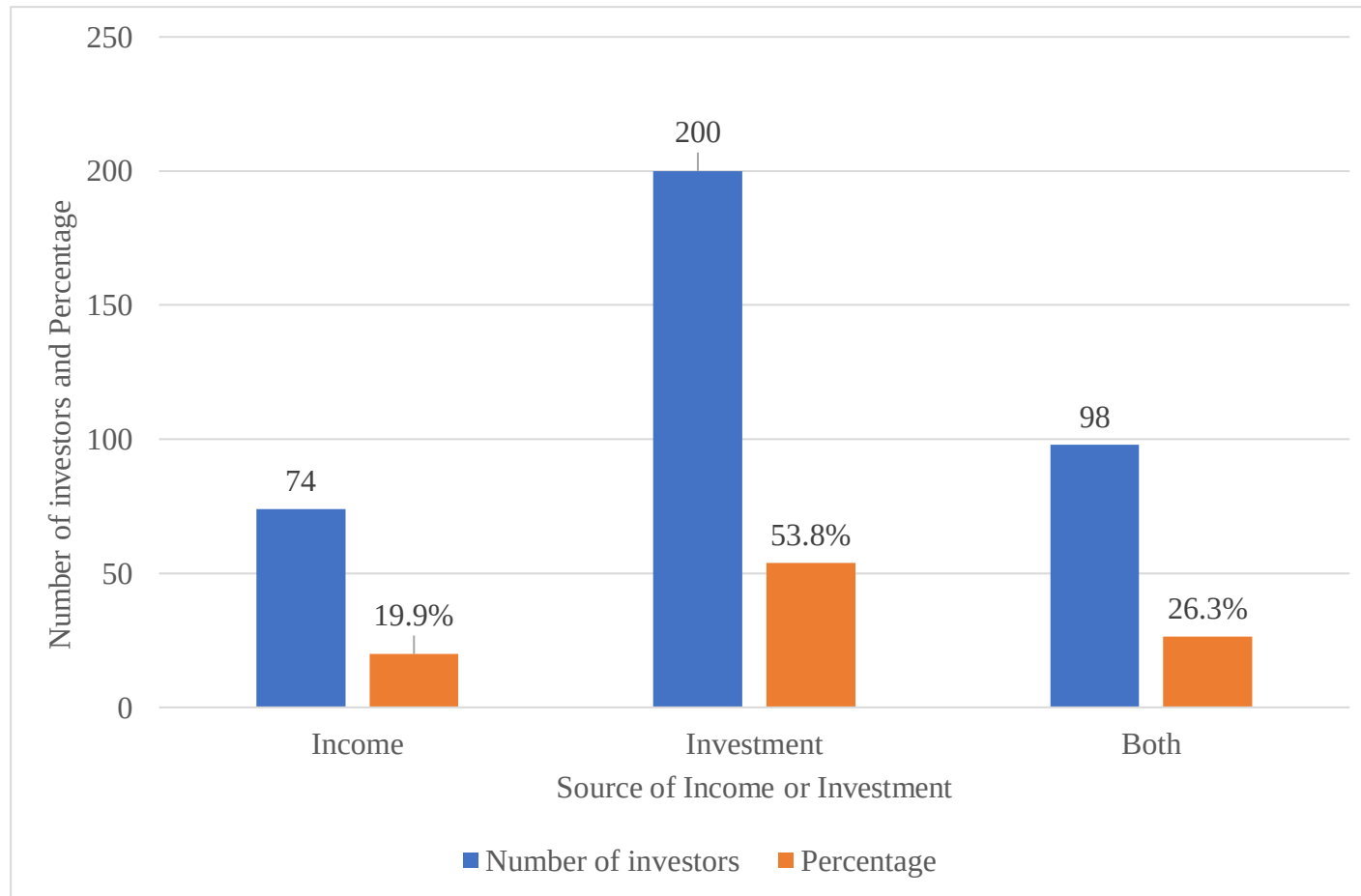
The graph shows in Rajkot city; most people start investing in equity at a young age. The majority, around (74.7%), begin between 18 and 25 years old. On the other hand, nobody (0%) starts investing at the age of 56 and Above. This shows that equity investing is more common among younger individuals, with much less interest developing later in life.

(Source: Author's Compilation.)

Figure 4.15: Purpose of Investment of Equity Investors of Rajkot City

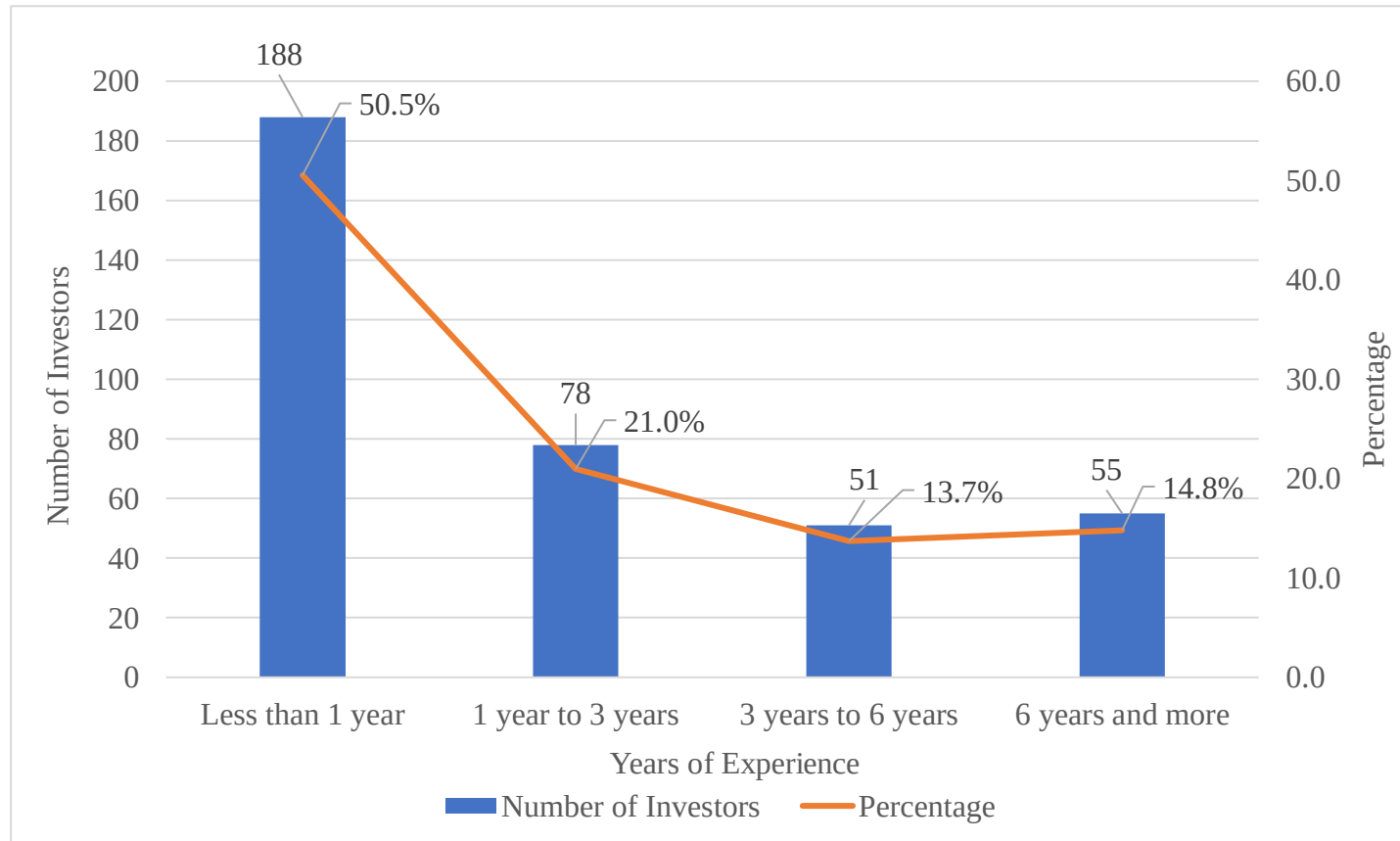
The graph shows that in Rajkot city, most people are in the market to invest, with (77.4%) focusing on long-term growth. About (21.2%) are involved in trading, likely aiming for shorter-term gains. Only a small group (1.3%), are into speculation, suggesting that high-risk strategies aren't very common in the area.

(Source: Author's Compilation.)

Figure 4.16: Is It Your Source of Income or Investment?

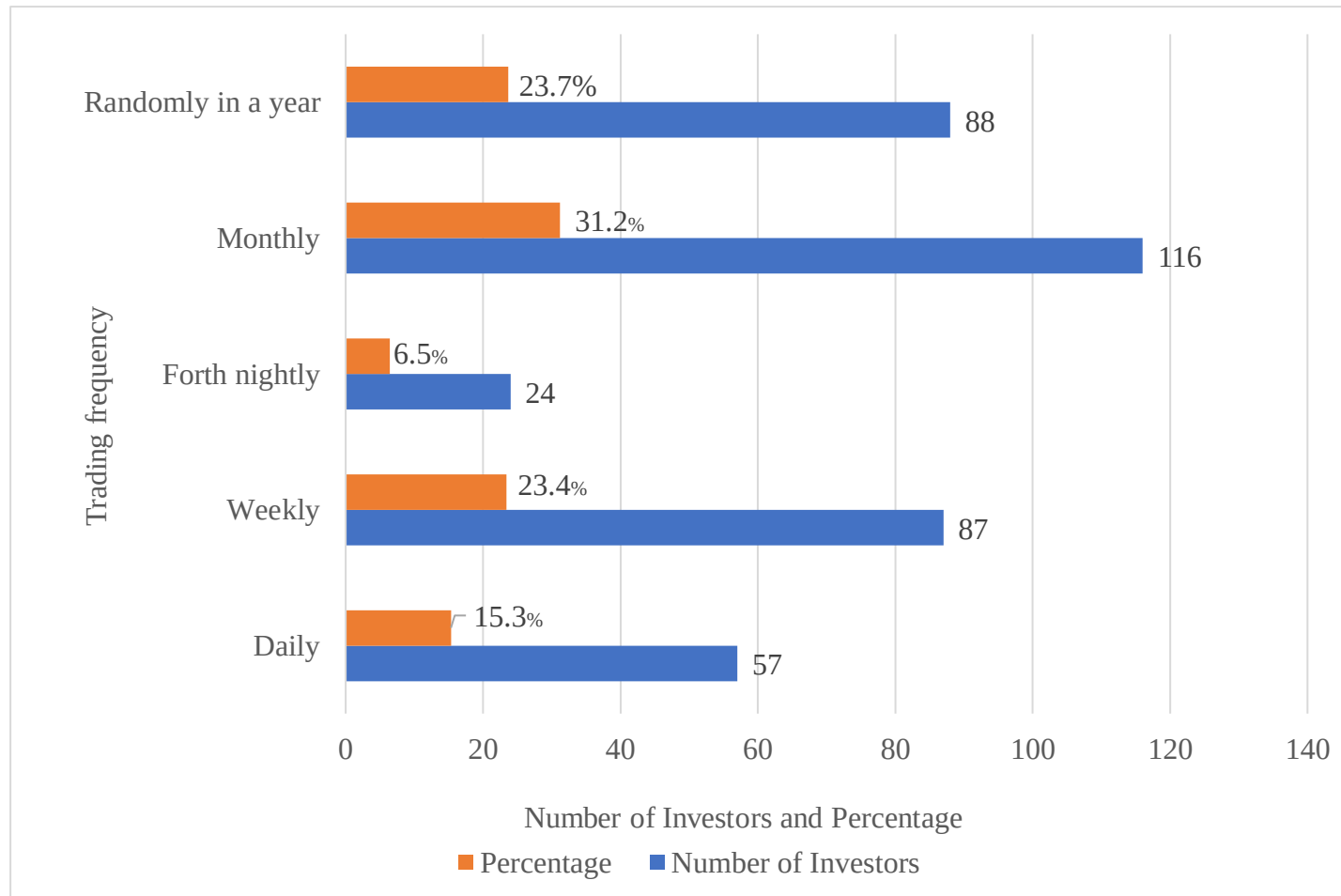
The graph indicates that in Rajkot, most investors (53.8%) primarily rely on investment returns, reflecting a notable shift toward passive income. A smaller portion (19.9%) depends only on regular income, like salary or business, while others (26.3%) draw from both. This highlights a growing awareness of financial planning and wealth building in the city.

(Source: Author's Compilation.)

Figure 4.17: Years of Experience in equity investors of Rajkot city

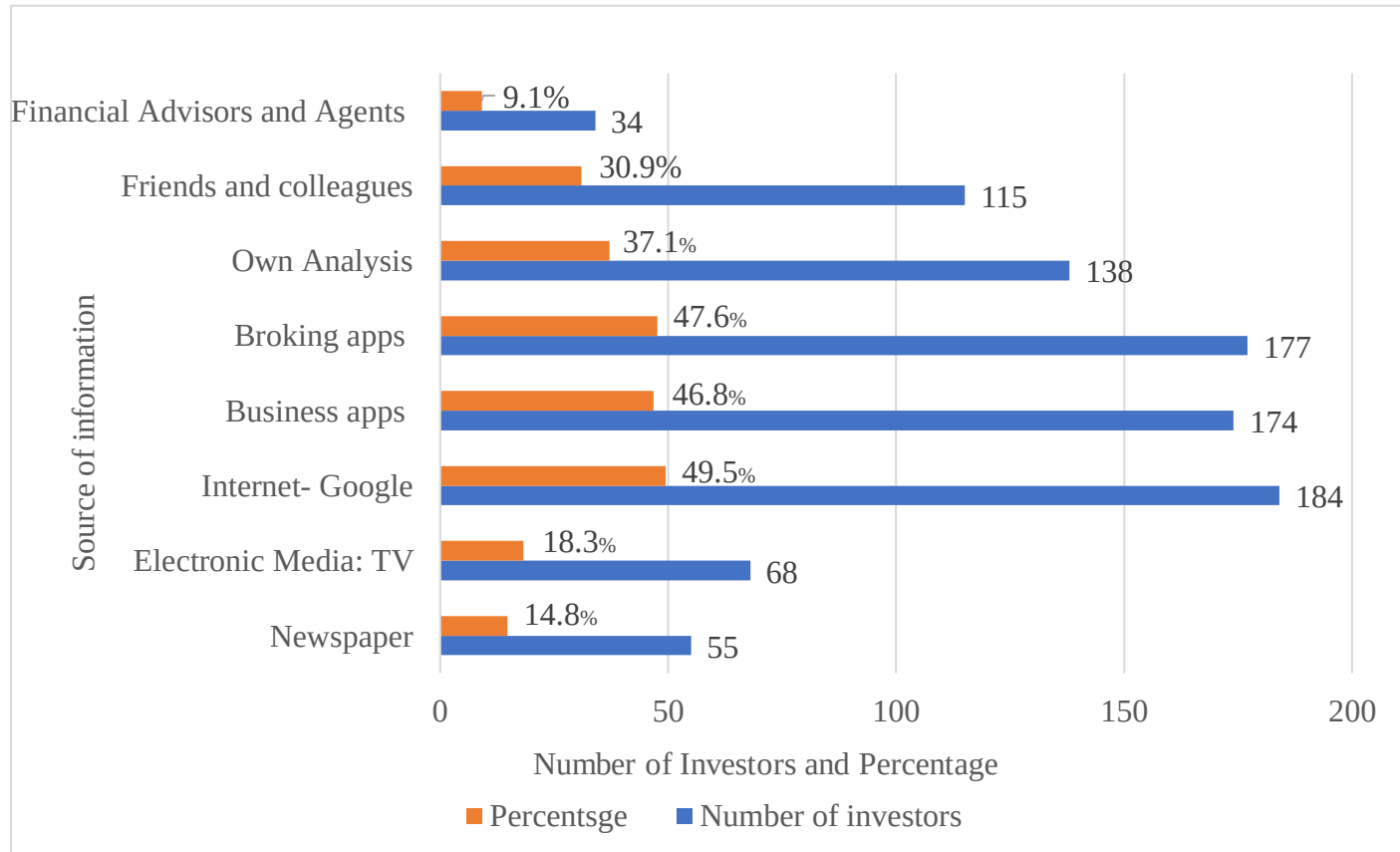
(Source: Author's Compilation.)

The graph shows that in Rajkot, most equity investors (50.5%) are new, with less than one year of experience, showing a recent rise in market participation. On the other hand, a smaller group (13.7%) has 3 to 6 years of experience, suggesting fewer mid-term investors in the city.

Figure 4.18: Trading frequency of equity investors of Rajkot city

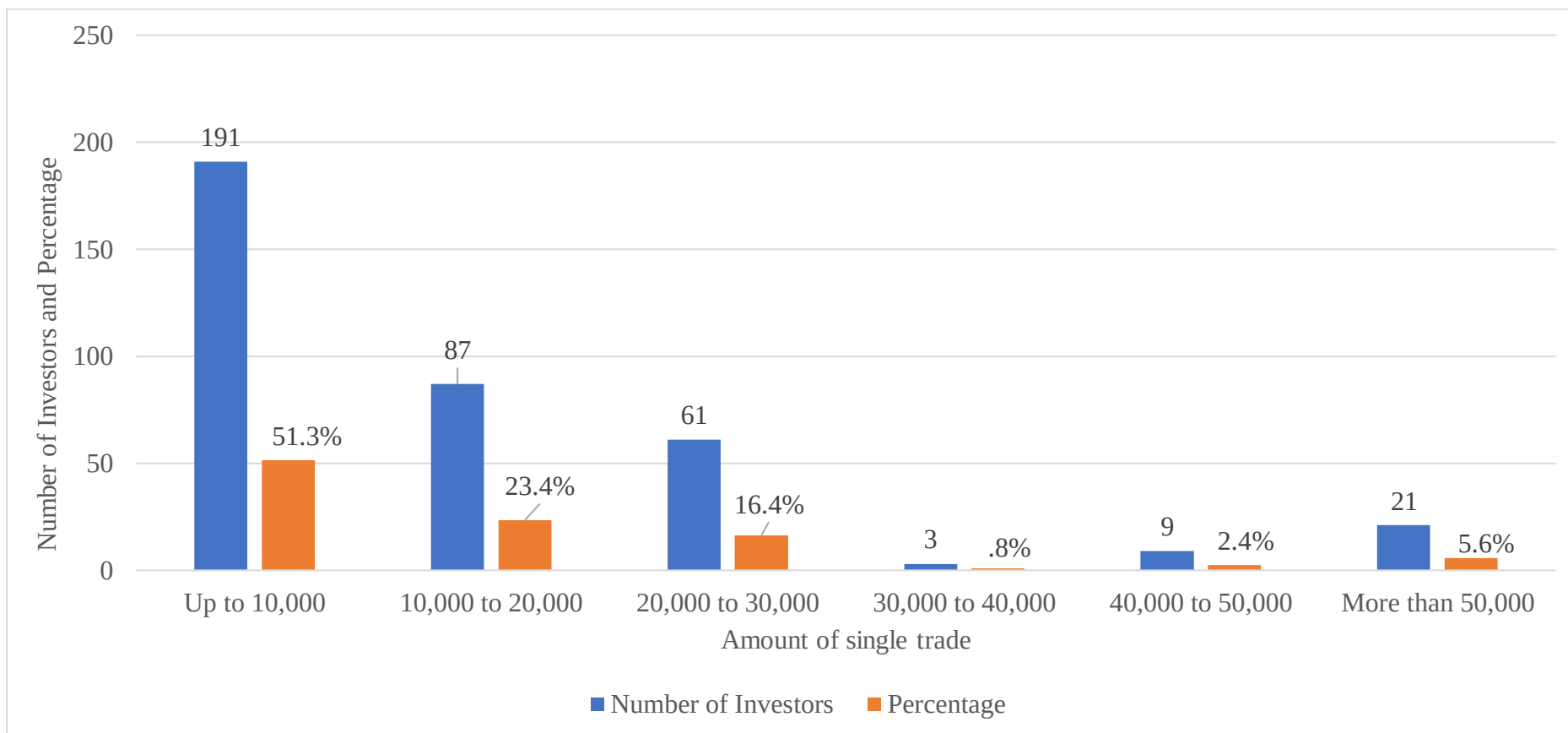
The graph shows in Rajkot, the highest number of equity investors trade monthly (31.2%), showing a steady and planned investment pattern. The fewest investors trade fortnightly (6.5%), making it the least preferred trading frequency in the city.

(Source: Author's Compilation.)

Figure 4.19: The source of information for equity investment

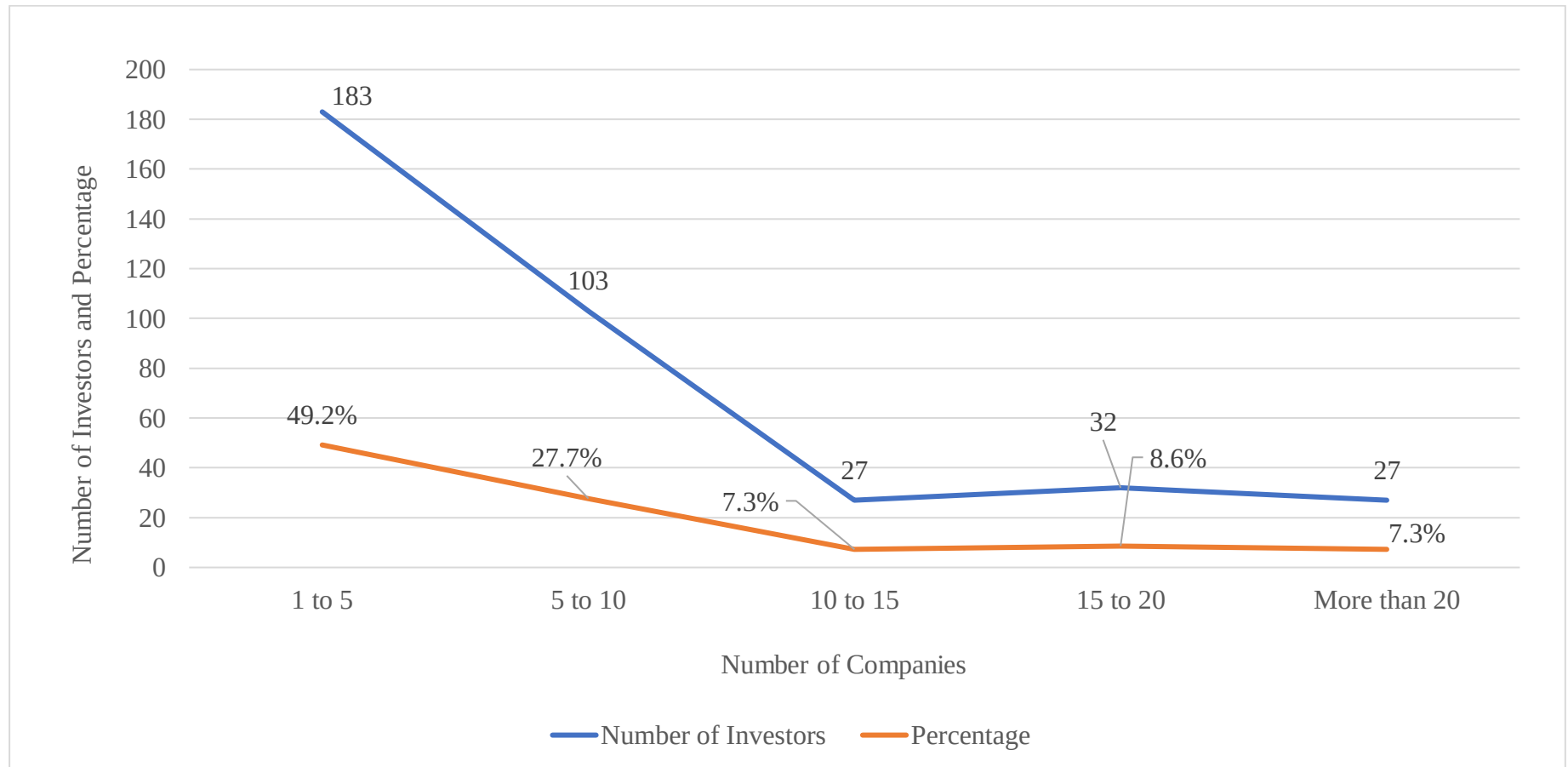
(Source: Author's Compilation.)

The graph shows that in Rajkot city, most equity investors rely on the internet (49.5%), broking apps (47.6%), and business apps (46.8%) as their main sources of investment information, reflecting a shift toward digital and self-driven research. The least used source is financial advisors and agents (9.1%), indicating a lower dependence on traditional advisory services.

Figure 4.20: How much amount of single trade do you execute?

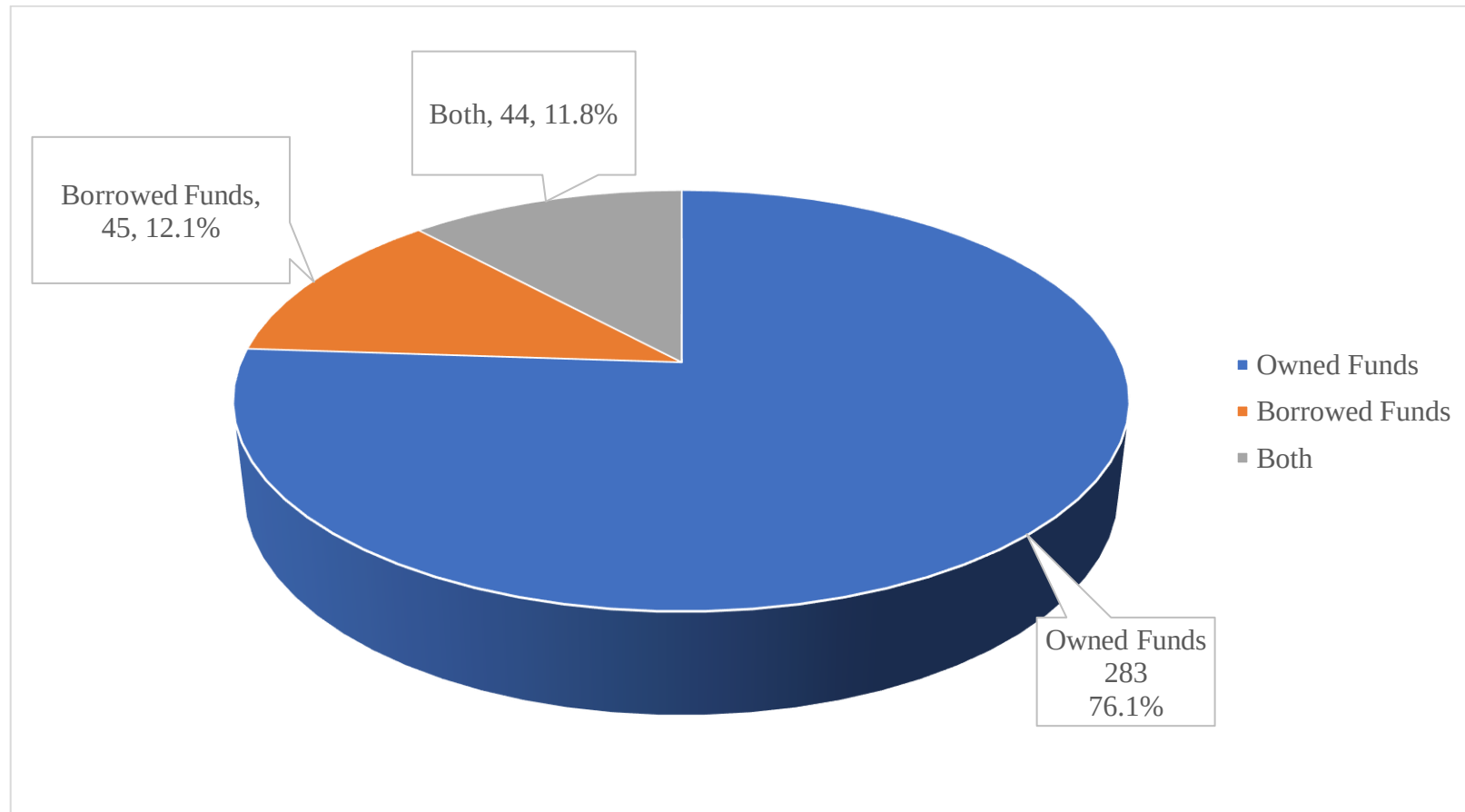
(Source: Author's Compilation.)

The Graph Shows that in Rajkot city, the highest number of investors (51.3%) execute trades up to ₹10,000, while the lowest (0.8%) trade between ₹30,000 to ₹40,000.

Figure 4.21: Number of companies in which investments are made by investors

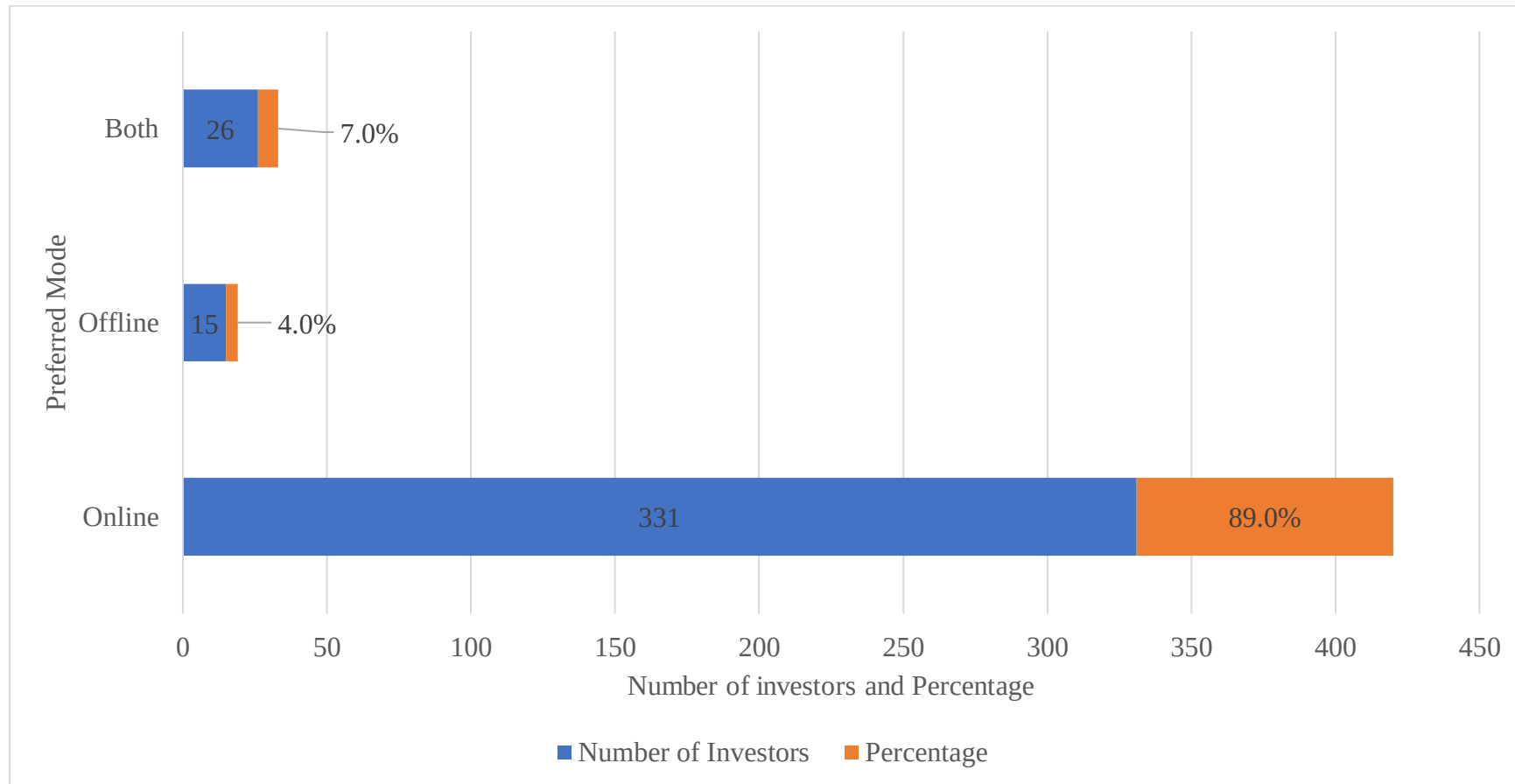
(Source: Author's Compilation.)

The graph shows that in Rajkot city, (49.2%) of investors have invested in just 1 to 5 companies, showing a conservative, low-risk approach. In contrast, only (7.3%) have invested in more than 20 companies, indicating that high diversification is rare.

Figure 4.22: Source of Investment of equity investors of Rajkot city

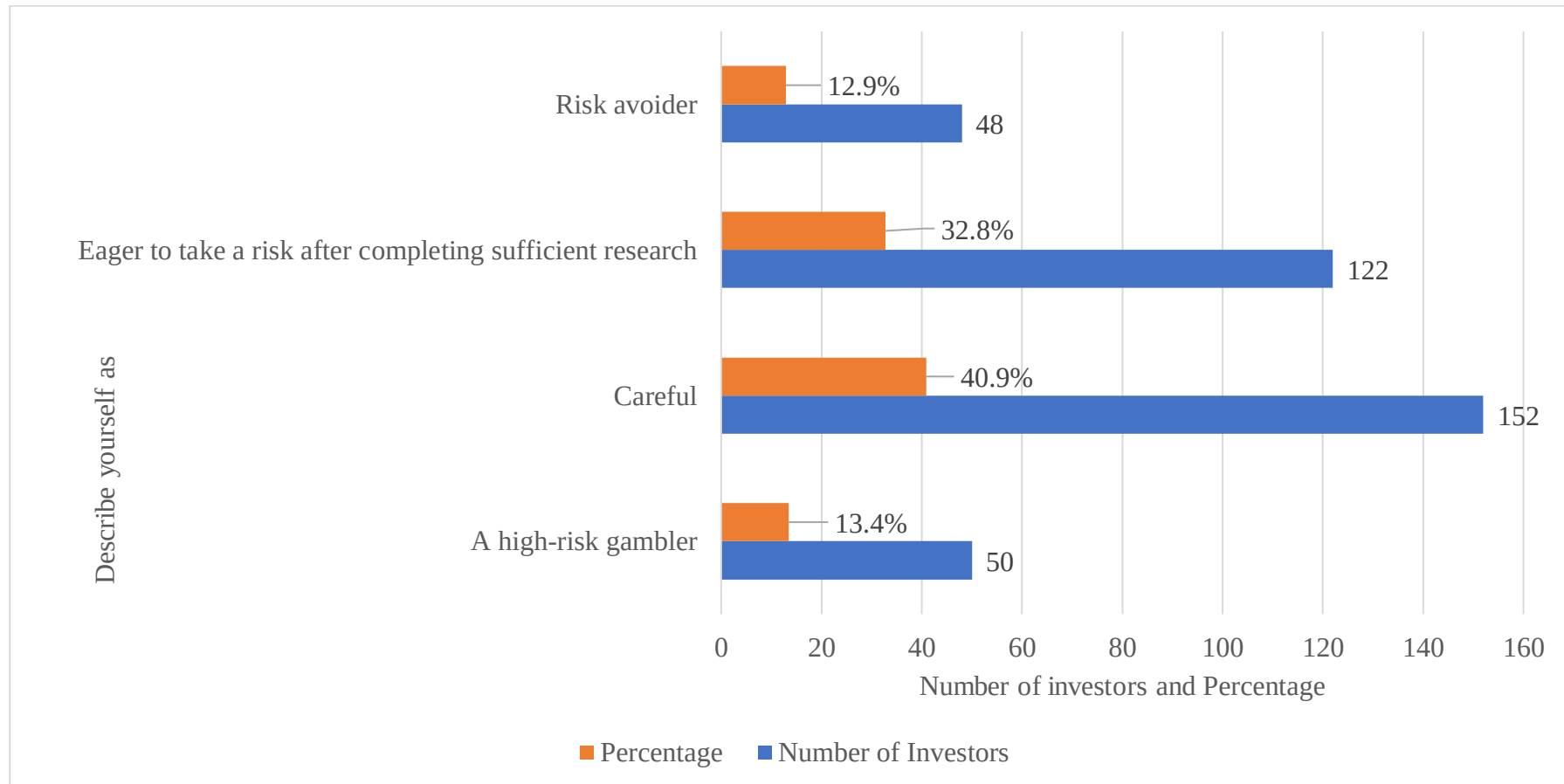
(Source: Author's Compilation.)

The Pie chart shows that in Rajkot city, (76.1%) of equity investors use owned funds, while (11.8%) rely on borrowed funds.

Figure 4.23: Preferred Mode of trading of equity investors of Rajkot city

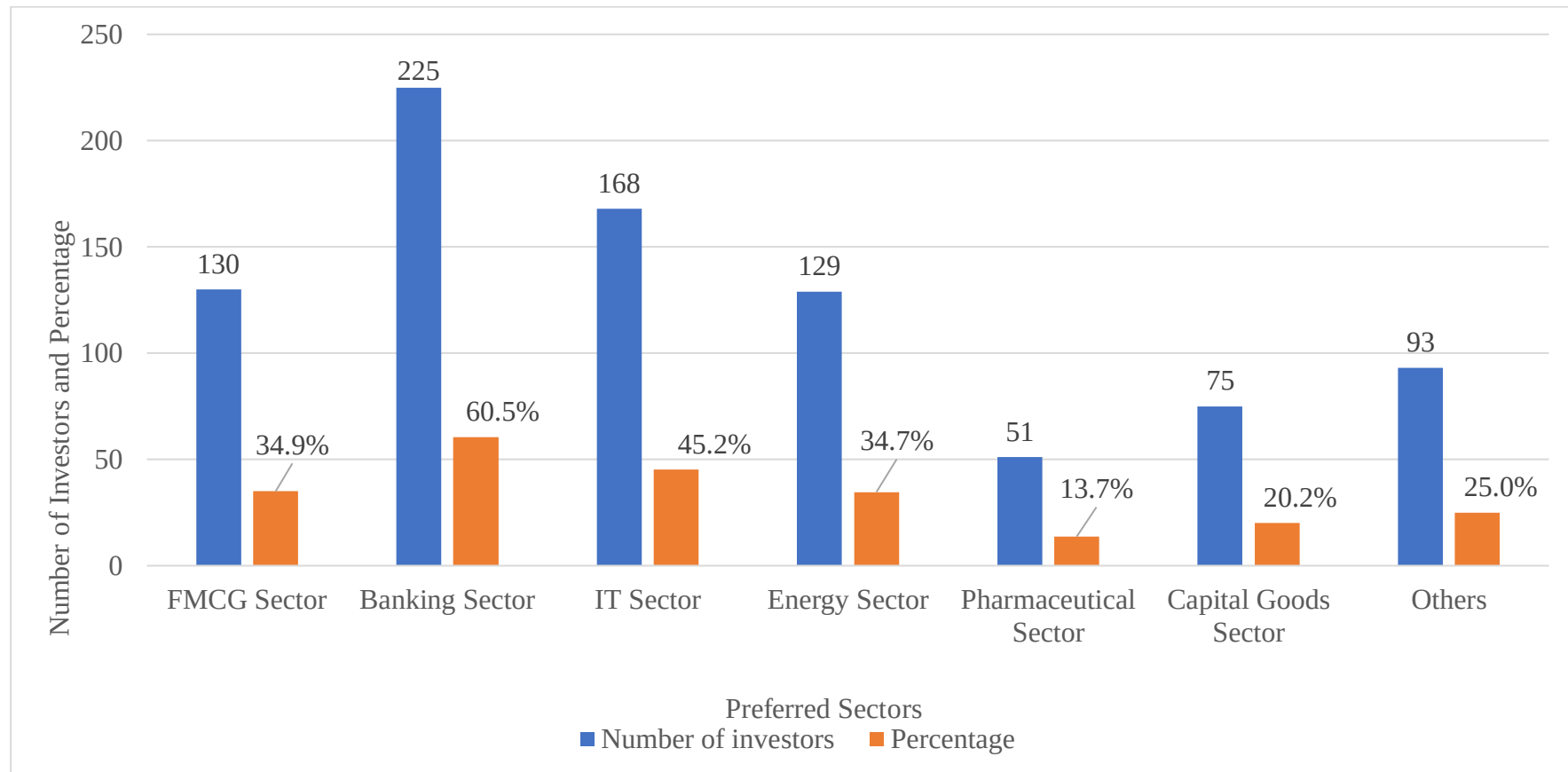
(Source: Author's Compilation.)

The graph indicates that (89%) of equity investors in Junagadh City prefer online trading, while only (4%) engage with offline trading.

Figure 4.24: You Describe yourself as

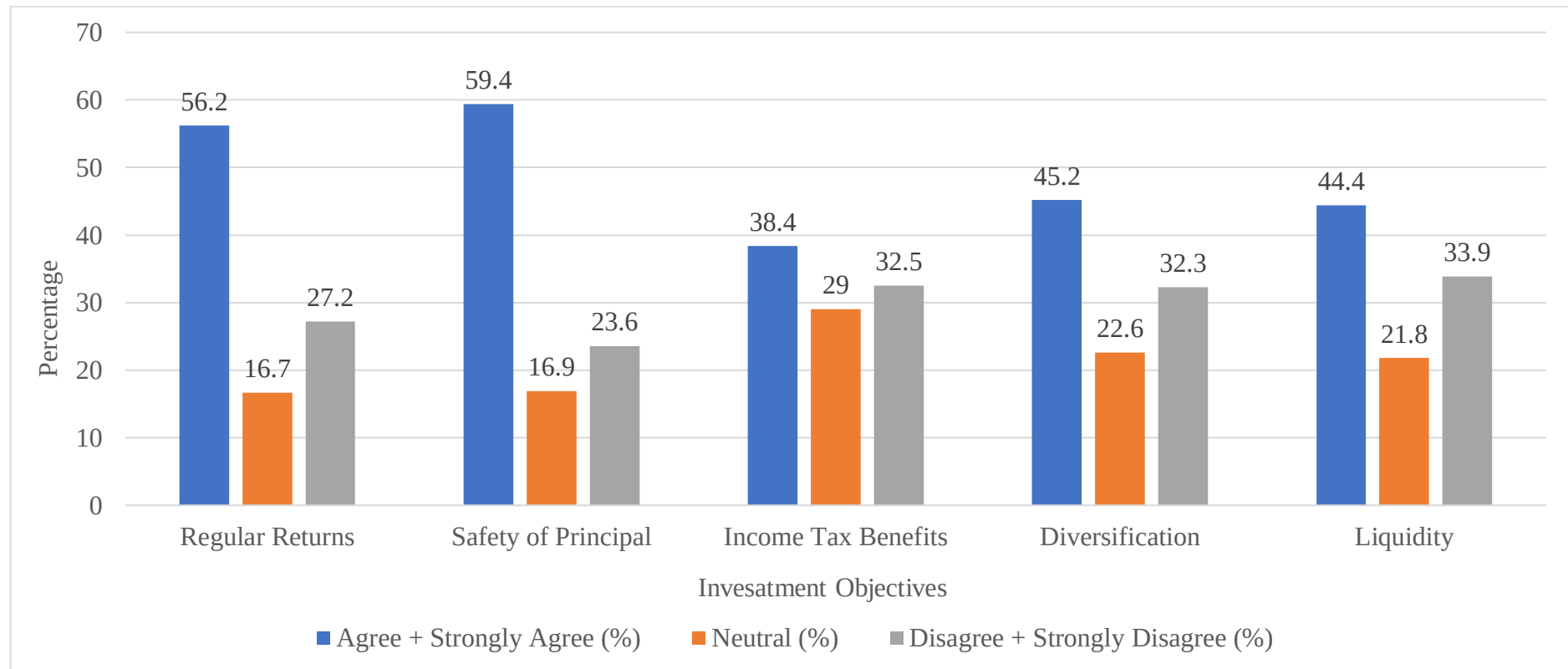
(Source: Author's Compilation.)

The Graph Shows that in Rajkot city, 40.9% of investors describe themselves as careful, showing a preference for low-risk strategies. Only 13.4% identify as high-risk gamblers, indicating that aggressive risk-taking is uncommon.

Figure 4.25: Preferred sectors of equity investors of Rajkot city

(Source: Author's Compilation.)

The graph indicates most equity investors prefer the Banking Sector (60.5%), indicating strong confidence in financial institutions. The Pharmaceutical Sector is the least preferred (13.7%), showing limited investor interest in that area.

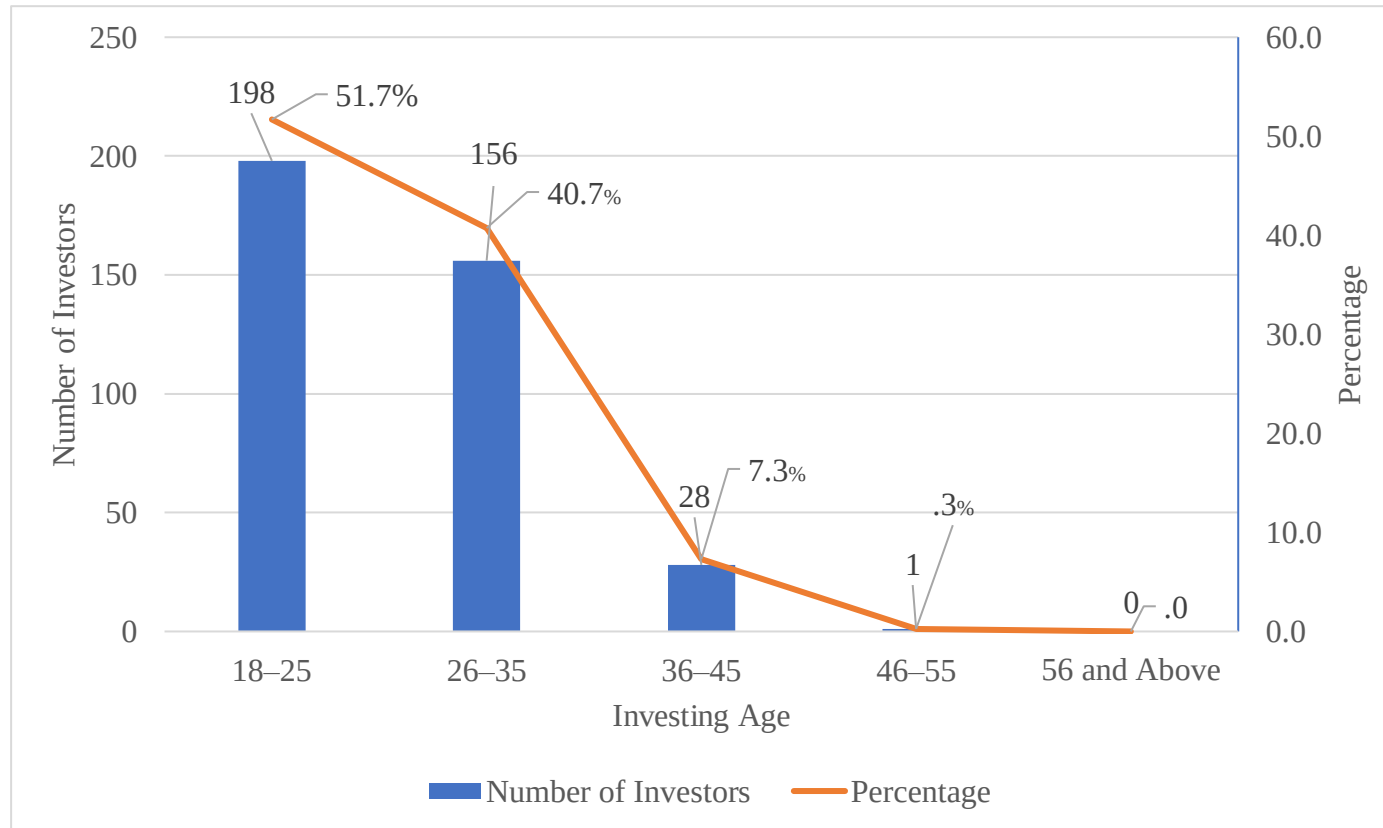
Figure 4.26: What are your investment objectives?

(Source: Author's Compilation.)

The Graph shows that in Rajkot, Safety of Principal (59.4%) is the top investment objective, showing a strong preference for capital protection. Income Tax Benefits (38.4%) received the least agreement. Investors are least neutral about Regular Returns (16.7%) and show the most disagreement with Liquidity (33.9%) as an objective.

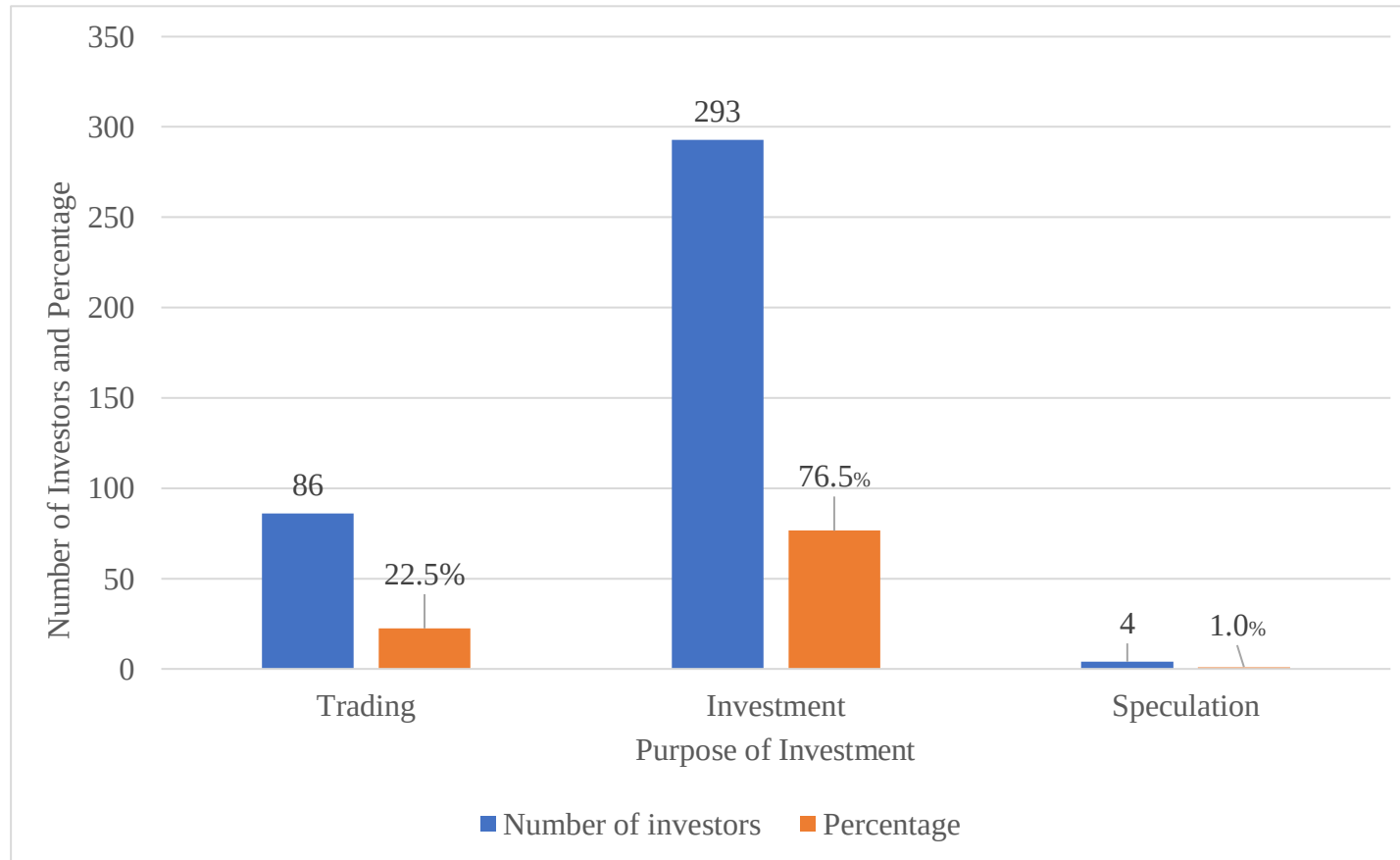
4.4.2.3 Equity Investors' Profile of Jamnagar City

Figure 4.27: At Which Age Have You Started Investing in Equity?



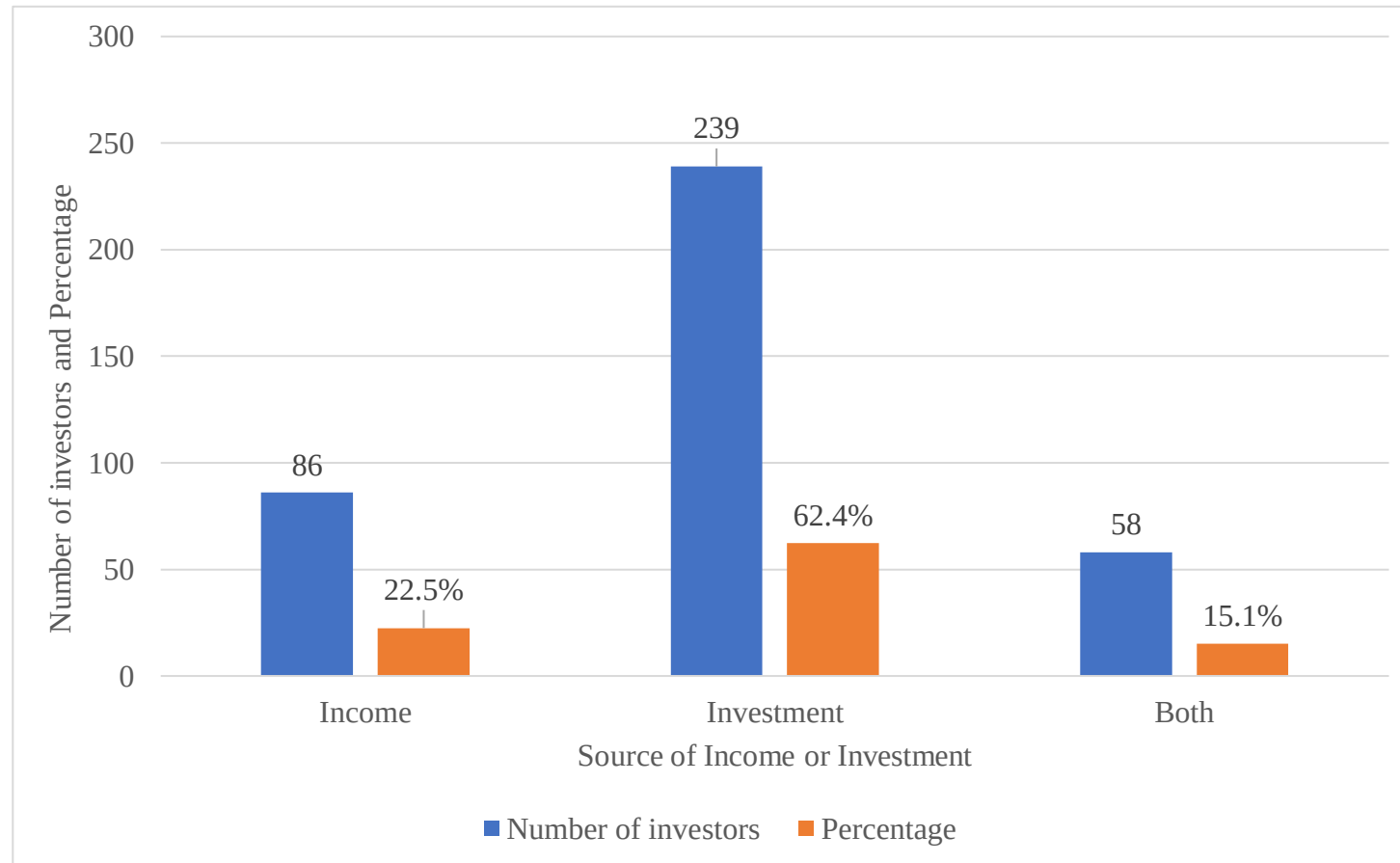
The graph shows that in Jamnagar city, most investors are young, with the 18–25 age group making up the largest share at 51.7%. On the other hand, there are no investors in the 56 and above age group, showing the lowest participation. This suggests that investing is more common among the younger population, while older individuals are less involved.

(Source: Author's Compilation.)

Figure 4.28: Purpose of Investment of Equity Investors of Jamnagar City

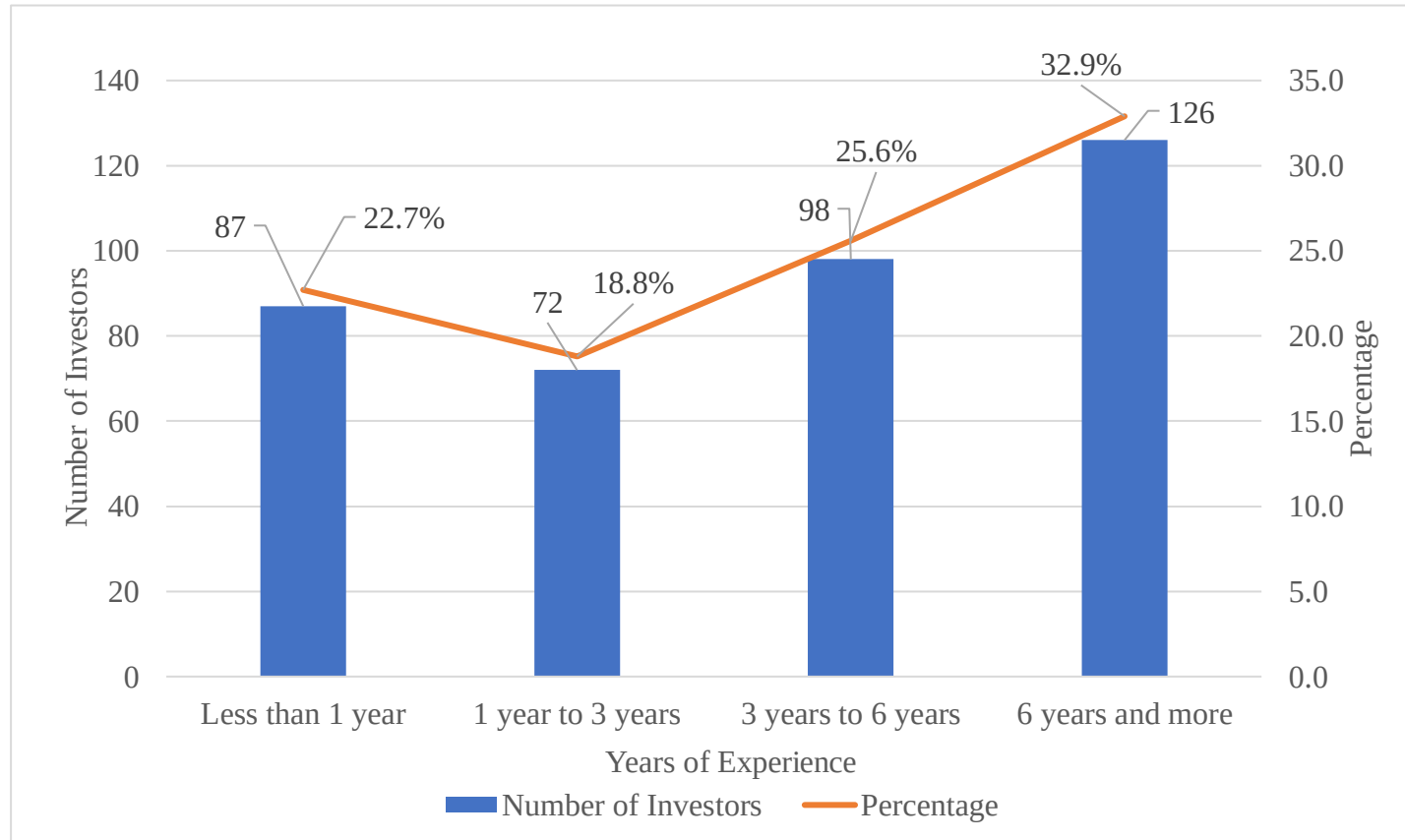
The graph shows that in Jamnagar city, most people are in the market to invest, with (76.5%) focusing on long-term growth. About (22.5%) are involved in trading, likely aiming for shorter-term gains. Only a small group, (1%), are into speculation, suggesting that high-risk strategies aren't very common in the area.

(Source: Author's Compilation.)

Figure 4.29: Is It Your Source of Income or Investment?

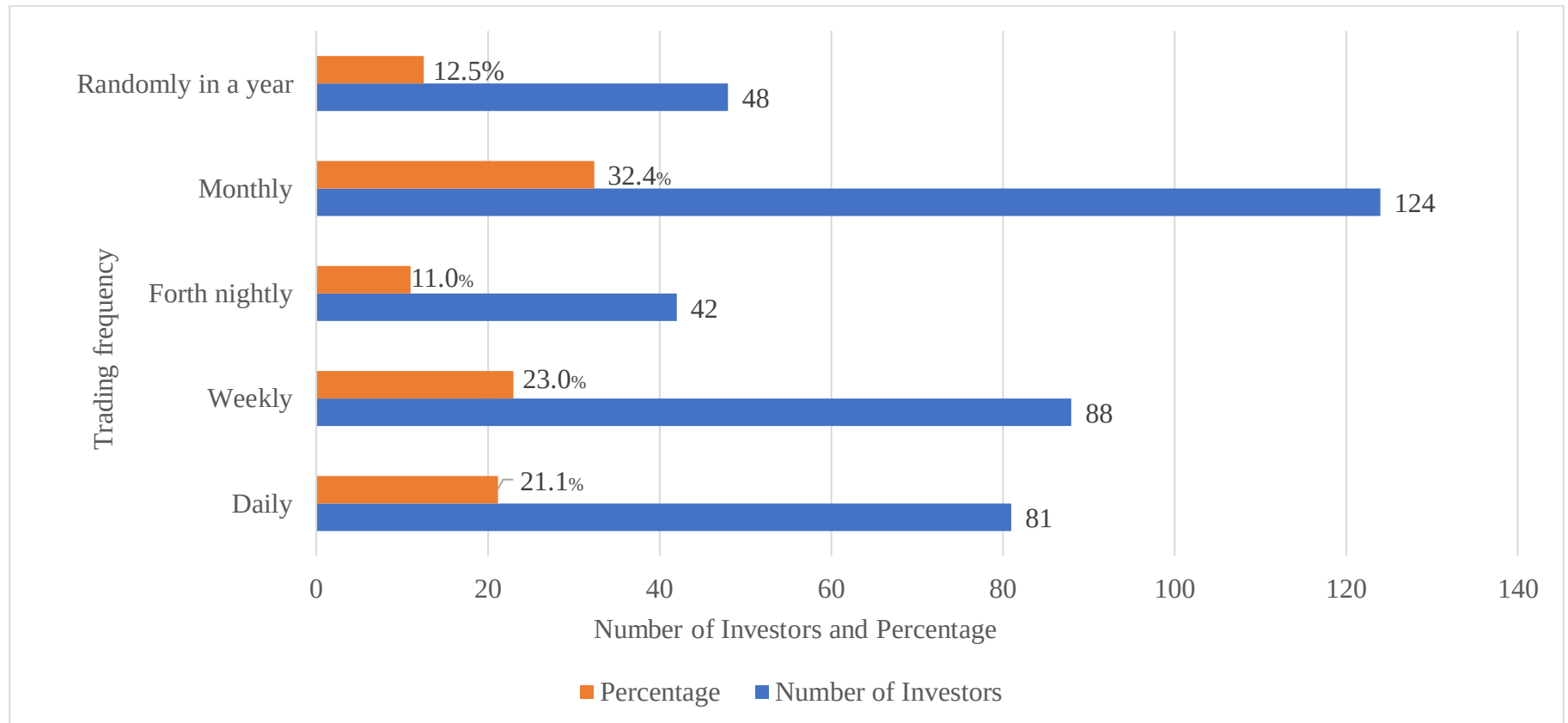
The graph indicates that in Jamnagar city, most investors (62.4%) primarily rely on investment returns, reflecting a notable shift toward passive income. A smaller portion (22.5%) depends only on regular income, like salary or business, while others (15.1%) draw from both. This highlights a growing awareness of financial planning and wealth building in the city.

(Source: Author's Compilation.)

Figure 4.30: Years of Experience in equity investors of Jamnagar city

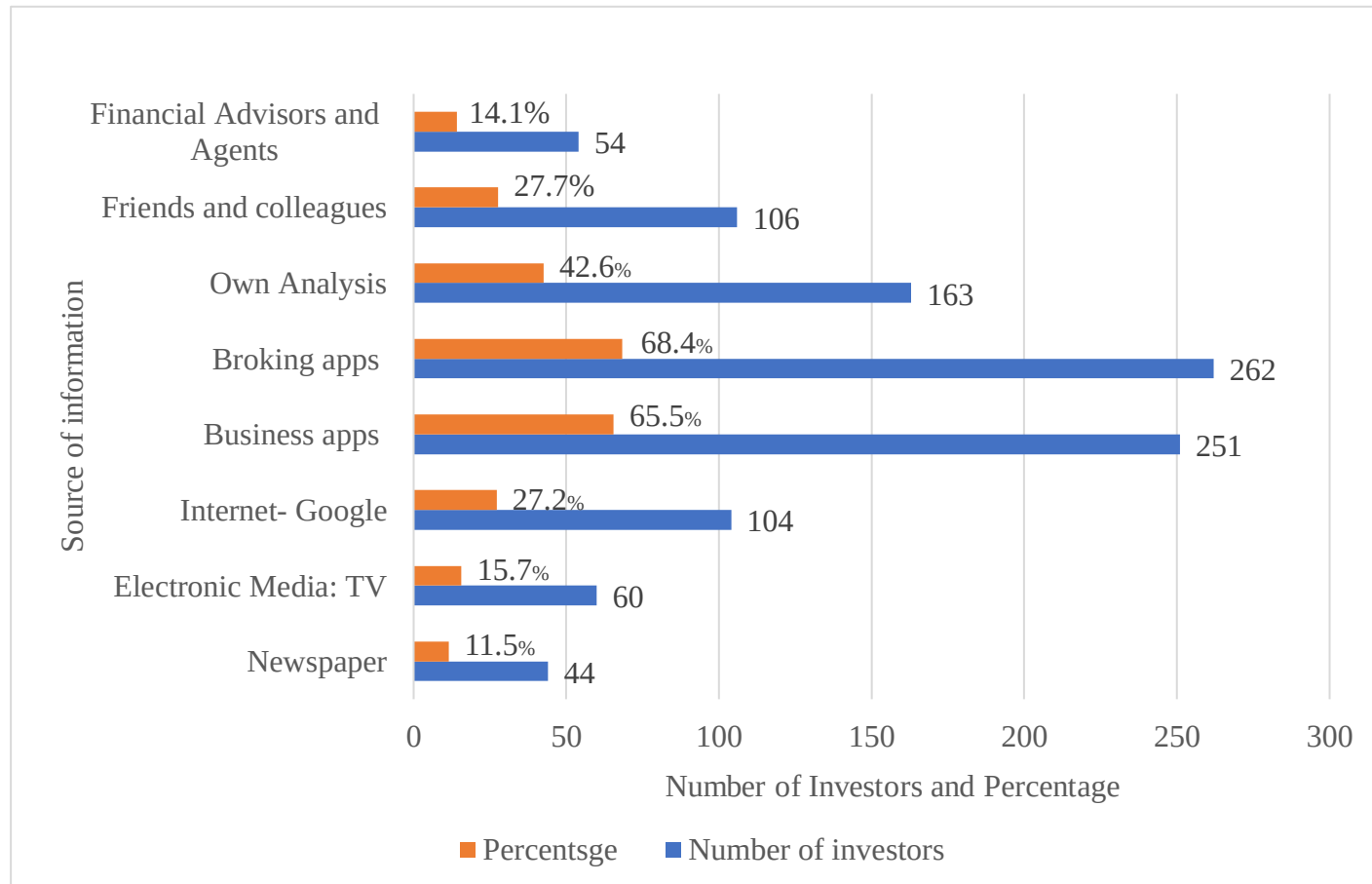
The graph shows that in Jamnagar city, the highest number of equity investors have 6 years or more of experience, accounting for 32.9%. In contrast, the lowest share of investors, 18.8%, have 1 to 3 years of experience. This indicates that a significant portion of investors are experienced, while relatively fewer are in the early-mid stages of their investment journey.

(Source: Author's Compilation.)

Figure 4.31: Trading frequency of equity investors of Jamnagar city

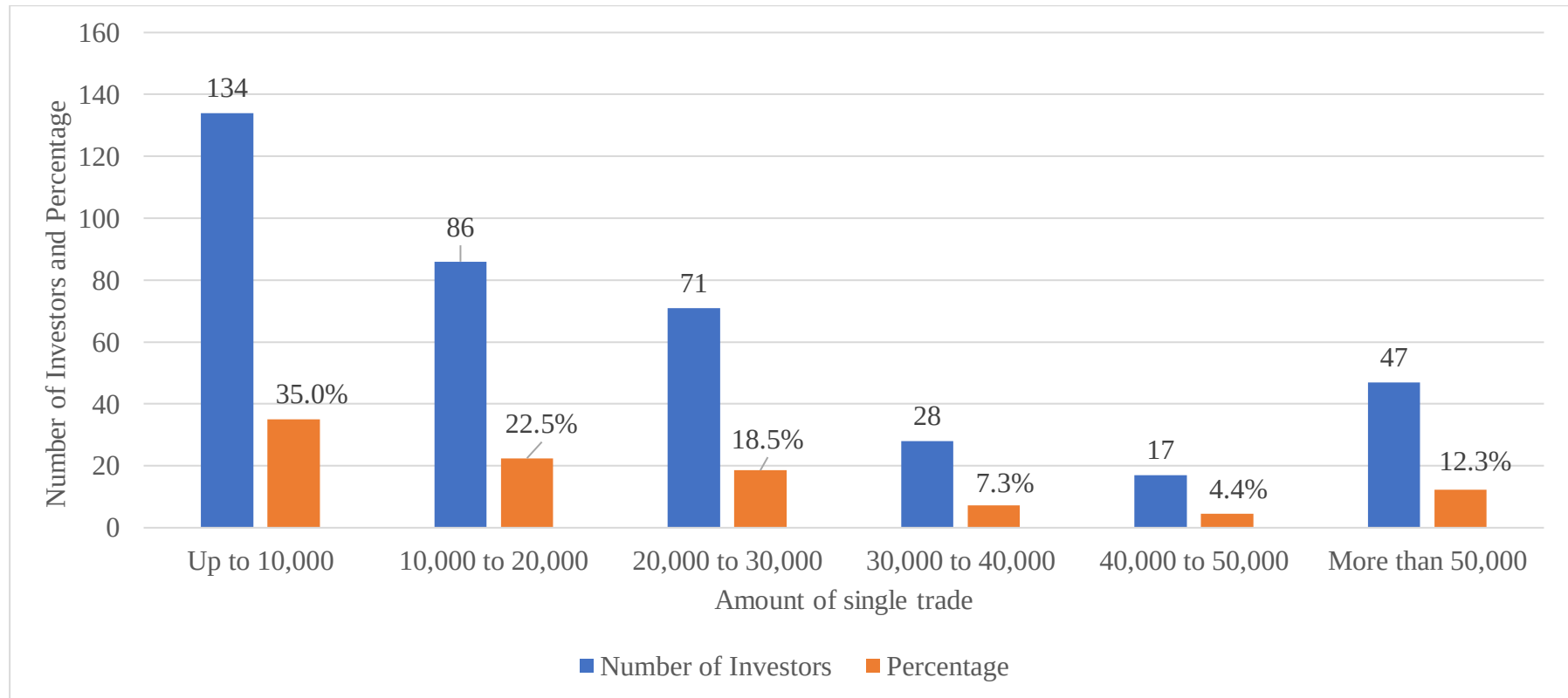
(Source: Author's Compilation.)

The graph shows that in Jamnagar city, the highest number of equity investors trade monthly (32.4%), showing a steady and planned investment pattern. The fewest investors trade fortnightly (11%), making it the least preferred trading frequency in the city.

Figure 4.32: The source of information for equity investment

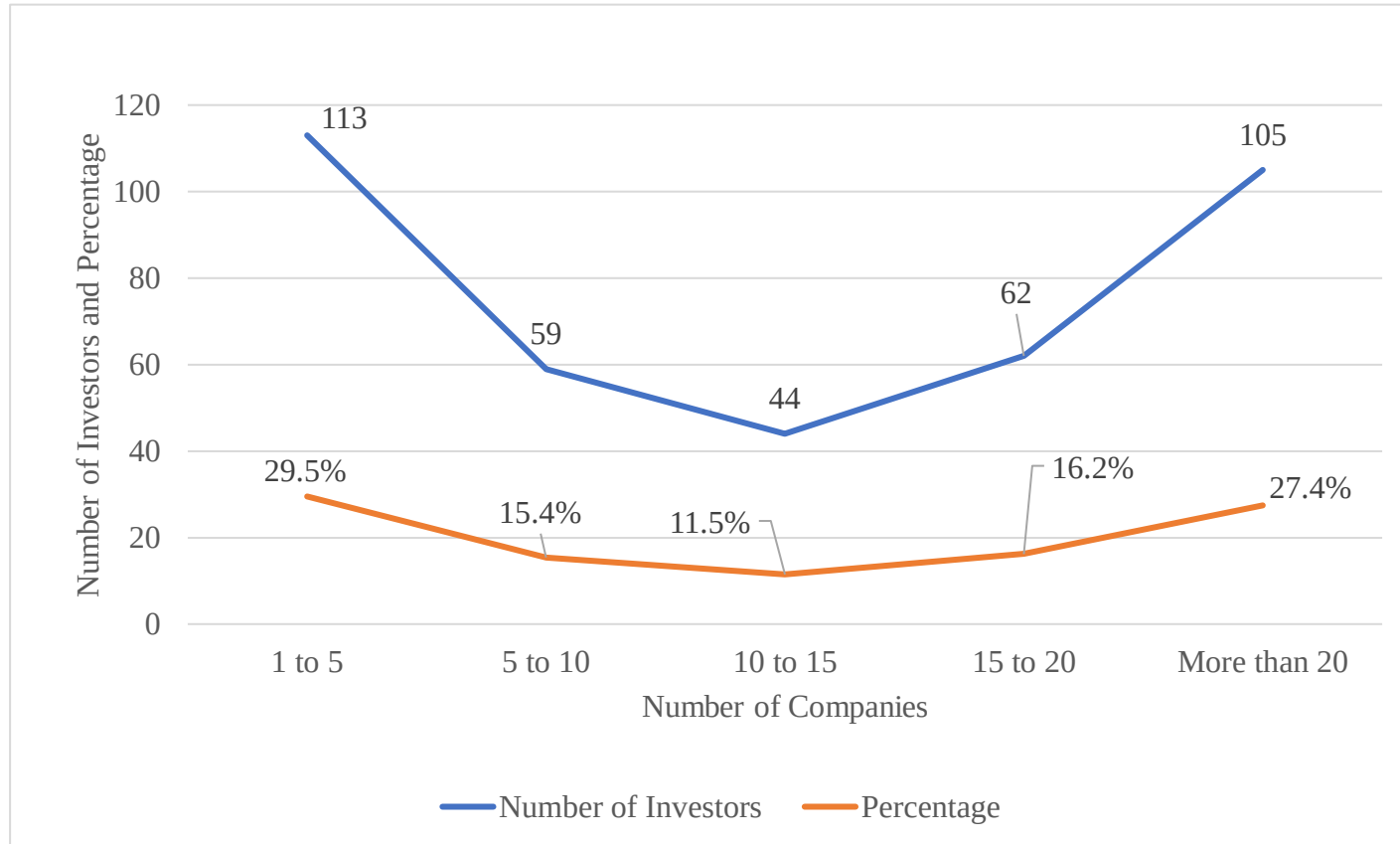
The graph shows that in Jamnagar city, in terms of sources for equity investment information, broking apps are the most popular among investors, used by 68.4%. On the other hand, newspapers are the least used source, with only 11.5% relying on them. This shows a clear shift toward digital platforms over traditional media for investment decisions.

(Source: Author's Compilation.)

Figure 4.33: How much amount of single trade do you execute?

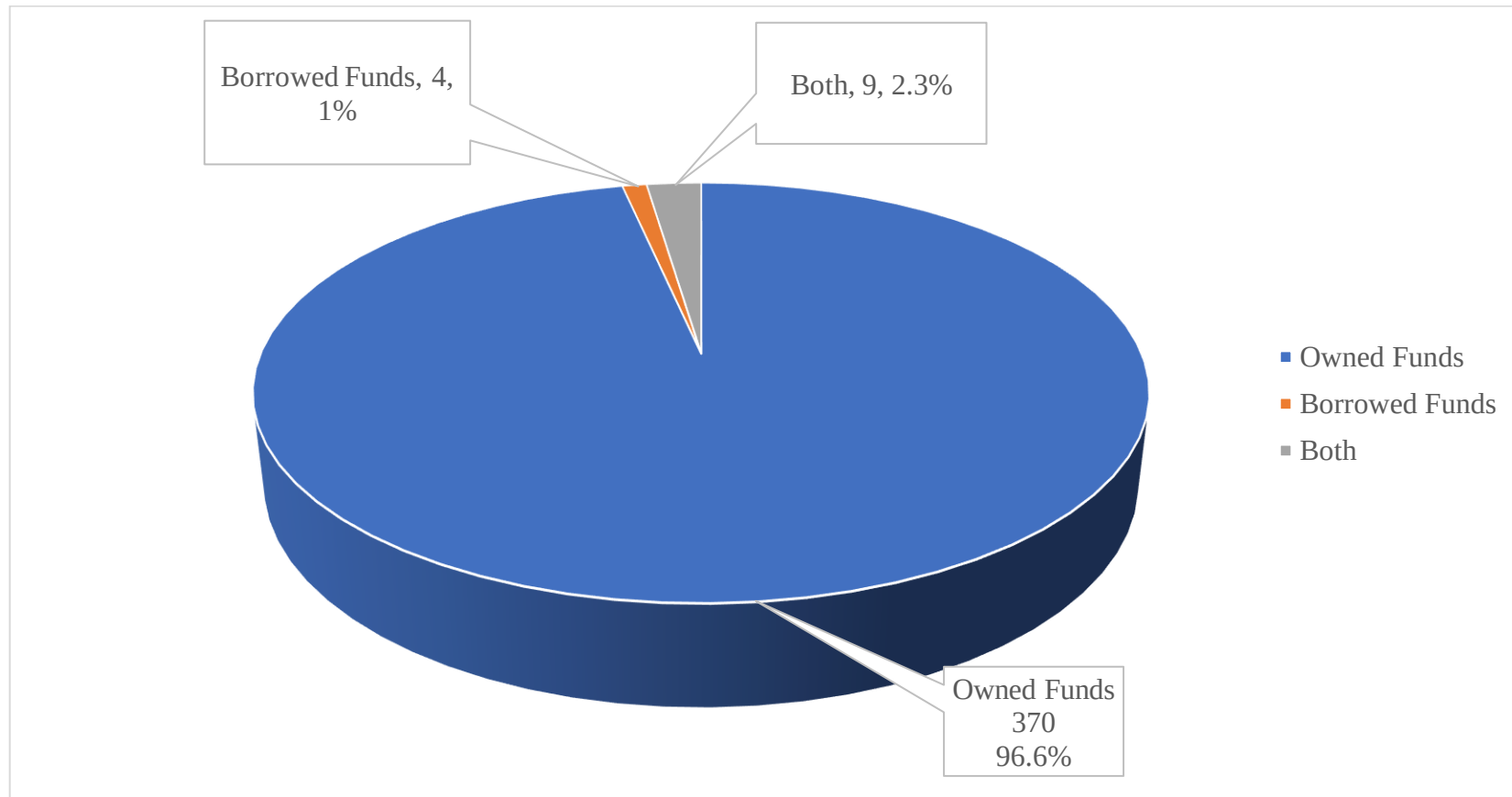
(Source: Author's Compilation.)

The Graph Shows that in Jamnagar city, the highest number of investors (35%) execute trades up to ₹10,000, while the lowest (4.4%) trade between ₹40,000 to ₹50,000.

Figure 4.34: Number of companies in which investments are made by investors

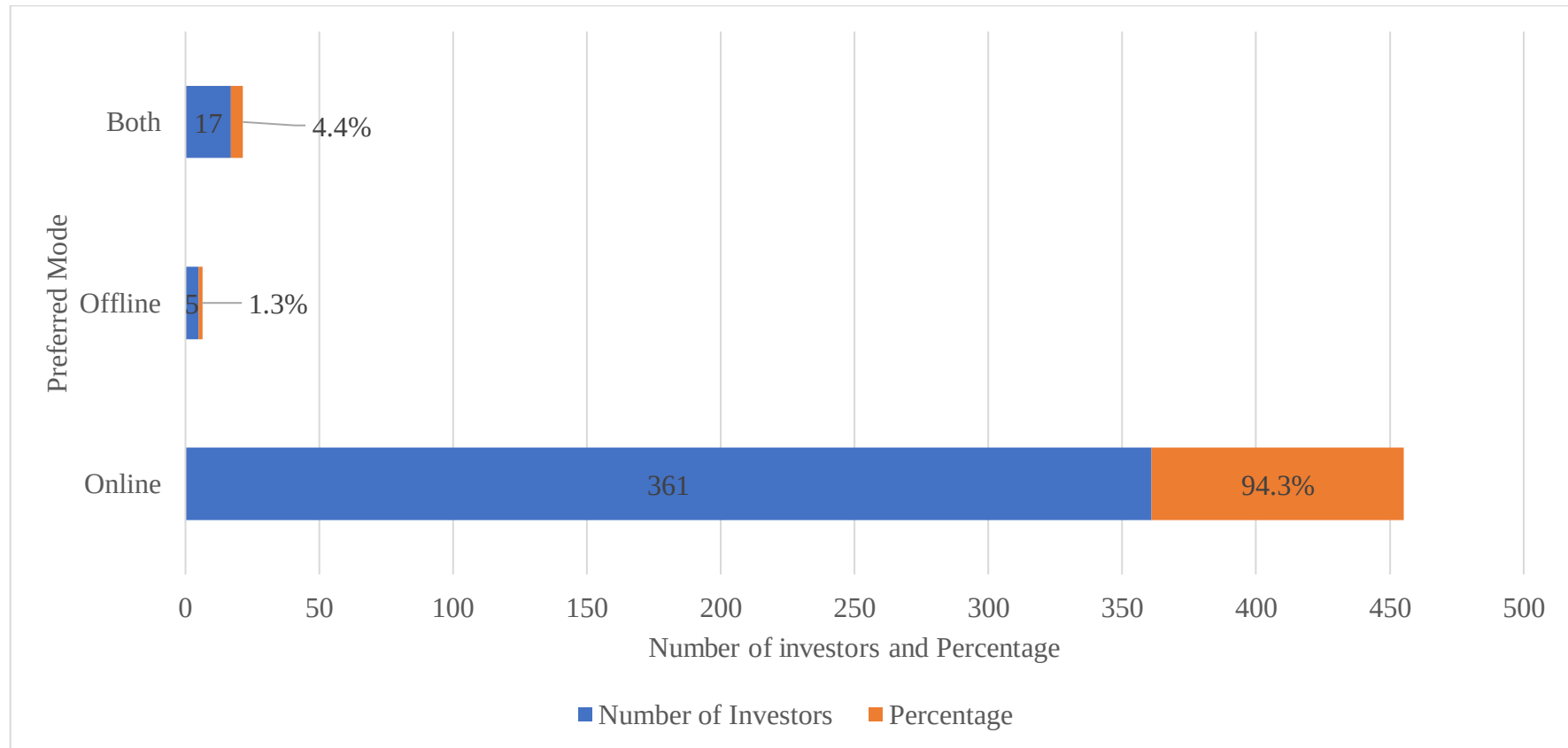
(Source: Author's Compilation.)

The graph shows that in Jamnagar city, most investors have chosen to invest in a limited number of companies, with 29.5% putting their money into just 1 to 5 companies. On the other end, only 11.5% have spread their investments across 10 to 15 companies, showing that fewer investors prefer broader diversification within that specific range.

Figure 4.35: Source of Investment of equity investors of Jamnagar city

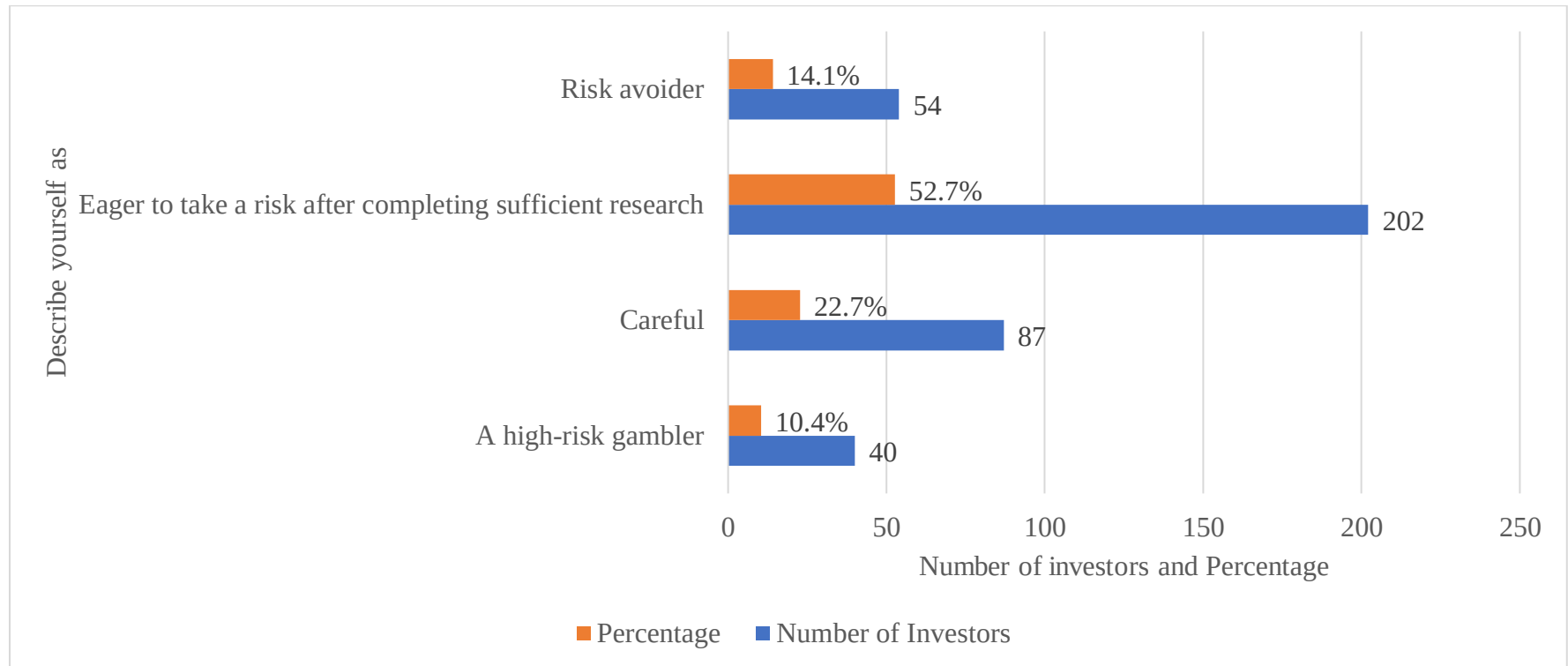
(Source: Author's Compilation.)

The Pie chart shows that in Jamnagar city, (96.6%) of equity investors use owned funds, while (1%) rely on borrowed funds.

Figure 4.36: Preferred Mode of trading of equity investors of Jamnagar city

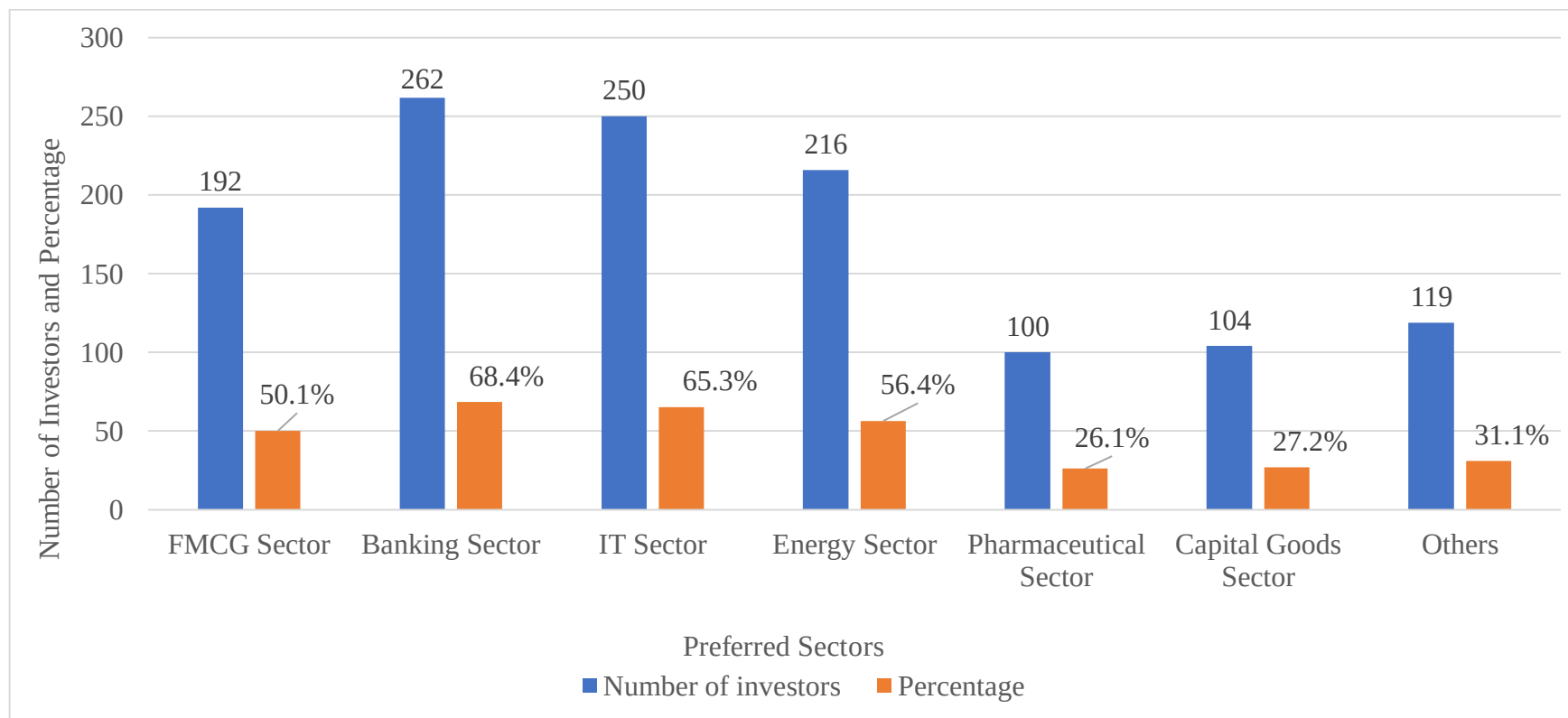
(Source: Author's Compilation.)

The graph indicates that (94.3%) of equity investors in Junagadh City prefer online trading, while only (1.3%) engage with offline trading.

Figure 4.37: You Describe yourself as

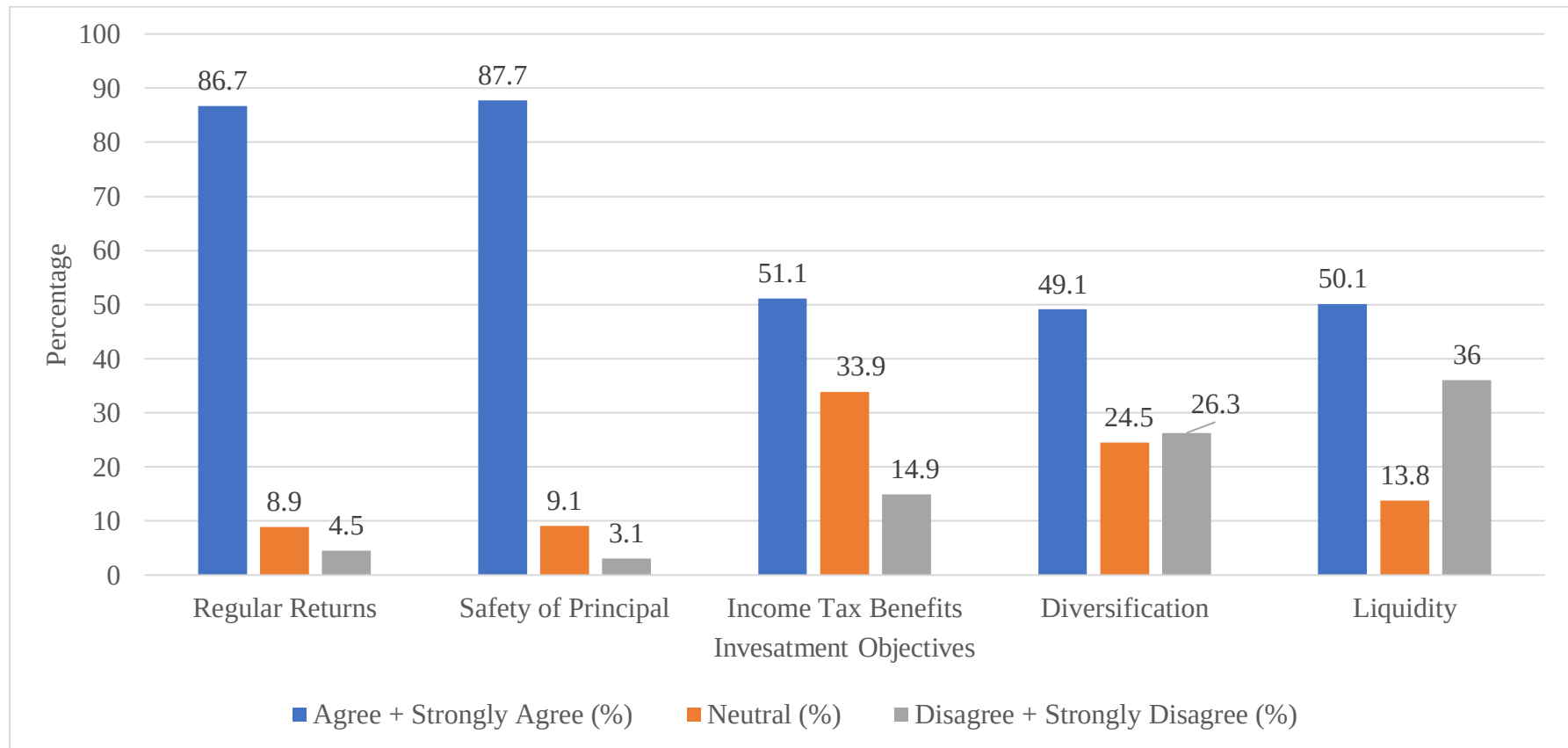
(Source: Author's Compilation.)

The Graph Shows that in Jamnagar city, the majority of investors (52.7%) said they are eager to take risks after doing proper research. In contrast, only 10.4% identified as high-risk gamblers, showing that while many are open to risk, most prefer a more informed and cautious approach.

Figure 4.38: Preferred sectors of equity investors of Jamnagar city

(Source: Author's Compilation.)

The graph indicates that in Jamnagar city, the Banking sector is the top choice among equity investors, preferred by 68.4%. On the other hand, the pharmaceutical sector sees the least interest, with only 26.1% of investors favoring it. This suggests a stronger inclination toward finance and technology over healthcare-related investments.

Figure 4.39: What are your investment objectives?

(Source: Author's Compilation.)

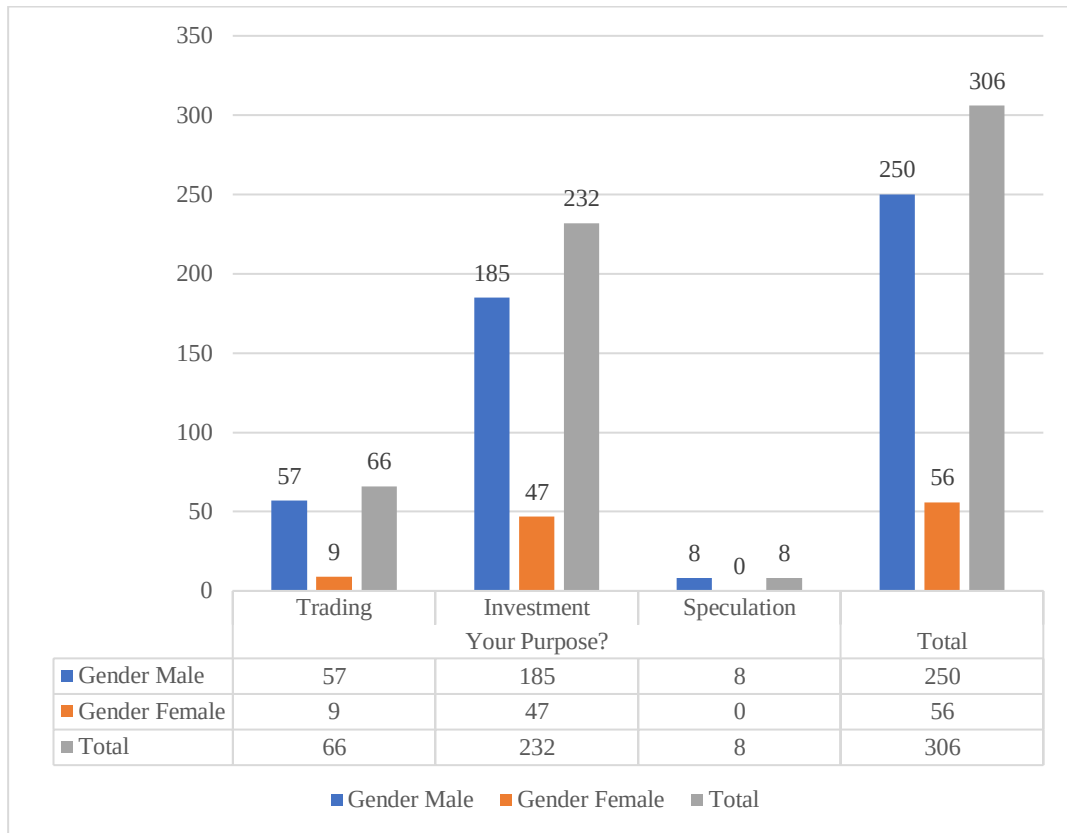
The Graph shows that in Jamnagar city, Safety of Principal is the most agreed-upon investment objective, with 87.7% of investors supporting it. In contrast, Diversification has the lowest agreement at 49.1, indicating it's the least prioritized objective among investors.

4.5.3 Objective 2: To know the preference of people towards equity Investment.

4.5.3.1 Cross-tabulation of Junagadh, Rajkot, and Jamnagar Cities

Cross-tabulation of Gender and Purpose of Investment

Figure 4.40: Cross-tabulation of Gender and Purpose of Investment of Junagadh City

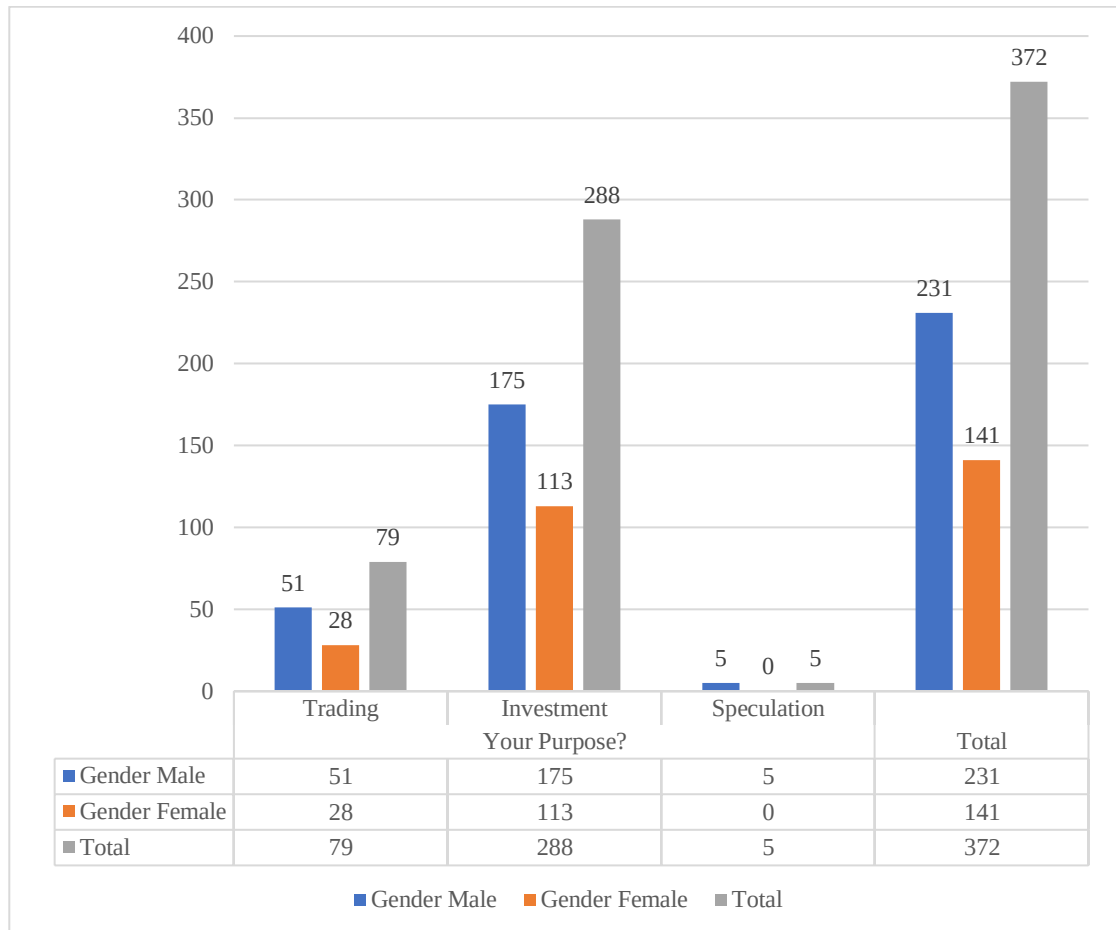


(Source: Authors Compilation)

The Graph of Cross Tabulation of Gender and Investment Purpose of Junagadh city, showing that most people, both men and women, are focused on investment activities. Out of 306 individuals, 232 reported investments as their main purpose. Among men, 185 out of 250 chose investment, while 47 out of 56 women did the same. Trading is the second most common activity, with 66 participants—57 men and 9 women. Speculation is the least chosen option, with only 8 male participants and none from the female group. These numbers suggest a preference for safer financial practices, particularly among women.

In short, in Junagadh a strong preference for investment over trading and speculation among both males and females, with women showing an even higher inclination toward investment.

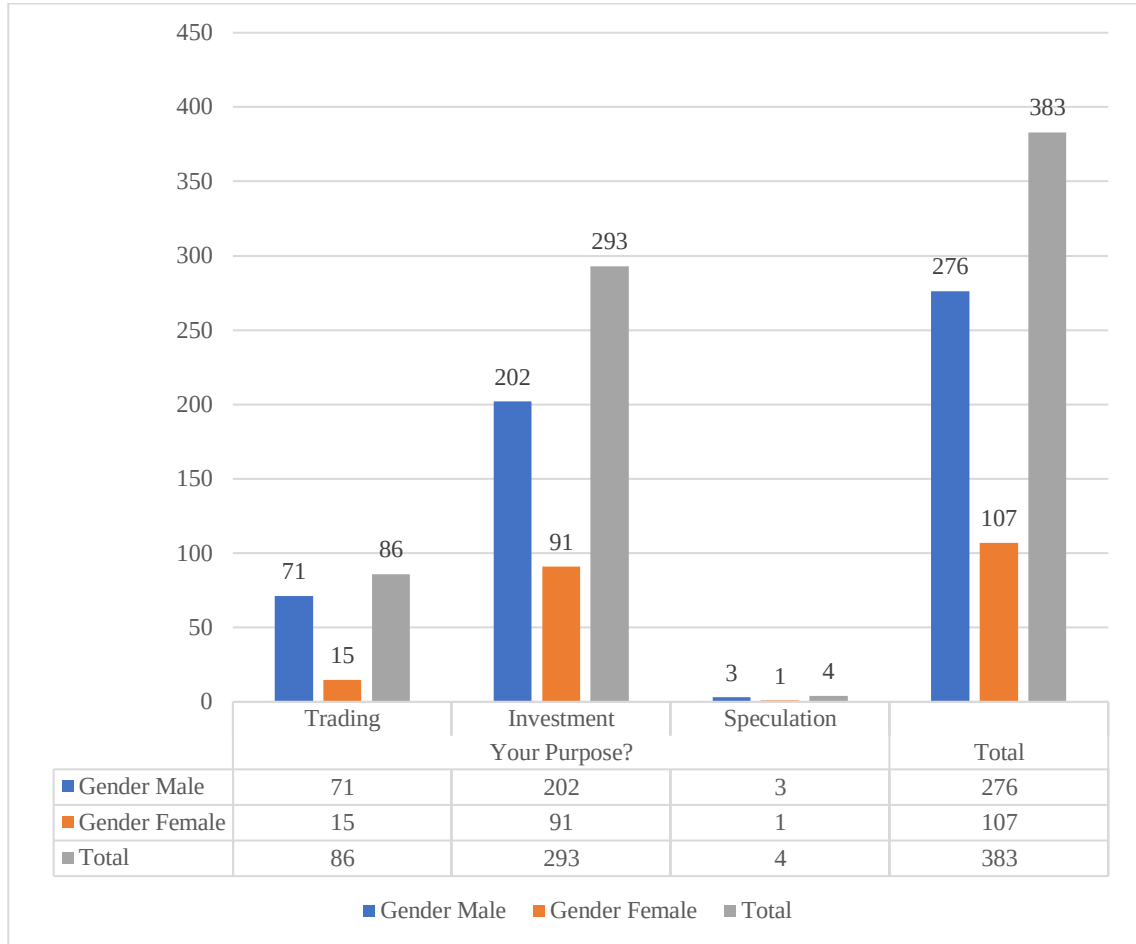
Figure 4.41: Cross-tabulation of Gender and Purpose of Investment of Rajkot City



(Source: Authors Compilation)

The Graph of Cross Tabulation of Gender and Investment Purpose of Rajkot city shows that out of 372 respondents, the majority (288) prefer investment as their financial purpose. Among 231 males, 175 chose investment, while among 141 females, 113 did the same, showing a slightly stronger preference among females. Trading is the second most common purpose, with 79 participants (51 males and 28 females). Speculation is very rare, with only 5 male participants and none among females. In short, the data reflect a clear preference for long-term investment strategies, particularly among women, and minimal interest in high-risk activities like speculation.

Figure 4.42: Cross-tabulation of Gender and Purpose of Investment of Jamnagar City



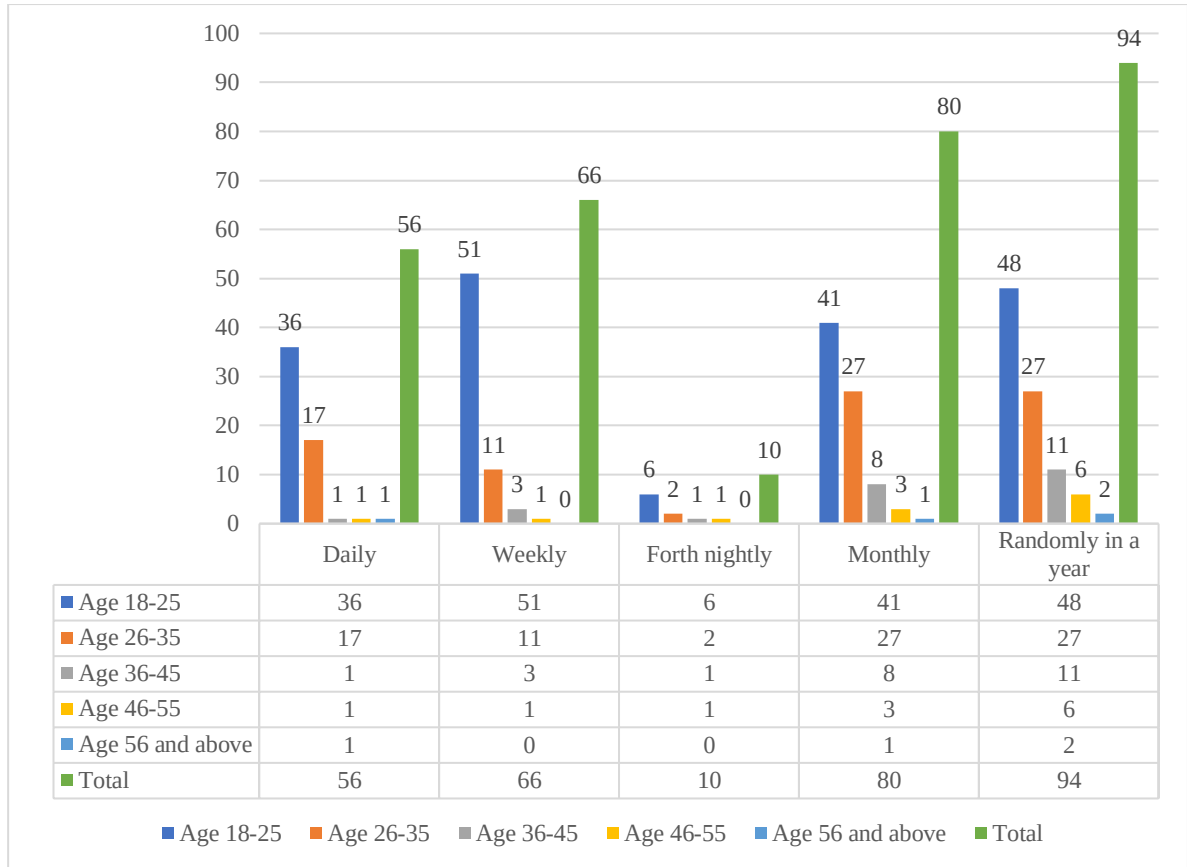
(Source: Authors Compilation)

The Graph of Cross Tabulation of Gender and Investment Purpose of Jamnagar city shows that out of 383 respondents, the majority (293) chose investment as their main financial purpose. Among 276 males, 202 selected investment, while 91 out of 107 females did the same. Trading is the next most common purpose, with 86 participants (71 males and 15 females). Speculation is the least chosen option, with only 4 respondents in total (3 males and 1 female).

This indicates a strong overall preference for investment, especially among women, and minimal involvement in speculative activities.

Cross-tabulation of Age and Trading Frequency

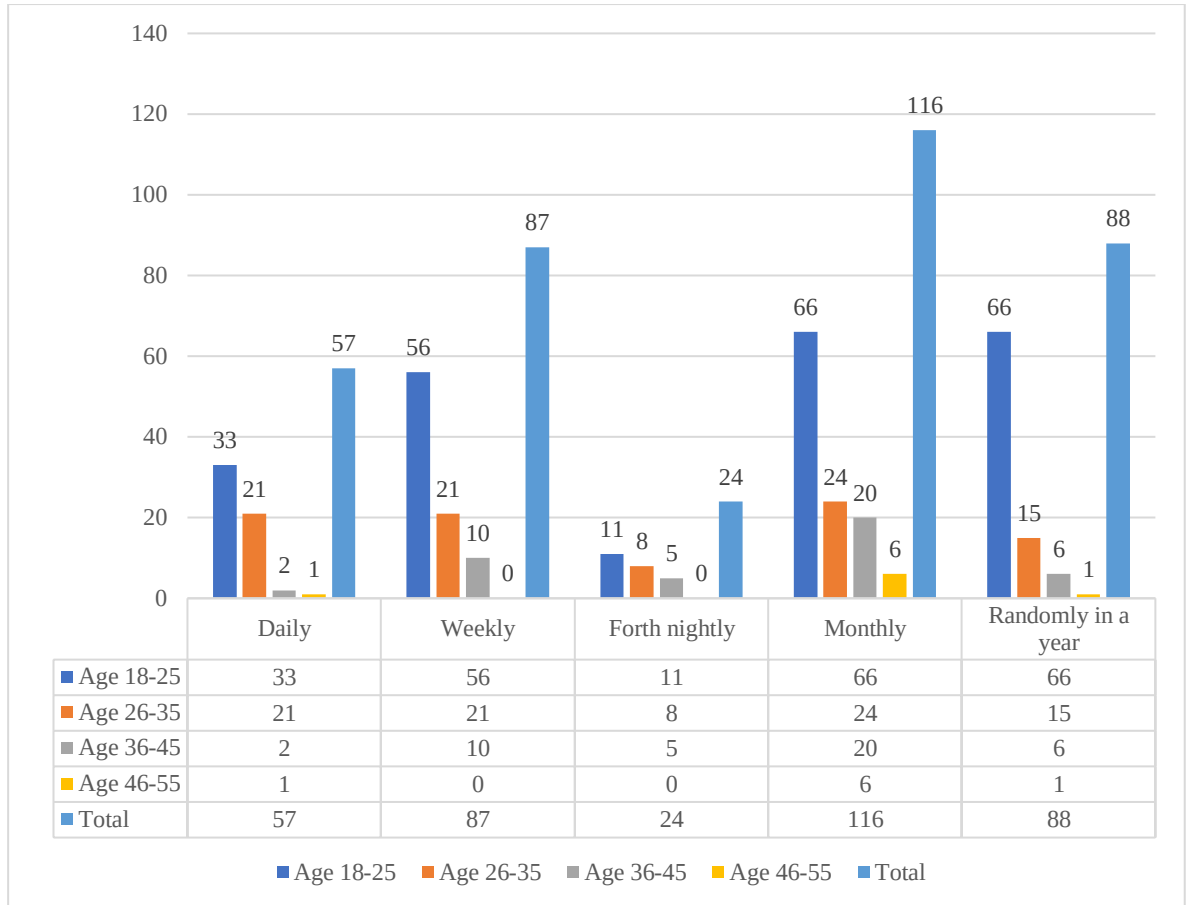
Figure 4.43: Cross-tabulation of Age and Trading Frequency of Junagadh City



(Source: Authors Compilation)

The Graph of Cross-tabulation of Age and Trading Frequency of Junagadh city shows that trading frequency by age group, based on responses from 306 individuals. The majority of participants fall in the 18–25 age group, with 182 individuals actively involved in trading. This group shows varied trading habits, with many trading weekly (51), daily (36), monthly (41), or at random intervals (48) throughout the year. The 26–35 age group includes 84 individuals, who also show interest in monthly (27) and random (27) trading. Participation gradually decreases in older age groups, with 24 individuals in the 36–45 range, 12 in 46–55, and only 4 in the 56+ category. These older groups show limited and less frequent trading activity, with most choosing to trade randomly or monthly.

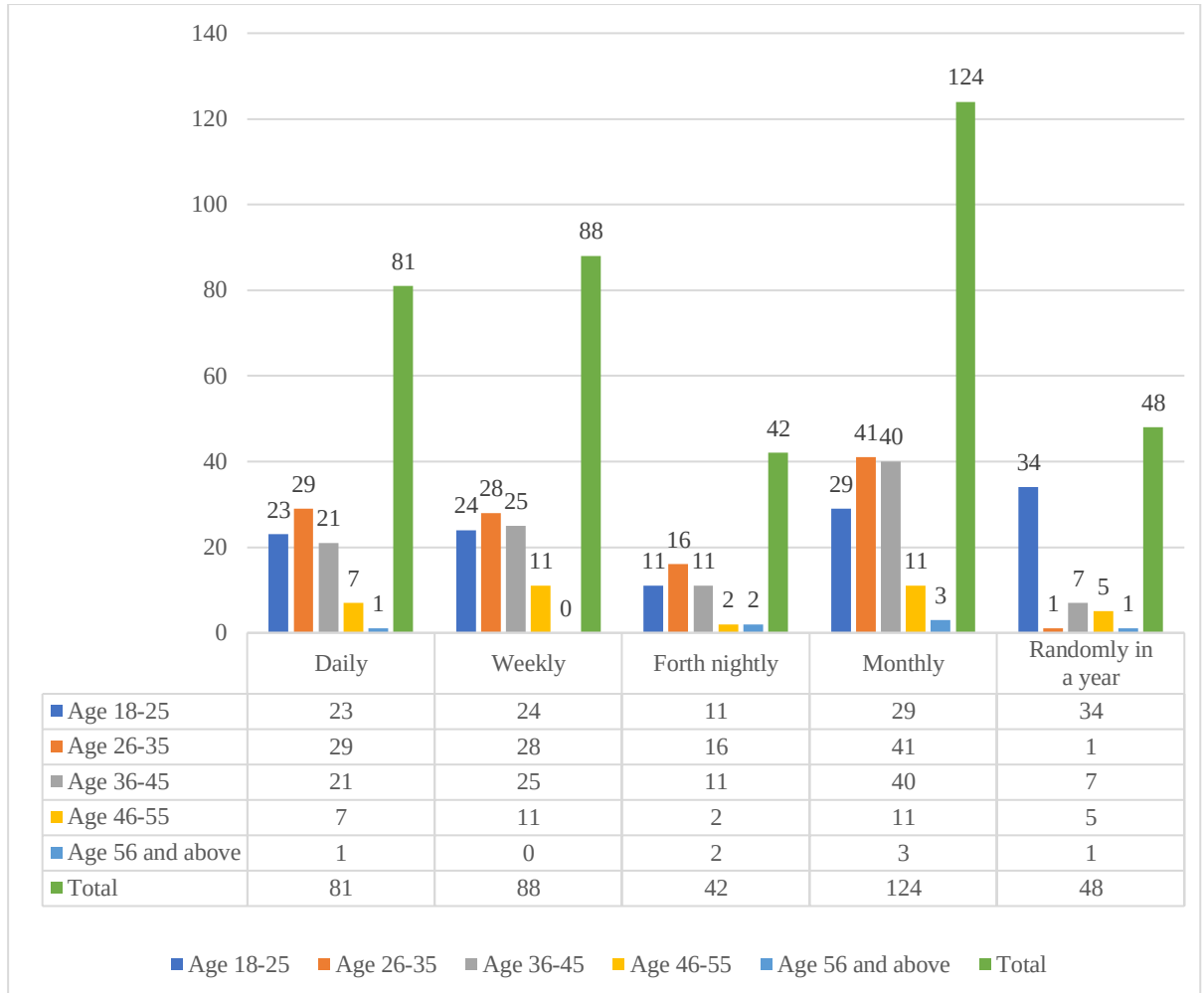
Overall, this suggests that younger people are more engaged in trading, while interest and activity taper off with age.

Figure 4.44: Cross-tabulation of Age and Trading Frequency of Rajkot City

(Source: Authors Compilation)

The Graph of Cross-tabulation of Age and Trading Frequency of Rajkot city shows based on responses from 372 individuals. The largest group is the 18–25 age range with 232 respondents, showing high trading activity across all frequencies—33 trade daily, 56 weekly, 11 fortnightly, 66 monthly, and 66 randomly during the year. The 26–35 group includes 89 individuals, with most trading monthly (24) and weekly (21), while 21 also trade daily. The 36–45 group has 43 participants, with notable activity in monthly (20) and weekly (10) trading. The 46–55 group has the fewest respondents (8), with limited trading primarily done monthly (6).

In short, trading is most active among younger age groups, especially those aged 18–25, and gradually decreases with age, indicating that younger individuals in Rajkot are more engaged in frequent trading activities.

Figure 4.45: Cross-tabulation of Age and Trading Frequency of Jamnagar City

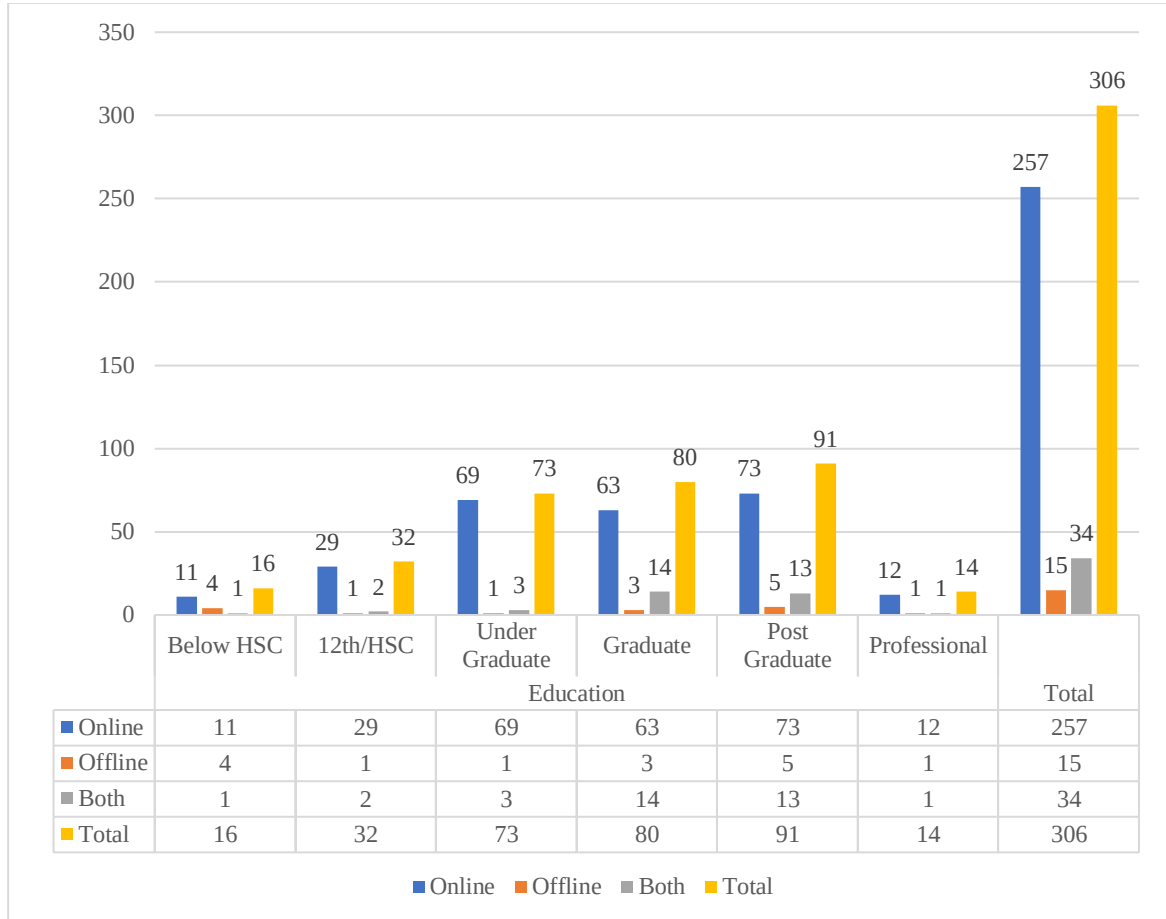
(Source: Authors Compilation)

The Graph of Cross-tabulation of Age and Trading Frequency shows that in Jamnagar, based on responses from 383 individuals. The 26–35 age group is the largest with 115 respondents, most of whom trade monthly (41), weekly (28), or daily (29). The 36–45 group follows closely with 104 individuals, showing similar trends with 40 trading monthly and 25 weekly. The 18–25 group has 121 participants, with many trading randomly in a year (34), monthly (29), and weekly (24). The 46–55 group includes 36 respondents, trading mostly monthly (11) and weekly (11). The 56 and above group is the smallest, with only 7 individuals and minimal trading activity.

In short, Monthly trading is the most common across all age groups, with the 26–45 age range showing the highest engagement in trading, while activity declines in older age brackets.

Cross-tabulation of Education and Preferred Mode of Trading

Figure 4.46: Cross-tabulation of Education and Preferred Mode of Trading of Junagadh City

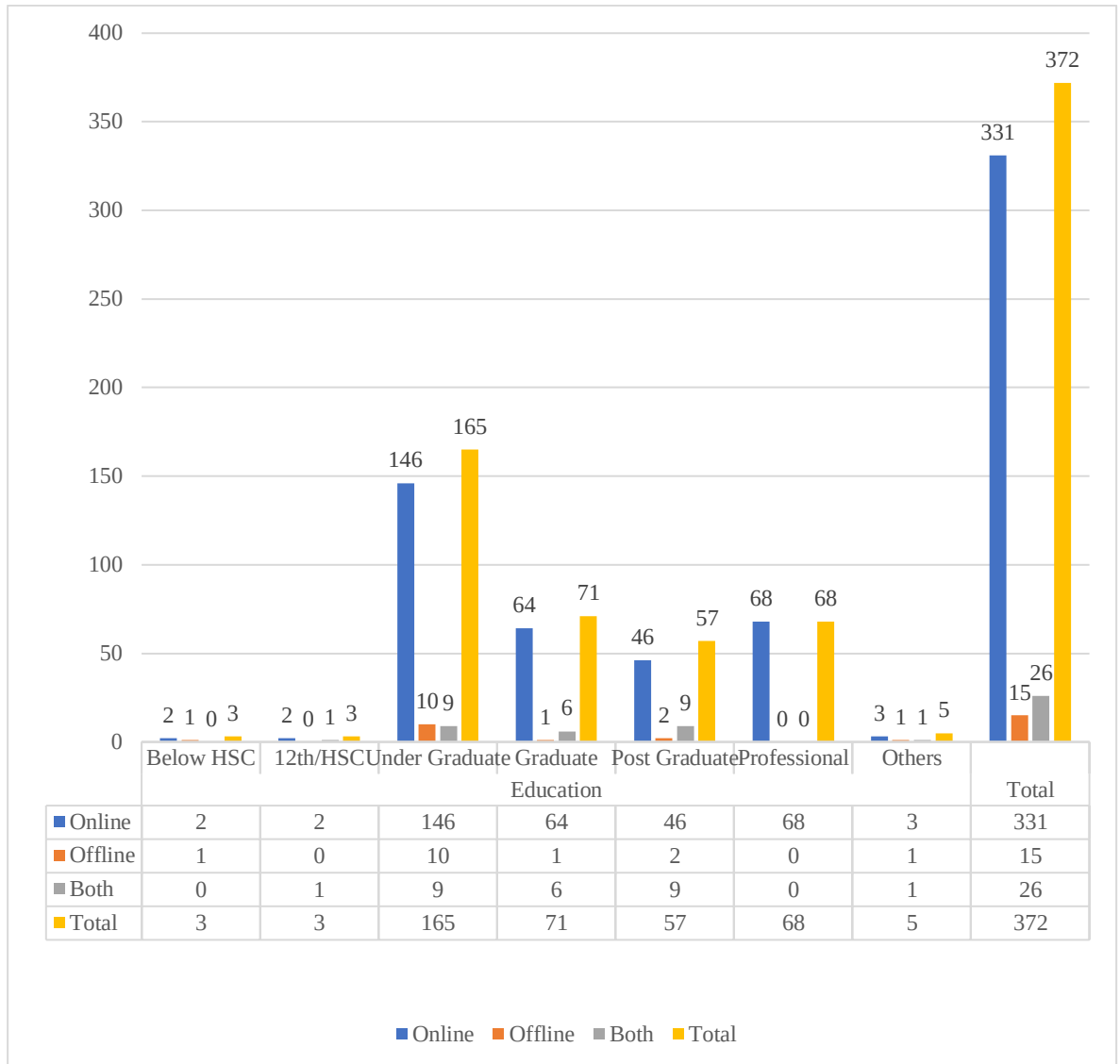


(Source: Authors Compilation)

The Graph of Cross-tabulation of Education and Preferred Mode of Trading shows that in Junagadh city, the preferred mode of trading is based on the education level of 306 respondents. The majority (257) prefer online trading, while 15 prefer offline, and 34 use both modes. Among postgraduates (91), 73 prefer online and 13 use both, showing a strong leaning toward digital platforms. Graduates (80) follow a similar pattern, with 63 choosing online and 14 using both. Undergraduates (73) also show a high preference for online (69). Even among those with lower education levels, such as 12th/HSC (32) and below HSC (16), online trading remains dominant.

In short, this trend indicates that online trading is the most preferred mode across all education levels, with higher education correlating with slightly more diversified usage, including both online and offline platforms.

Figure 4.47: Cross-tabulation of Education and Preferred Mode of Trading of Rajkot City

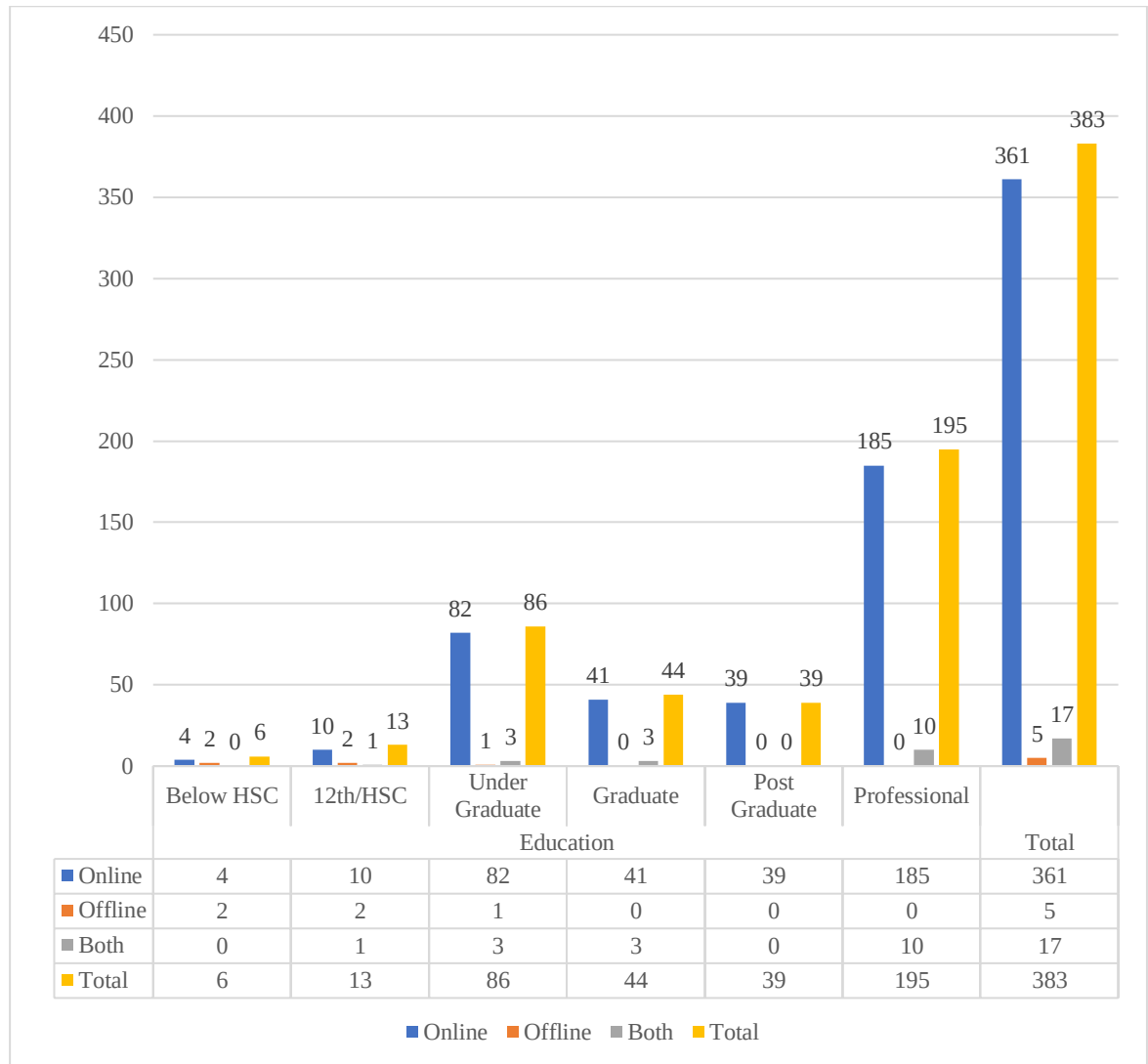


(Source: Authors Compilation)

The Graph of Cross-tabulation of Education and Preferred Mode of Trading shows that in Rajkot city, based on responses from 372 individuals. A significant majority (331) prefer online trading, while 15 opt for offline, and 26 use both. Undergraduates (165) form the largest group, with 146 favoring online. Similarly, all 68 professionals prefer online trading exclusively. Among graduates (71) and postgraduates (57), most also prefer online, though a small number use both modes. Lower education levels, like below HSC (3) and 12th/HSC (3) show minimal participation but still lean toward online or mixed modes.

In short, this graph highlights a strong preference for online trading across all education levels, especially among professionally and academically qualified individuals.

Figure 4.48: Cross-tabulation of Education and Preferred Mode of Trading of Jamnagar City



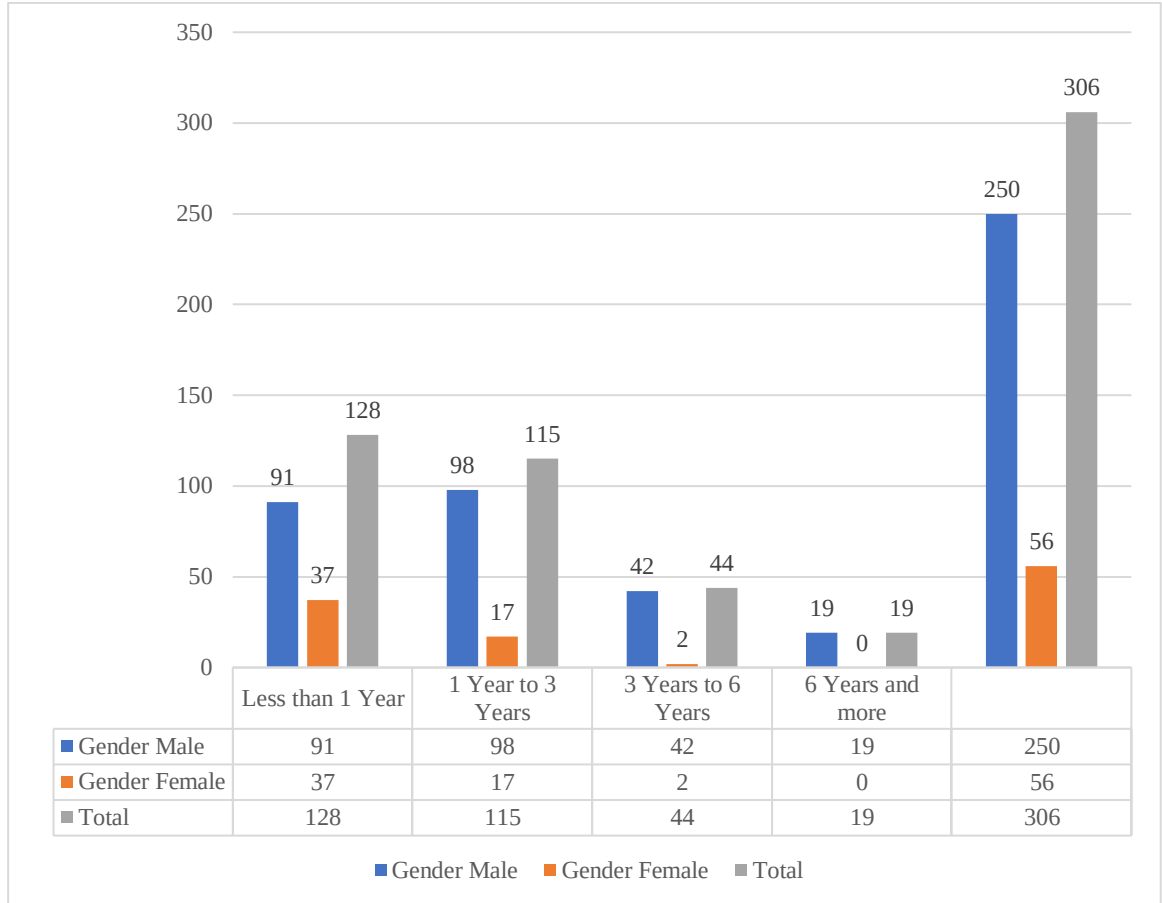
(Source: Authors Compilation)

The Graph of Cross-tabulation of Education and Preferred Mode of Trading shows that in Jamnagar city, based on responses from 383 individuals. A dominant 361 respondents prefer online trading, while only 5 prefer offline, and 17 use both. The largest group is professionals (195), with 185 trading online and 10 using both modes. Among undergraduates (86) and graduates (44), the preference is strongly online, with very few using both and almost none offline. Postgraduates (39) exclusively prefer online trading. Lower education levels, like below HSC (6) and 12th/HSC (13), show limited participation, but online trading is still the most common.

In short, the data demonstrates a strong and clear preference for online trading across all education levels, especially among professionally qualified individuals.

Cross-tabulation of Gender and Experience in Equity Investment

Figure 4.49: Cross-tabulation of Gender and Experience in Equity Investment of Junagadh City

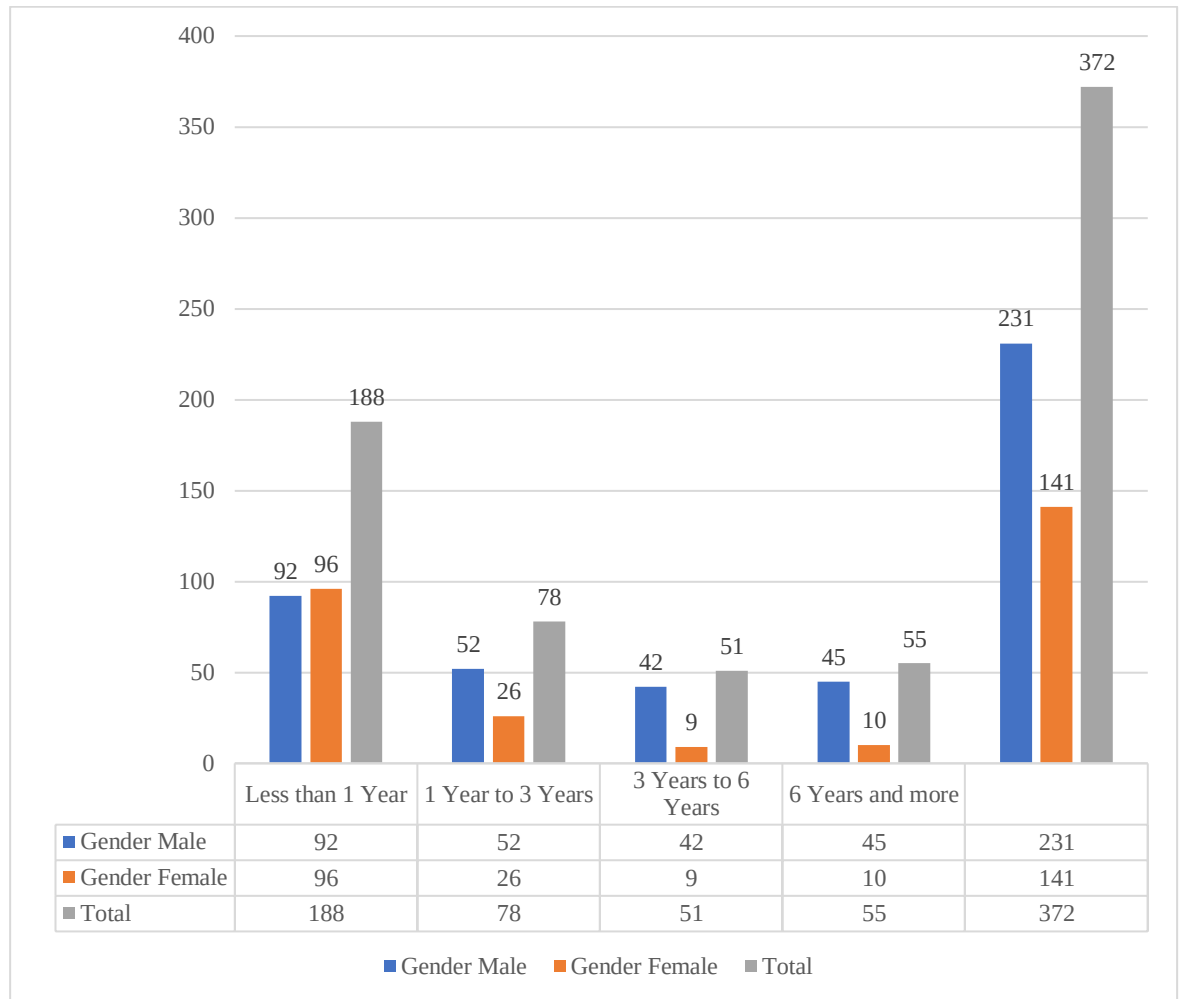


(Source: Authors Compilation)

The Graph of Cross-tabulation of Gender and Experience in Equity Investment of Junagadh City shows that equity investment in Junagadh is largely male-driven, with 250 out of 306 participants being men. Most male investors have less than 3 years of experience, indicating a predominantly new investor base. Female representation is low, with only 56 participants, and none having more than 3 years of experience, suggesting limited long-term engagement. A majority of female investors (37 out of 56) are in the early stage with less than 1 year of experience.

In short, in Junagadh, equity investment is male-dominated, with 250 males and 56 females, and most investors—189 males and 54 females—have less than 3 years of experience, highlighting both a gender gap and limited investor maturity.

Figure 4.50: Cross-tabulation of Gender and Experience in Equity Investment of Rajkot City

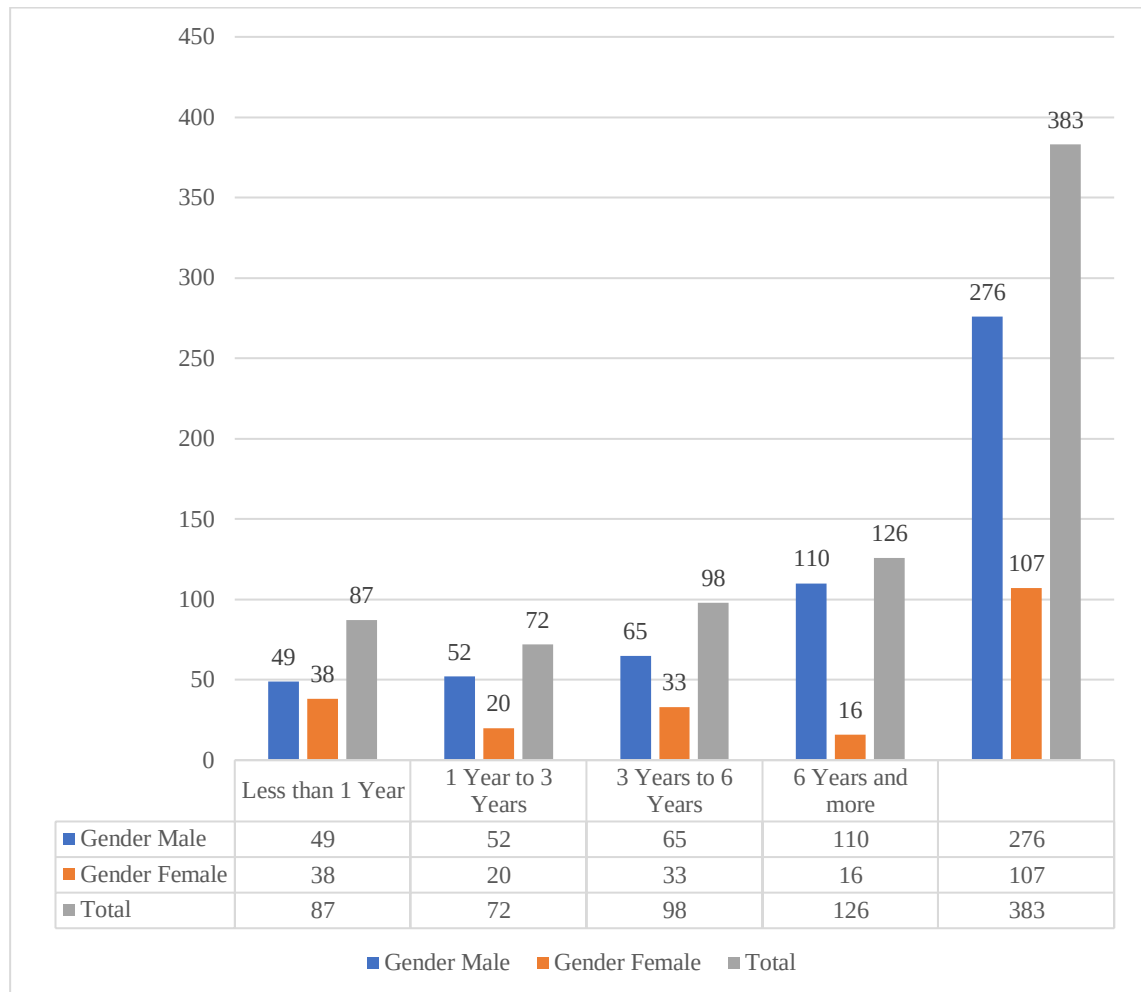


(Source: Authors Compilation)

The Graph of Cross-tabulation of Gender and Experience in equity investment in Rajkot city equity investment reveals a more balanced gender participation compared to other locations, with 231 males and 141 females out of 372 respondents. Among males, most have less than 1 year (92) or more than 6 years (45) of experience, suggesting a mix of new and seasoned investors. Among females, the majority (96) have less than 1 year of experience, indicating a newer entry into investing.

In short, Most female investors are beginners with less than 1 year of experience, whereas male investors are more evenly distributed across all experience levels, but more number of male investors possess less than 1 year of experience, as well as female investors.

Figure 4.51: Cross-tabulation of Gender and Experience in Equity Investment of Jamnagar City



(Source: Authors Compilation)

The Graph of Cross-tabulation of Gender and Experience in equity investment of Jamnagar city shows that the equity investors consist of 276 males and 107 females out of a total of 383 respondents. Among males, the largest group has more than 6 years of experience (110), followed by those with 3 to 6 years (65), showing a relatively experienced male investor base. Female investors are fewer, with the highest number in the 3 to 6 years category (33), but overall, their experience is more evenly spread across all levels.

In short, males show higher long-term experience (110 with over 6 years), while female experience is more evenly distributed, though their overall participation is lower.

Cross-tabulation of Age and Self-Description as an Investor

Table 4.9: Cross-tabulation of Age and Self-Description as an Investor of Junagadh City

		You describe yourself as				Total
		A high-risk gambler	Careful	Eager to take a risk after completing sufficient research	Risk avoider	
Age	18-25	18	74	58	32	182
	26-35	8	33	29	14	84
	36-45	1	12	5	6	24
	46-55	0	10	1	1	12
	56 and above	0	3	0	1	4
Total		27	132	93	54	306
a. Location (City) = Junagadh						

(Source: SPSS-2022)

The cross-tabulation of Age and Self-Description as an Investor in Junagadh city shows that most investors are in the 18–25 age group (182 out of 306), with many identifying as careful (74) or eager to take risks after research (58), and a notable number as high-risk gamblers (18). The 26–35 group also leans towards careful investing (33), while risk appetite declines with age. In the 36–45, 46–55, and 56+ age groups, very few describe themselves as high-risk takers, with most choosing careful or risk-averse profiles.

In short, younger investors tend to be more open to risk, while older investors prefer safer approaches.

Table 4.10: Cross-tabulation of Age and Self-Description as an Investor of Rajkot City

		You describe yourself as				Total
		A high-risk gambler	Careful	Eager to take a risk after completing sufficient research	Risk avoider	
Age	18-25	36	119	54	23	232
	26-35	7	26	44	12	89
	36-45	6	7	21	9	43
	46-55	1	0	3	4	8
Total		50	152	122	48	372
a. Location (City) = Rajkot						

(Source: SPSS-2022)

The cross-tabulation of Age and Self-Description as an Investor in Rajkot city shows that the majority of investors fall within the 18–25 age group, making up 232 out of 372 individuals surveyed. Most in this group identify as cautious (119), though a significant number are open to taking risks after conducting research (54), and a smaller portion (36) consider themselves high-risk takers. The 26–35 age bracket shows a strong preference for calculated risk-taking, with 44 investors leaning toward informed decisions and only 7 identifying as high-risk. Among those aged 36–45, investment attitudes are more balanced, but a cautious or research-driven approach still prevails. Investors in the 46–55 range form the smallest demographic and generally prefer to avoid risk.

In short, younger investors in Rajkot appear more receptive to taking risks, especially when supported by research, while older age groups tend to adopt more conservative strategies.

**Table 4.11: Cross-tabulation of Age and Self-Description as an Investor
Jamnagar City**

		You Describe yourself as				Total
		A high-risk gambler	Careful	Eager to take a risk after completing sufficient research	Risk avoider	
Age	18-25	11	29	62	19	121
	26-35	13	25	58	19	115
	36-45	12	23	61	8	104
	46-55	4	6	20	6	36
	56 and above	0	4	1	2	7
Total		40	87	202	54	383
a. Location (City) = Jamnagar						

(Source: SPSS-2022)

The cross-tabulation of Age and Self-Description as an Investor in Jamnagar city shows that in Jamnagar city, most investors are between 18 and 25 years old (121 in total), with a clear preference for taking risks after doing their homework (62). Many in this group also describe themselves as careful (29), while fewer either avoid risk entirely (19) or identify as high-risk gamblers (11). The next largest group, aged 26–35 (115), shows a similar pattern—most are open to taking informed risks (58), while others are more cautious (25), risk-averse (19), or comfortable with high risk (13). Among the 36–45 age range (104), investment attitudes are more mixed, though research-based risk-taking remains common (61), with 23 careful investors, 12 high-risk takers, and 8 who avoid risk. In the 46–55 group (36), most prefer to make decisions backed by research (20), while the rest are split between being careful (6), risk-averse (6), and high-risk (4). The oldest group, 56 and above, includes only 7 people, most of whom are careful (4) or avoid risk altogether.

In short, younger investors in Jamnagar show a stronger appetite for risk—especially when supported by research—while older investors tend to play it safe.

Cross-tabulation of Education and Preferred Mode of Trading

Table 4.12: Cross-tabulation of Occupation and Amount of single trades executed by the Investor of Junagadh City

		How much amount of single trades do you execute?						Total
		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	
Occupation	Salaried	57	30	7	3	3	4	104
	Businessman	26	18	12	1	1	2	60
	Professional	8	3	2	0	0	2	15
	Retired	1	1	0	0	0	0	2
	House Wife	1	3	0	0	0	0	4
	Student	54	27	10	3	4	5	103
	Equity Trader	2	2	1	0	1	3	9
	Others	4	1	1	0	0	3	9
Total		153	85	33	7	9	19	306
a. Location (City) = Junagadh								

(Source: SPSS-2022)

The cross-tabulation of Occupation and Amount of single trades shows that in Junagadh, the majority of investors, especially salaried individuals (57) and students (54), execute single trades up to ₹10,000. Businessmen are more active in mid to high trade ranges, with 12 trading between ₹20,000–30,000 and 2 above ₹50,000.

In short, the data shows that small trades (up to 20,000) are most common across all occupations, especially among salaried individuals and students, while businessmen and professionals are more likely to engage in higher-value trades.

Table 4.13: Cross-tabulation of Occupation and Amount of single trades executed by the Investor of Rajkot City

		How much amount of single trade do you execute?						Total
		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	
Occupation	Salaried	42	39	33	2	3	4	123
	Businessman	25	9	10	0	4	3	51
	Professional	6	11	9	1	0	1	28
	House Wife	7	1	1	0	0	0	9
	Student	86	22	7	0	1	7	123
	Equity Trader	4	2	0	0	0	1	7
	Others	21	3	1	0	1	5	31
Total		191	87	61	3	9	21	372
a. Location (City) = Rajkot								

(Source: SPSS-2022)

The cross-tabulation of Occupation and Amount of single trades shows that In Rajkot, most investors across different occupations prefer executing trades of up to ₹10,000, with 191 out of 372 falling into this category. This includes a large number of students (86) and salaried individuals (42). The next most common range is ₹10,000–20,000, with 87 people, mainly salaried (39) and professionals (11). Trades between ₹20,000–30,000 were carried out by 61 individuals, again mostly salaried (33). Higher trade amounts, like ₹30,000–40,000 (3), ₹40,000–50,000 (9), and above ₹50,000 (21), were less frequent and mostly seen among businessmen, students, and others.

In short, trades up to ₹20,000 dominate, accounting for 278 respondents, showing a preference for smaller trades across all occupations, with higher-value trades concentrated among salaried, business, and professional groups.

Table 4.14: Cross-tabulation of Occupation and Amount of single trades executed by the Investor of Jamnagar City

		How much amount of single trade do you execute?						Total
		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	
Occupation	Salaried	37	46	29	12	1	4	129
	Businessman	5	4	3	2	1	4	19
	Professional	6	20	31	12	14	32	115
	Retired	0	0	0	0	1	1	2
	House Wife	2	1	0	0	0	0	3
	Student	82	14	8	0	0	3	107
	Equity Trader	1	1	0	1	0	3	6
	Others	1	0	0	1	0	0	2
Total		134	86	71	28	17	47	383
a. Location (City) = Jamnagar								

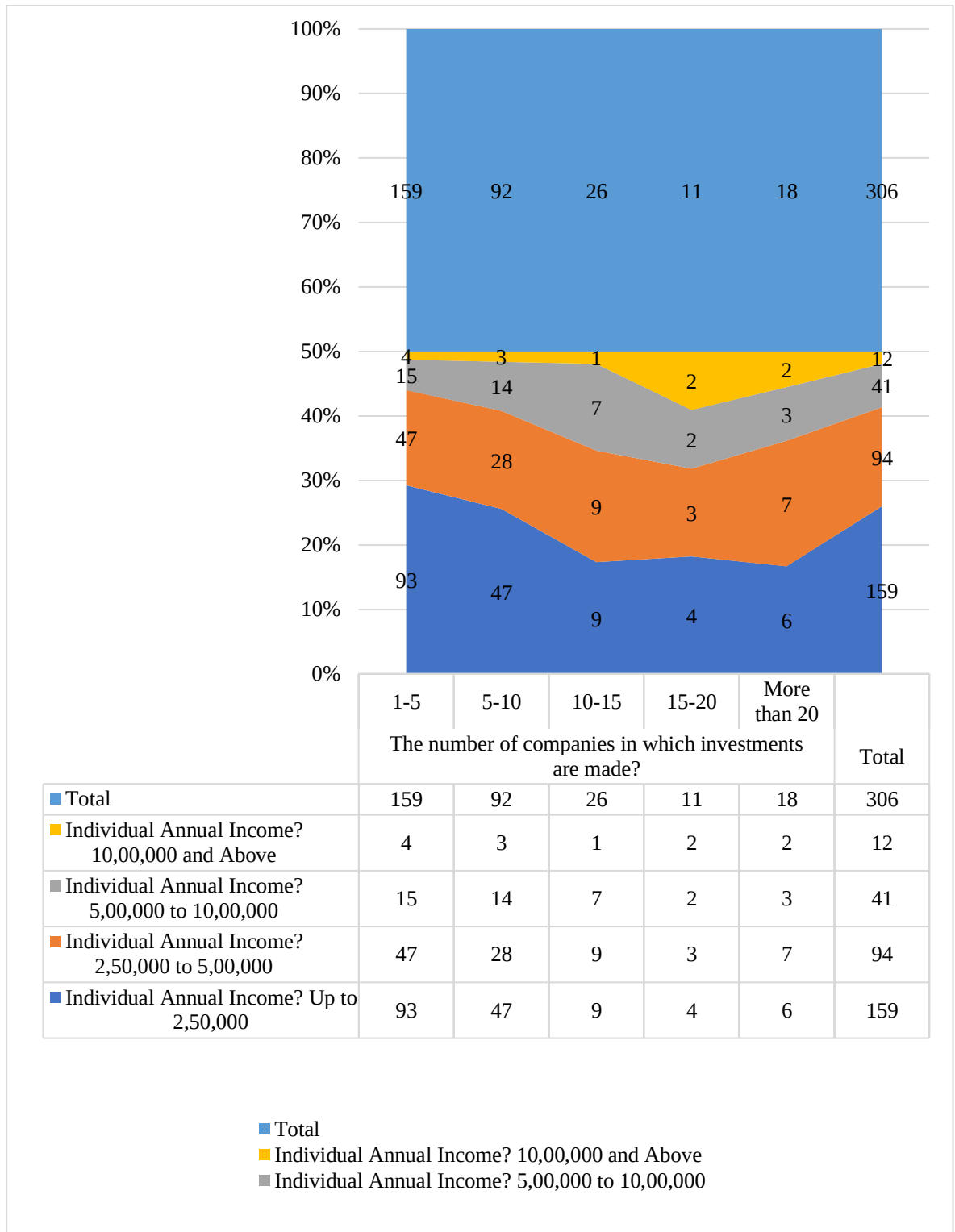
(Source: SPSS-2022)

The cross-tabulation of Occupation and Amount of single trades shows that in Jamnagar, most investors conduct trades up to ₹10,000, with 134 out of 383 respondents in this range, led by students (82) and salaried individuals (37). The ₹10,000–20,000 range includes 86 participants, mainly salaried (46) and professionals (20). Trades between ₹20,000–30,000 (71 total) are dominated by professionals (31) and salaried (29). Higher trade ranges like ₹30,000–40,000 (28) and ₹40,000–50,000 (17) also show strong involvement from professionals, with 12 and 14 respectively. The highest bracket, above ₹50,000, includes 47 respondents, led by professionals (32).

In short, small trades up to ₹20,000 (220) are most common, professionals stand out for executing higher-value trades, unlike students, who mostly stay within the lowest trade category.

Cross-tabulation of Age and Self-Description as an Investor

Figure 4.52: Cross-tabulation of Income and the number of companies in which investments are made in Junagadh city

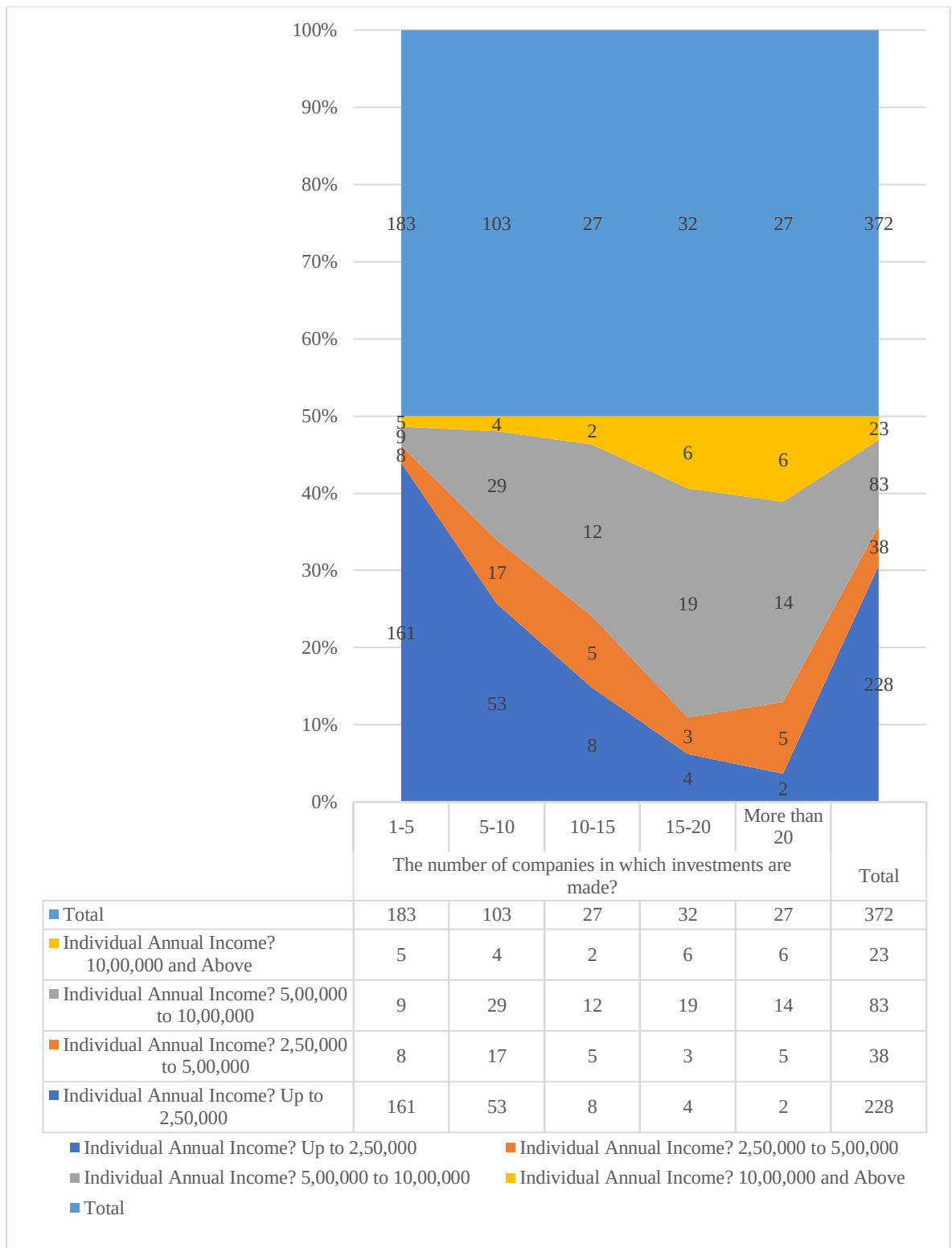


(Source: Authors Compilation)

The Graph of Cross-tabulation of Income and the number of companies in which investments are made in Junagadh city shows that most investors fall into the lower income brackets, with 159 individuals earning up to ₹2,50,000 annually. Of these, the majority (93) have invested in 1–5 companies, followed by 47 in 5–10, and much smaller numbers in higher brackets. The ₹2.5 to ₹5 lakh income group includes 94 investors, where 47 have spread their investments across 1–5 companies, and 28 in 5–10, with only a few going beyond that. As income rises, the number of investors decreases. For those earning between ₹5–10 lakh (41 individuals), investments are more evenly distributed, though 15 still stay within 1–5 companies. The highest income group—earning ₹10 lakh and above—is the smallest, with only 12 people, most of whom also limit their investments to 1–5 companies.

In short, the clear trend shows that individuals with lower annual incomes are more likely to invest in fewer companies, while those with higher incomes tend to diversify slightly more, though still conservatively.

Figure 4.53: Cross-tabulation of Income and the number of companies in which investments are made in Rajkot city

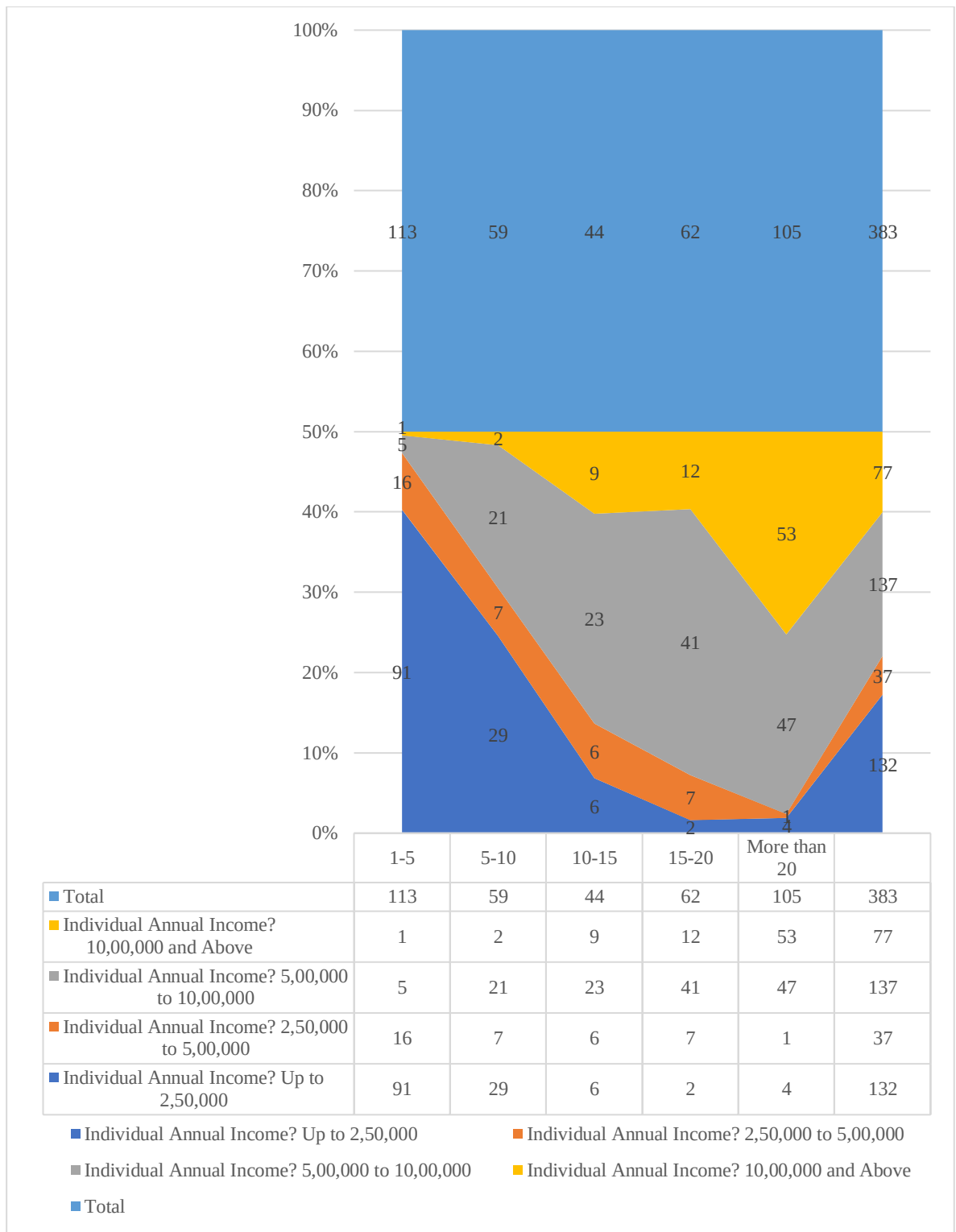


(Source: Authors Compilation)

The Graph of Cross-tabulation of Income and the number of companies in which investments are made in Rajkot city shows that most investors are in the lower income bracket, with 228 people earning up to ₹2.5 lakh a year. A large number of them (161) have put their money into just 1–5 companies, suggesting a cautious or limited approach to investing, possibly due to budget constraints. As income levels rise, so does diversification. In the ₹2.5–5 lakh range, there are 38 investors, and while fewer in number, they seem slightly more open to spreading their investments—17 have invested in 5–10 companies. The pattern becomes even more noticeable in the ₹5–10 lakh group, which includes 83 individuals. Here, many are branching out: 29 have invested in 5–10 companies, and a good number have gone further, with 19 investing in 15–20 companies and 14 in more than 20. At the top of the income scale, those earning over ₹10 lakh (just 23 people) show a clear comfort with broader investment portfolios—6 each have stakes in 15–20 and more than 20 companies.

In short, out of 372 investors in Rajkot, lower-income individuals tend to concentrate their investments in fewer companies, while higher earners show a clear tendency to diversify across a broader range.

Figure 4.54: Cross-tabulation of Income and the number of companies in which investments are made in Jamnagar city



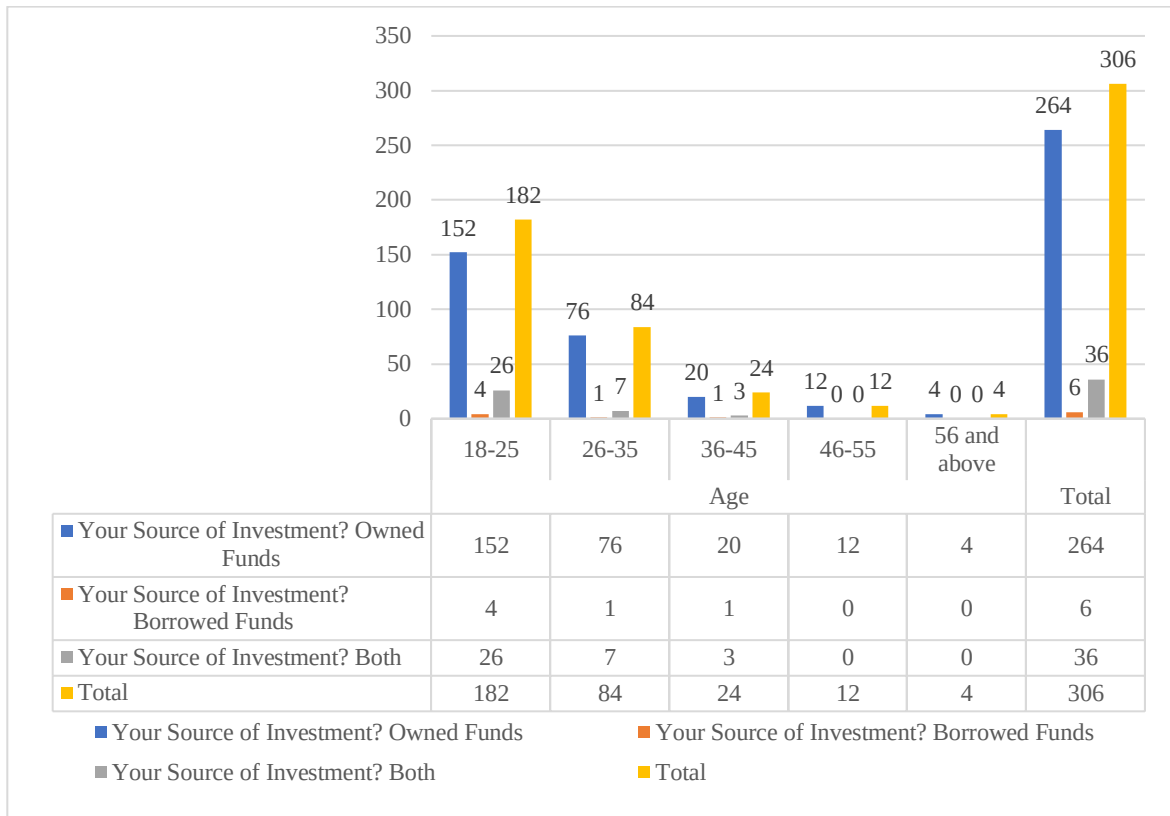
(Source: Authors Compilation)

The Graph of Cross-tabulation of Income and the number of companies in which investments are made in Jamnagar city, shows a clear connection between income levels and how widely people invest. Among those earning up to ₹2.5 lakh a year, a large portion—91 out of 132—have invested in just 1 to 5 companies, with only a few venturing into more. The group earning between ₹2.5 lakh and ₹5 lakh includes 37 individuals, and while some are starting to diversify, most still keep their investments limited, with 16 staying in the lowest range. Things start to look different in the ₹5 to ₹10 lakh income group. Out of 137 people in this bracket, many are much more spread out—47 have invested in more than 20 companies, and 41 in 15 to 20. This shows a clear shift toward broader investment choices. The highest income group, earning above ₹10 lakh, includes 77 individuals. A majority of them—53 have invested in more than 20 companies, showing a strong tendency to diversify.

In short, the overall pattern is hard to miss: lower-income individuals generally concentrate their investments in fewer companies, while those with higher earnings tend to branch out much more widely.

Cross-tabulation of Age and Source of Investment

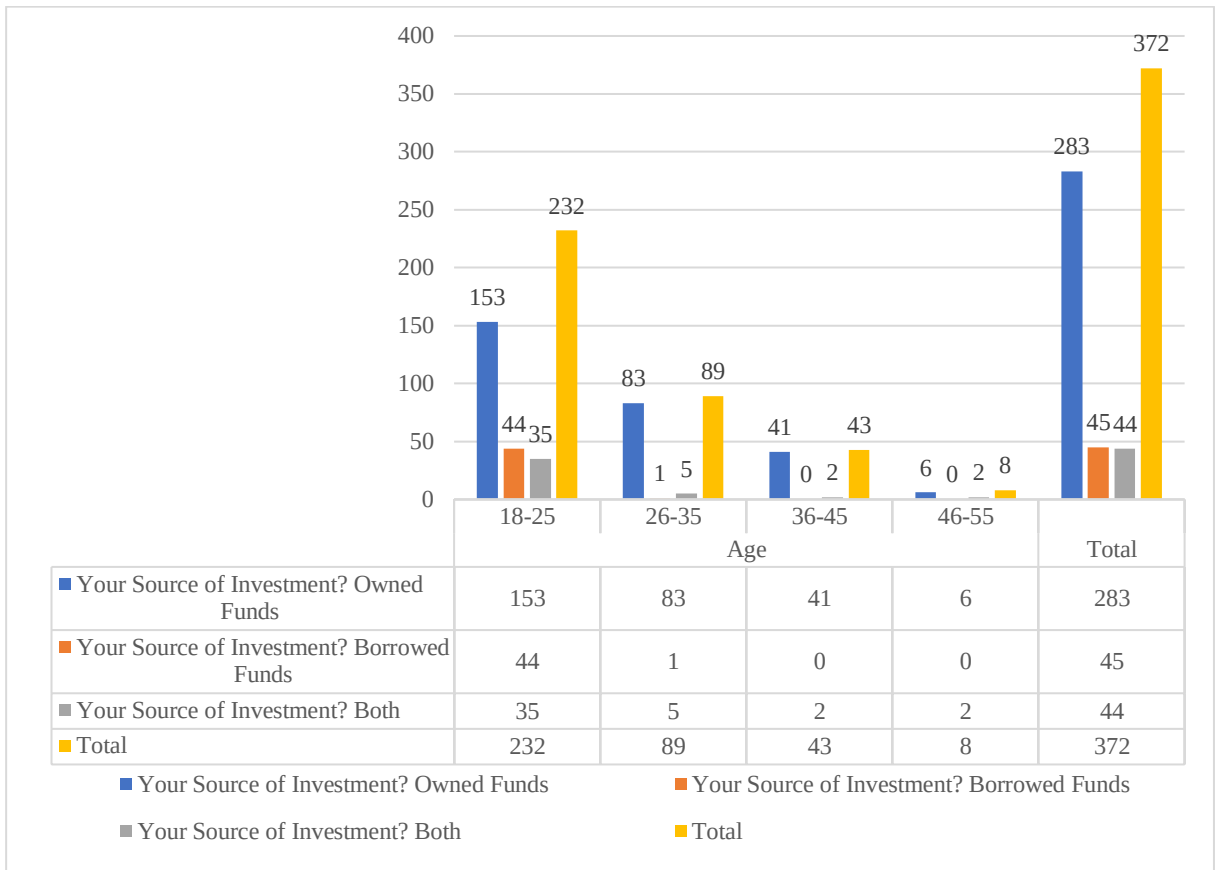
Figure 4.55: Cross-tabulation of Age and Source of Investment Fund of Junagadh city



(Source: Authors Compilation)

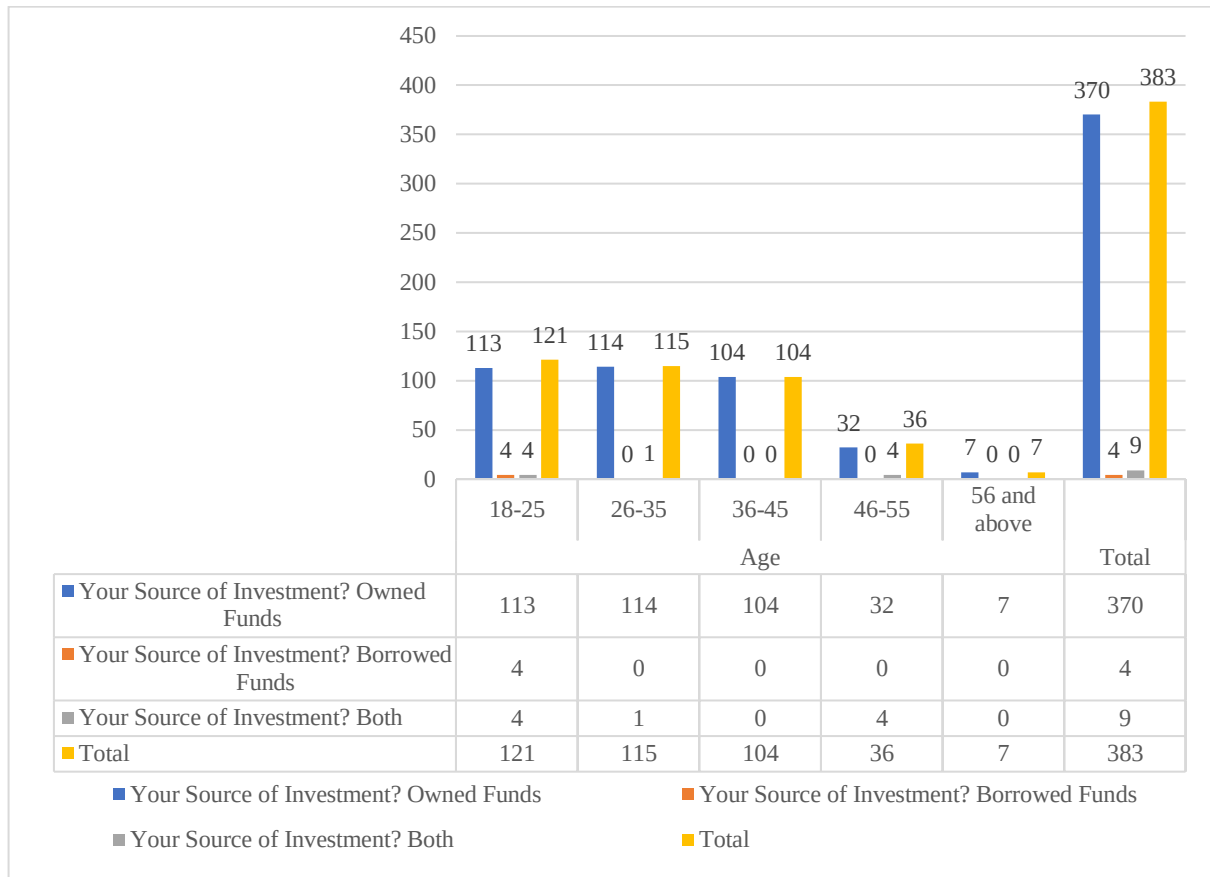
The Graph of Cross-tabulation of Age and Source of Investment Fund in Junagadh city shows that most investors prefer using their own money rather than borrowing. Among the 182 people aged 18–25, a large majority (152) rely on owned funds, with 26 using both personal and borrowed money, and just 4 depending solely on loans. The 26–35 group shows a similar pattern: 76 out of 84 invest with their own savings. In the 36–45 range, 20 out of 24 follow the same approach. All 12 investors aged 46–55 and all 4 over 56 invest only from their own funds.

In short, out of 306 investors, 264 use only their own money, 36 combine sources, and just 6 rely entirely on borrowed funds.

Figure 4.56: Cross-tabulation of Age and Source of Investment Fund of Rajkot city

(Source: Authors Compilation)

The Graph of Cross-tabulation of Age and Source of Investment Fund in Rajkot, most investors still prefer to use their own money, but younger age groups show a higher tendency to borrow. Among the 232 investors aged 18–25, 153 rely on owned funds, while 44 use borrowed money, and 35 use a mix of both. In contrast, the 26–35 group (89 people) is more financially independent, with 83 using only their own funds and very few turning to borrowing. The trend continues with older investors—41 out of 43 in the 36–45 group and 6 out of 8 in the 46–55 group invest solely with personal funds. In short, out of 372 investors in Rajkot, 283 use only their own money, 44 combine sources, and 45 rely entirely on borrowed funds. Younger investors are more open to borrowing, while older ones tend to stick with what they already have, showing a shift in risk comfort with age.

Figure 4.57: Cross-tabulation of Age and Source of Investment Fund of Jamnagar city

(Source: Authors Compilation)

The Graph of Cross-tabulation of Age and Source of Investment Fund in Jamnagar city most investors rely on their own funds across all age groups. Among the 18–25 age group, 113 out of 121 use their own money, with only a few (4 each) depending on borrowed funds or a mix of both. The trend continues in the 26–35 and 36–45 brackets, where 114 out of 115 and all 104 respondents, respectively, use their own resources exclusively. Even in older age groups, self-funding dominates. Of those aged 46–55, 32 invest their own money, and just 4 use a mix. In the 56 and above group, all 7 rely solely on their own funds.

In short, out of a total of 383 respondents, a strong 370 use owned funds, with only 4 using borrowed money and 9 combining both.

Cross-tabulation of Education Level and Preferred Sectors of Equity Investment**Table 4.15: Cross-tabulation of Education Level and Preferred Sectors of Equity Investment of Junagadh city**

Education Level	FMCG	Banking	IT	Energy	Pharma	Capital Goods	Others	Total Respondents
Below HSC	6	13	12	10	8	5	4	16
12th/HSC	7	22	19	18	9	8	6	32
Under Graduate	18	51	38	41	25	22	22	73
Graduate	28	54	51	49	33	25	23	80
Post Graduate	29	54	51	51	37	23	32	91
Professional	4	9	9	6	5	5	5	14
Total Yes	92	203	180	175	117	88	92	306

(Source: Authors Compilation)

The table of Cross-tabulation of Education Level and Preferred Sectors of Equity Investment of Junagadh city shows how people with different education levels are distributed across various sectors like FMCG, Banking, IT, Energy, Pharma, Capital Goods, and Others. Most respondents have a post-graduate degree (91 out of 306), followed closely by graduates (80) and undergraduates (73). These groups are especially active in Banking, IT, and Energy, suggesting these industries attract highly educated individuals.

Interestingly, even those with education below HSC or just up to 12th grade are involved across all sectors, though in smaller numbers. The Banking sector seems to have the highest participation across almost every education level, while Capital Goods and Others have relatively fewer respondents.

In short, this data reflects that as education level increases, so does the likelihood of involvement across industries, particularly in more technical and finance-driven sectors. make it more effective

Table 4.16: Cross-tabulation of Education Level and Preferred Sectors of Equity Investment of Rajkot City

Education Level	FMCG	Banking	IT	Energy	Pharma	Capital Goods	Others	Total Respondents
Below HSC	1	3	2	1	0	0	2	3
12th/HSC	0	1	1	3	0	0	1	3
Under Graduate	38	87	52	32	14	21	40	165
Graduate	30	43	42	37	19	18	14	71
Post Graduate	25	36	28	26	13	17	13	57
Professional	35	53	42	29	5	19	21	68
Others	1	2	1	1	0	0	2	5
Total	130	225	168	129	51	75	93	372

(Source: Authors Compilation)

The cross-tabulation of education level and preferred sectors of equity investment in Rajkot reveals that individuals with higher education—particularly Undergraduates (165), Graduates (71), Professionals (68), and Postgraduates (57)—are significantly more active in investing across various sectors. The Banking sector is the most preferred, with 225 respondents, led by Undergraduates (87) and Professionals (53). IT follows closely with 168 investors, mainly from the same groups. FMCG also attracts strong interest (130), especially from Undergraduates (38), Professionals (35), and Graduates (30). The Energy sector has 129 investors, showing relatively balanced participation. In contrast, sectors like Pharmaceuticals (51) and Capital Goods (75) see fewer investors, particularly from less-educated groups. Although individuals with lower education levels such as Below HSC (3) and HSC (3) participate in investments, their involvement is minimal.

In short, the data suggests that as education level increases, so does both the likelihood and diversity of sectoral investments, with a clear preference among educated individuals for finance- and technology-driven sectors.

Table 4.17: Cross-tabulation of Education Level and Preferred Sectors of Equity Investment of Jamnagar City

Education Level	FMCG	Banking	IT	Energy	Pharma	Capital Goods	Others	Total Respondents
Below HSC	3	3	3	4	2	3	2	6
12th/HSC	3	9	2	2	3	1	2	13
Under Graduate	43	55	58	43	13	24	22	86
Graduate	27	27	17	24	6	10	11	44
Post Graduate	26	32	27	21	4	4	6	39
Professional	90	136	143	122	72	62	76	195
Total	192	262	250	216	100	104	119	383

(Source: Authors Compilation)

The cross-tabulation of education level and preferred sectors of equity investment in Jamnagar city shows that investors with higher education, especially Professionals (195 respondents) and Undergraduates (86 respondents), dominate investment choices across all sectors. The Banking sector is the most preferred overall with 262 investors, led by Professionals (136) and Undergraduates (55). The IT sector closely follows with 250 investors, again mainly Professionals (143) and Undergraduates (58). The FMCG sector attracts 192 investors, mostly Professionals (90). Sectors like Pharmaceuticals (100) and Capital Goods (104) see comparatively lower interest, even among highly educated groups. Participation from lower education levels (Below HSC and 12th/HSC) is minimal across all sectors.

In short, the data highlights that in Jamnagar, higher education is strongly linked to greater investment activity, particularly in Banking, Capital goods, and Information technology sectors.

Cross-tabulation of Gender, Source of Income or Investment, and Education**Table 4.18: Cross-tabulation of Gender, Source of Income or Investment, and Education of Junagadh City**

Education			Is It Your Source of Income or Investment?			Total
			Income	Investment	Both	
Below HSC	Gender	Male	3	8	5	16
	Total		3	8	5	16
12th/HSC	Gender	Male	3	17	12	32
	Total		3	17	12	32
Under Graduate	Gender	Male	5	30	29	64
		Female	2	4	3	9
	Total		7	34	32	73
Graduate	Gender	Male	7	26	31	64
		Female	2	6	8	16
	Total		9	32	39	80
Post Graduate	Gender	Male	10	25	29	64
		Female	3	10	14	27
	Total		13	35	43	91
Professional	Gender	Male	3	5	2	10
		Female	0	2	2	4
	Total		3	7	4	14
Total	Gender	Male	31	111	108	250
		Female	7	22	27	56
	Total		38	133	135	306

a. Location (City) = Junagadh

(Source: SPSS-2022)

The cross-tabulation of Gender, Source of Income or Investment, and Education of Junagadh City shows how people from Junagadh with different education levels and genders think about their money, whether they see it mainly as income, an investment, or both. Out of 306 respondents, most treat their money as both income and investment (135 people) or mostly as an investment (133 people), with fewer considering it purely as income (38 people). Men make up the majority in all groups, especially among those who view their money as both income and investment (108 men) or just investment (111 men). Those with higher education, like Graduates and post-graduates, are more likely to see their money as serving both purposes. Women, while fewer in number, generally share this perspective too.

In short, it shows that many educated people in Junagadh carefully balance earning and investing their money.

Table 4.19: Cross-tabulation of Gender, Source of Income or Investment, and Education of Rajkot City

Education			Is It Your Source of Income or Investment?			Total
			Income	Investment	Both	
Below HSC	Gender	Male	0	2		2
		Female	1	0		1
	Total		1	2		3
12th/HSC	Gender	Male	1	0	1	2
		Female	0	1	0	1
	Total		1	1	1	3
Under Graduate	Gender	Male	23	38	26	87
		Female	12	50	16	78
	Total		35	88	42	165
Graduate	Gender	Male	12	23	17	52
		Female	4	10	5	19
	Total		16	33	22	71
Post Graduate	Gender	Male	6	16	10	32
		Female	4	15	6	25
	Total		10	31	16	57
Professional	Gender	Male	7	35	12	54
		Female	2	9	3	14
	Total		9	44	15	68
Others	Gender	Male	1	0	1	2
		Female	1	1	1	3
	Total		2	1	2	5
Total	Gender	Male	50	114	67	231
		Female	24	86	31	141
	Total		74	200	98	372

a. Location (City) = Rajkot

(Source: SPSS-2022)

The cross-tabulation of Gender, Source of Income or Investment, and Education of Rajkot City shows, people's views on money—as income, investment, or both—differ across gender and education levels. Out of 372 respondents, 200 consider it an investment, 98 see it as both income and investment, and 74 treat it solely as income.

Men (231) are more dominant in viewing money as an investment (114) or both (67), while women (141) also show a strong leaning toward investment (86). The Undergraduate group is the most active, with 165 individuals, where female Undergraduates lead in identifying money as an investment (50), followed closely by male Undergraduates who are distributed across all three categories.

In short, people in Rajkot—especially those with higher education—are more likely to see their money as a tool for long-term financial growth rather than just immediate income.

Table 4.20: Cross-tabulation of Gender, Source of Income or Investment, and Education of Jamnagar City

Education			Is It Your Source of Income or Investment?			Total
			Income	Investment	Both	
Below HSC	Gender	Male	3	0	1	4
		Female	0	2	0	2
	Total		3	2	1	6
12th/HSC	Gender	Male	1	10	1	12
		Female	0	1	0	1
	Total		1	11	1	13
Under Graduate	Gender	Male	17	25	3	45
		Female	3	26	12	41
	Total		20	51	15	86
Graduate	Gender	Male	9	17	5	31
		Female	2	11	0	13
	Total		11	28	5	44
Post Graduate	Gender	Male	13	15	1	29
		Female	2	7	1	10
	Total		15	22	2	39
Professional	Gender	Male	27	95	33	155
		Female	9	30	1	40
	Total		36	125	34	195
Total	Gender	Male	70	162	44	276
		Female	16	77	14	107
	Total		86	239	58	383

a. Location (City) = Jamnagar

(Source: SPSS-2022)

The cross-tabulation of Gender, Source of Income or Investment, and Education of Jamnagar City shows financial behaviour varies across education levels and gender when it comes to viewing money as income, investment, or both. Out of 383 total respondents, the majority—239—consider it an investment, followed by 58 who see it as both, and 86 who treat it purely as income. Men clearly lead the participation with 276 respondents, showing a stronger preference for investment (162) and both income and investment (44), while women (totalling 107) are more likely to view money as investment (77) rather than income (16). Among all education levels, the Professional group is the most active with 195 respondents, especially males (155) who predominantly treat it as an investment (95). Notably, female undergraduates also show high involvement, with 26 considering it an investment.

In short, in Jamnagar—particularly among educated males and younger females—about treating money as a tool for long-term wealth building (Investment) rather than just day-to-day income.

4.5.4 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.

Hypothesis 1

- **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

Table 4.21: ANOVA Test- Age of Investors and Behavioural Biases

Factor	Age Group	N	Mean	F-value	P-value	> / <	Level of Sign.	Result
Overconfidence	18-25	535	3.3855	6.634	.000	<	.050	H0 is Rejected
	26-35	288	3.5634					
	36-45	171	3.5395					
	46-55	56	3.7321					
	56 and above	11	4.3182					
	Total	1061	3.4866					
Familiarity	18-25	535	3.7701	5.229	.000	<	.050	H0 is Rejected
	26-35	288	3.9861					
	36-45	171	4.0292					
	46-55	56	4.0714					
	56 and above	11	3.7273					
	Total	1061	3.8860					
Confirmation Bias	18-25	535	3.5409	9.170	.000	<	.050	H0 is Rejected
	26-35	288	3.7382					
	36-45	171	3.8211					
	46-55	56	3.8571					
	56 and above	11	3.7091					
	Total	1061	3.6581					
Regret Aversion	18-25	535	3.1938	34.359	.000	<	.050	H0 is Rejected
	26-35	288	3.7789					
	36-45	171	3.8869					
	46-55	56	3.6250					
	56 and above	11	2.9091					
	Total	1061	3.4841					
Narrow Framing	18-25	535	3.6280	20.203	.000	<	.050	H0 is Rejected
	26-35	288	3.9468					
	36-45	171	4.1248					
	46-55	56	4.1369					

	56 and above	11	4.2424					
	Total	1061	3.8278					
Shadow Of The Past	18-25	535	3.5766	12.522	.000	<	.050	H0 is Rejected
	26-35	288	3.8889					
	36-45	171	4.0088					
	46-55	56	3.8750					
	56 and above	11	3.2273					
	Total	1061	3.7432					
Loss Aversion	18-25	535	3.4370	23.091	.000	<	.050	H0 is Rejected
	26-35	288	3.7958					
	36-45	171	3.9216					
	46-55	56	3.6786					
	56 and above	11	3.1636					
	Total	1061	3.6224					
Heard Instincts	18-25	535	3.1327	11.901	.000	<	.050	H0 is Rejected
	26-35	288	3.5046					
	36-45	171	3.5867					
	46-55	56	3.5357					
	56 and above	11	3.0909					
	Total	1061	3.3277					

(Source: SPSS-22 ANOVA test Output)

The above table, "ANOVA Results for Behavioural Biases and Different Age Groups," indicates a comparative analysis of Eight Behavioural Biases: Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts with the different age groups of investors. The results show that the P value of all these Behavioural Biases is (0.000), which is below the significance level of ($p=0.05$). This means the null hypothesis is rejected for every Bias, indicating statistically significant differences exist among different Age groups of investors and all eight behavioural biases.

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.

Hypothesis 2

- **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

Table 4.22: ANOVA Test- Education Levels of Investors and Behavioural Biases

Factor	Education Level	N	Mean	F-value	P-value	> / <	Level of Sign.	Result
Overconfidence	Below HSC	25	3.4600	11.202	.000	<	.050	H0 is Rejected
	12th/HSC	48	3.3854					
	Under Graduate	324	3.3164					
	Graduate	195	3.4705					
	Post Graduate	187	3.3917					
	Professional	277	3.8014					
	Others	5	2.3500					
	Total	1061	3.4866					
Familiarity	Below HSC	25	3.8200	13.609	.000	<	.050	H0 is Rejected
	12th/HSC	48	3.7500					
	Under Graduate	324	3.8349					
	Graduate	195	3.6590					
	Post Graduate	187	3.7914					
	Professional	277	4.2274					
	Others	5	2.3000					
	Total	1061	3.8860					
Confirmation Bias	Below HSC	25	3.7680	12.947	.000	<	.050	H0 is Rejected
	12th/HSC	48	3.5708					
	Under Graduate	324	3.4920					
	Graduate	195	3.6390					
	Post Graduate	187	3.6096					
	Professional	277	3.9191					

	Others	5	2.8000					
	Total	1061	3.6581					
Regret Aversion	Below HSC	25	3.3600	26.502	.000	<	.050	H0 is Rejected
	12th/HSC	48	3.3958					
	Under Graduate	324	3.1214					
	Graduate	195	3.4342					
	Post Graduate	187	3.5045					
	Professional	277	3.9759					
	Others	5	2.4000					
	Total	1061	3.4841					
Narrow Framing	Below HSC	25	3.9200	19.205	.000	<	.050	H0 is Rejected
	12th/HSC	48	3.8681					
	Under Graduate	324	3.5864					
	Graduate	195	3.6427					
	Post Graduate	187	3.8717					
	Professional	277	4.2034					
	Others	5	3.4000					
	Total	1061	3.8278					
Shadow of the Past	Below HSC	25	3.7600	9.641	.000	<	.050	H0 is Rejected
	12th/HSC	48	3.6458					
	Under Graduate	324	3.5864					
	Graduate	195	3.6256					
	Post Graduate	187	3.7246					
	Professional	277	4.0542					
	Others	5	2.8000					
	Total	1061	3.7432					
Loss Aversion	Below HSC	25	3.6640	15.603	.000	<	.050	H0 is Rejected
	12th/HSC	48	3.6375					
	Under Graduate	324	3.4105					
	Graduate	195	3.5621					
	Post Graduate	187	3.5807					
	Professional	277	3.9437					
	Others	5	3.1200					
	Total	1061	3.6224					
Herd Instincts	Below HSC	25	3.3200	13.620	.000	<	.050	H0 is Rejected
	12th/HSC	48	3.2222					
	Under Graduate	324	3.0658					
	Graduate	195	3.2239					

	Post Graduate	187	3.2959				
	Professional	277	3.7437				
	Others	5	3.5333				
	Total	1061	3.3277				

(Source: SPSS-22 ANOVA test Output)

The above table, "ANOVA Results for Behavioural Biases and Different Education levels of an investor," indicates a comparative analysis of Eight Behavioural Biases: Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts with the different Education levels of investors. The results show that the P value of all these Behavioural Biases is (0.000), which is below the significance level of ($p=0.05$). This means the null hypothesis is rejected for every Bias, indicating statistically significant differences exist among different Education levels of investors and all eight behavioural biases.

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.

Hypothesis 3

- **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

Table 4.23: ANOVA Test- Occupation of Investors and Behavioural Biases

Factor	Occupation	N	Mean	F-value	P-value	> / <	Level of Sign.	Result
Overconfidence	Salaried	356	3.4614	10.051	.000	<	.050	H0 is Rejected
	Businessman	130	3.5500					
	Professional	158	3.9035					
	Retired	4	3.5000					
	House Wife	16	2.7813					
	Student	333	3.3476					
	Equity Trader	22	3.7159					
	Others	42	3.1845					
	Total	1061	3.4866					
Familiarity	Salaried	356	3.8862	4.750	.000	<	.050	H0 is Rejected
	Businessman	130	3.8500					
	Professional	158	4.2089					
	Retired	4	3.3750					
	House Wife	16	4.0000					
	Student	333	3.7973					
	Equity Trader	22	3.6136					
	Others	42	3.6310					
	Total	1061	3.8860					
Confirmation Bias	Salaried	356	3.6860	8.864	.000	<	.050	H0 is Rejected
	Businessman	130	3.5815					
	Professional	158	3.9620					
	Retired	4	3.9000					
	House Wife	16	3.8375					
	Student	333	3.5489					
	Equity Trader	22	3.6818					
	Others	42	3.2762					
	Total	1061	3.6581					
Regret Aversion	Salaried	356	3.7125	19.423	.000	<	.050	H0 is Rejected
	Businessman	130	3.3692					
	Professional	158	3.9177					
	Retired	4	3.5000					
	House Wife	16	3.4375					
	Student	333	3.2022					
	Equity Trader	22	2.8333					
	Others	42	2.8651					
	Total	1061	3.4841					
Narrow Framing	Salaried	356	3.9401	20.385	.000	<	.050	H0 is Rejected
	Businessman	130	3.8949					

	Professional	158	4.2553					
	Retired	4	3.6667					
	House Wife	16	4.0208					
	Student	333	3.5766					
	Equity Trader	22	3.6818					
	Others	42	3.0714					
	Total	1061	3.8278					
Shadow of the Past	Salaried	356	3.8315	7.841	.000	<	.050	H0 is Rejected
	Businessman	130	3.8077					
	Professional	158	4.0032					
	Retired	4	2.6250					
	House Wife	16	3.6875					
	Student	333	3.6096					
	Equity Trader	22	3.1591					
	Others	42	3.3095					
	Total	1061	3.7432					
Loss Aversion	Salaried	356	3.7365	12.163	.000	<	.050	H0 is Rejected
	Businessman	130	3.5846					
	Professional	158	3.9051					
	Retired	4	3.3500					
	House Wife	16	3.5375					
	Student	333	3.4865					
	Equity Trader	22	3.2909					
	Others	42	3.0190					
	Total	1061	3.6224					
Herd Instincts	Salaried	356	3.4822	12.423	.000	<	.050	H0 is Rejected
	Businessman	130	3.1897					
	Professional	158	3.7426					
	Retired	4	3.7500					
	House Wife	16	3.4375					
	Student	333	3.1301					
	Equity Trader	22	2.6364					
	Others	42	2.7302					
	Total	1061	3.3277					

(Source: SPSS-22 ANOVA test Output)

The above table, "ANOVA Results for Behavioural Biases and Different Occupation of Investors," indicates a comparative analysis of Eight Behavioural Biases: Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts, with the different Occupation of Investors. The results show that the P value of all these Behavioural Biases is (0.000),

which is below the significance level of ($p=0.05$). This means the null hypothesis is rejected for every Bias, indicating statistically significant differences exist among different occupations of investors and all eight behavioural biases.

To examine the effect of occupation on behavioral 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, behavioral 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.

Hypothesis 4

- **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

Table 4.24: ANOVA Test- Income of Investors and Behavioural Biases

Factor	Income	N	Mean	F-value	P-value	> / <	Level of Sign.	Result
Overconfidence	Up to 2,50,000	519	3.3064	27.240	.000	<	.050	H0 is Rejected
	2,50,000 to 5,00,000	169	3.4822					
	5,00,000 to 10,00,000	261	3.6130					

	10,00,000 and Above	112	4.0335					
	Total	1061	3.4866					
Familiarity	Up to 2,50,000	519	3.7303	15.733	.000	<	.050	H0 is Rejected
	2,50,000 to 5,00,000	169	3.8639					
	5,00,000 to 10,00,000	261	4.1705					
	10,00,000 and Above	112	3.9777					
	Total	1061	3.8860					
Confirmation Bias	Up to 2,50,000	519	3.5264	16.832	.000	<	.050	H0 is Rejected
	2,50,000 to 5,00,000	169	3.6639					
	5,00,000 to 10,00,000	261	3.8636					
	10,00,000 and Above	112	3.7804					
	Total	1061	3.6581					
Regret Aversion	Up to 2,50,000	519	3.2299	48.754	.000	<	.050	H0 is Rejected
	2,50,000 to 5,00,000	169	3.4339					
	5,00,000 to 10,00,000	261	4.0179					
	10,00,000 and Above	112	3.4940					
	Total	1061	3.4841					
Narrow Framing	Up to 2,50,000	519	3.6095	31.545	.000	<	.050	H0 is Rejected
	2,50,000 to 5,00,000	169	3.8935					
	5,00,000 to 10,00,000	261	4.0575					
	10,00,000 and Above	112	4.2054					
	Total	1061	3.8278					
Shadow of the Past	Up to 2,50,000	519	3.6002	18.092	.000	<	.050	H0 is Rejected
	2,50,000 to 5,00,000	169	3.6479					
	5,00,000 to 10,00,000	261	4.0670					

	10,00,000 and Above	112	3.7946					
	Total	1061	3.7432					
Loss Aversion	Up to 2,50,000	519	3.4493	39.278	.000	<	.050	H0 is Rejected
	2,50,000 to 5,00,000	169	3.6178					
	5,00,000 to 10,00,000	261	4.0107					
	10,00,000 and Above	112	3.5268					
	Total	1061	3.6224					
Herd Instincts	Up to 2,50,000	519	3.1509	18.875	.000	<	.050	H0 is Rejected
	2,50,000 to 5,00,000	169	3.2367					
	5,00,000 to 10,00,000	261	3.6769					
	10,00,000 and Above	112	3.4702					
	Total	1061	3.3277					

(Source: SPSS-22 ANOVA test Output)

The above table, "ANOVA Results for Behavioural Biases and Different Income Level of Investors," indicates a comparative analysis of Eight Behavioural Biases: Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts, with the different Income levels of Investors. The results show that the P value of all these Behavioural Biases is (0.000), which is below the significance level of ($p=0.05$). This means the null hypothesis is rejected for every Bias, indicating statistically significant differences exist among different Income levels of investors and all eight behavioural biases.

To examine the effect of income on behavioral 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, behavioral 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.

Hypothesis 5

- **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

Table 4.25: ANOVA Test- Marital Status of Investors and Behavioural Biases

Factor	Income	N	Mean	F-value	P-value	> / <	Level of Sign.	Result
Overconfidence	Married	415	3.6108	5.042	.002	<	.050	H0 is Rejected
	Unmarried	637	3.4082					
	Separated	5	3.4000					
	Others	4	3.1875					
	Total	1061	3.4866					
Familiarity	Married	415	3.9976	3.805	.010	<	.050	H0 is Rejected
	Unmarried	637	3.8124					
	Separated	5	4.0000					
	Others	4	3.8750					
	Total	1061	3.8860					
Confirmation Bias	Married	415	3.7682	6.515	.000	<	.050	H0 is Rejected
	Unmarried	637	3.5890					
	Separated	5	3.3200					
	Others	4	3.6500					
	Total	1061	3.6581					
Regret Aversion	Married	415	3.7839	26.038	.000	<	.050	H0 is Rejected
	Unmarried	637	3.2904					
	Separated	5	3.4000					
	Others	4	3.3333					
	Total	1061	3.4841					
Narrow Framing	Married	415	4.0305	16.021	.000	<	.050	H0 is Rejected
	Unmarried	637	3.6970					

	Separated	5	4.0667					
	Others	4	3.3333					
	Total	1061	3.8278					
Shadow of the Past	Married	415	3.8940	7.165	.000	<	.050	H0 is Rejected
	Unmarried	637	3.6476					
	Separated	5	3.8000					
	Others	4	3.2500					
	Total	1061	3.7432					
Loss Aversion	Married	415	3.8116	16.432	.000	<	.050	H0 is Rejected
	Unmarried	637	3.5039					
	Separated	5	3.3600					
	Others	4	3.2000					
	Total	1061	3.6224					
Herd Instincts	Married	415	3.5486	12.191	.000	<	.050	H0 is Rejected
	Unmarried	637	3.1821					
	Separated	5	3.3333					
	Others	4	3.5833					
	Total	1061	3.3277					

(Source: SPSS-22 ANOVA test Output)

The above table, "ANOVA Results for Behavioural Biases and Marital Status of Investors," indicates a comparative analysis of Eight Behavioural Biases: Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts, with the Marital status of Investors. The results show that the P value of all these Behavioural Biases is (0.000), which is below the significance level of ($p=0.05$). This means the null hypothesis is rejected for every Bias, indicating statistically significant differences exist among the Marital status of investors and all eight behavioural biases.

To examine the effect of marital status on behavioral 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, behavioral 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.

Hypothesis 6

- **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

Table 4.26: ANOVA Test- Family Type of Investors and Behavioural Biases

Factor	Family Type	N	Mean	F-value	P-value	> / <	Level of Sign.	Result
Overconfidence	Nuclear Family	356	3.3890	7.150	.008	<	.050	H0 is Rejected
	Joint Family	705	3.5358					
	Total	1061	3.4866					
Familiarity	Nuclear Family	356	3.8385	1.576	.210	>	.050	H0 is Accepted
	Joint Family	705	3.9099					
	Total	1061	3.8860					
Confirmation Bias	Nuclear Family	356	3.5938	4.941	.026	<	.050	H0 is Rejected
	Joint Family	705	3.6905					
	Total	1061	3.6581					
Regret Aversion	Nuclear Family	356	3.3596	9.974	.002	<	.050	H0 is Rejected
	Joint Family	705	3.5470					
	Total	1061	3.4841					
Narrow Framing	Nuclear Family	356	3.7388	6.745	.010	<	.050	H0 is Rejected
	Joint Family	705	3.8728					
	Total	1061	3.8278					
Shadow of the Past	Nuclear Family	356	3.6292	9.115	.003	<	.050	H0 is Rejected

	Joint Family	705	3.8007					
	Total	1061	3.7432					
Loss Aversion	Nuclear Family	356	3.5326	8.277	.004	<	.050	H0 is Rejected
	Joint Family	705	3.6678					
	Total	1061	3.6224					
Herd Instincts	Nuclear Family	356	3.2182	6.733	.010	<	.050	H0 is Rejected
	Joint Family	705	3.3830					
	Total	1061	3.3277					

(Source: SPSS-22 ANOVA test Output)

The above table, "ANOVA Results for Behavioural Biases and Different Family Types of Family Investors," indicates a comparative analysis of Eight Behavioural Biases: Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts, with the different Family types of Investors. The results show that the P value of all these Behavioural Biases is (0.000), which is below the significance level of ($p=0.05$). This means the null hypothesis is rejected for every Bias, indicating statistically significant differences exist among different Family Types of investors and all eight behavioural biases.

To examine the effect of family type on behavioral biases, an ANOVA was conducted. Significant differences were observed across family types for most biases ($p < 0.05$), except familiarity ($p = 0.210$). Overconfidence was highest among Joint Family participants (3.54) and lowest in Nuclear Family participants (3.39). Confirmation bias was highest in Joint Family participants (3.69) and lowest in Nuclear Family participants (3.59). Regret aversion peaked in Joint Family participants (3.55) and was lowest in Nuclear Family participants (3.36). Narrow framing was highest in Joint Family participants (3.87) and lowest in Nuclear Family participants (3.74). Shadow of the past and loss aversion were highest in Joint Family participants (3.80 and 3.67) and lowest in Nuclear Family participants (3.63 and 3.53), respectively. Herd instincts were highest in Joint Family participants (3.38) and lowest in Nuclear Family participants (3.22). Overall, behavioral biases tend to be stronger among individuals from joint families, suggesting family structure influences decision-making tendencies.

Hypothesis 7

- **H0:** Different Number of Family Members of respondents assign the same mean towards behavioural biases
- **H1:** Different Number of Family Members of respondents do not assign the same mean towards behavioural biases

Table 4.27: ANOVA Test- Number of Family Members of Investors and Behavioural Biases

Factor	Number of Family Members	N	Mean	F-value	P-value	> / <	Level of Sign.	Result
Overconfidence	Two	39	3.6154	0.669	.571	>	.050	H0 is Accepted
	Three	153	3.5343					
	Four	291	3.4476					
	More than Four	578	3.4849					
	Total	1061	3.4866					
Familiarity	Two	39	3.9744	0.501	.681	>	.050	H0 is Accepted
	Three	153	3.8758					
	Four	291	3.8402					
	More than Four	578	3.9057					
	Total	1061	3.8860					
Confirmation Bias	Two	39	3.6410	1.709	.163	>	.050	H0 is Accepted
	Three	153	3.6693					
	Four	291	3.5849					
	More than Four	578	3.6931					
	Total	1061	3.6581					
Regret Aversion	Two	39	3.5556	4.939	.002	<	.050	H0 is Rejected
	Three	153	3.4641					
	Four	291	3.3184					
	More than Four	578	3.5681					
	Total	1061	3.4841					
Narrow Framing	Two	39	3.7436	0.957	.412	>	.050	H0 is Accepted
	Three	153	3.7582					
	Four	291	3.8076					
	More than Four	578	3.8622					
	Total	1061	3.8278					

Shadow of the Past	Two	39	3.7564	3.278	.020	<	.050	H0 is Rejected
	Three	153	3.7059					
	Four	291	3.6203					
	More than Four	578	3.8140					
	Total	1061	3.7432					
Loss Aversion	Two	39	3.5692	3.703	.011	<	.050	H0 is Rejected
	Three	153	3.6366					
	Four	291	3.5086					
	More than Four	578	3.6796					
	Total	1061	3.6224					
Herd Instincts	Two	39	3.2650	5.076	.002	<	.050	H0 is Rejected
	Three	153	3.2571					
	Four	291	3.1684					
	More than Four	578	3.4308					
	Total	1061	3.3277					

(Source: SPSS-22 ANOVA test Output)

The above table, "ANOVA Results for Behavioural Biases and Different Number of family members of Investors," indicates a comparative analysis of Eight Behavioural Biases: Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts, with the different number of family members of investors. The results show that the number of family members has a meaningful effect on certain behavioural biases. Specifically, Regret Aversion ($p = .002$), Shadow of the Past ($p = .020$), Loss Aversion ($p = .011$), and Herd Instincts ($p = .002$) all have p-values below the 0.05 threshold. This means the null hypothesis is rejected for these factors, suggesting that family size may influence how individuals respond to these behavioural biases. On the other hand, Overconfidence ($p = .571$), Familiarity ($p = .681$), Confirmation Bias ($p = .163$), and Narrow Framing ($p = .412$) all have higher p-values, leading to acceptance of the null hypothesis. This indicates that for these factors, the number of family members does not appear to make a significant difference.

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). 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, behavioral biases tend to be higher in families with more than four members and relatively lower in families with four or fewer members.

Hypothesis 8

- **H0:** Different Number of Earning Members of respondents assign the same mean towards behavioural biases
- **H1:** Different Number of Earning Members of respondents do not assign the same mean towards behavioural biases

Table 4.28: ANOVA Test- Number of Earning Members of Investors and Behavioural Biases

Factor	Age	N	Mean	F-value	P-value	> / <	Level of Sign.	Result
Overconfidence	One	323	3.4899	0.470	.758	>	.050	H0 is Accepted
	Two	510	3.4765					
	Three	158	3.5301					
	Four	40	3.5438					
	More than Four	30	3.3167					
	Total	1061	3.4866					
Familiarity	One	323	3.8529	2.125	.076	>	.050	H0 is Accepted
	Two	510	3.9373					
	Three	158	3.8987					
	Four	40	3.7000					
	More than Four	30	3.5500					
	Total	1061	3.8860					
Confirmation Bias	One	323	3.5796	4.399	.002	<	.050	H0 is Rejected
	Two	510	3.6894					
	Three	158	3.7810					
	Four	40	3.6400					

	More than Four	30	3.3467					
	Total	1061	3.6581					
Regret Aversion	One	323	3.4056	4.254	.002	<	.050	H0 is Rejected
	Two	510	3.5379					
	Three	158	3.6160					
	Four	40	3.2250					
	More than Four	30	3.0667					
	Total	1061	3.4841					
Narrow Framing	One	323	3.7090	3.132	.014	<	.050	H0 is Rejected
	Two	510	3.8778					
	Three	158	3.9346					
	Four	40	3.7583					
	More than Four	30	3.7889					
	Total	1061	3.8278					
Shadow Of The Past	One	323	3.6641	2.807	.025	<	.050	H0 is Rejected
	Two	510	3.8049					
	Three	158	3.8006					
	Four	40	3.6250					
	More than Four	30	3.4000					
	Total	1061	3.7432					
Loss Aversion	One	323	3.5319	3.549	.007	<	.050	H0 is Rejected
	Two	510	3.6659					
	Three	158	3.7367					
	Four	40	3.4600					
	More than Four	30	3.4733					
	Total	1061	3.6224					
Heard Instincts	One	323	3.1940	3.854	.004	<	.050	H0 is Rejected
	Two	510	3.4078					
	Three	158	3.4388					
	Four	40	3.1667					
	More than Four	30	3.0333					
	Total	1061	3.3277					

(Source: SPSS-22 ANOVA test Output)

The above table, "ANOVA Results for Behavioural Biases and Different Number of Earning Members of Investors," indicates a comparative analysis of Eight Behavioural Biases: Overconfidence, Familiarity, Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Herd Instincts, with the different Number of Earning Members of Investors. The results show that family size appears to play a role in how people respond to certain financial behaviours. For six of the Behavioural biases—Confirmation Bias ($p = .002$), Regret Aversion ($p = .002$), Narrow Framing ($p = .014$), Shadow of the Past ($p = .025$), Loss Aversion ($p = .007$), and Herd Instincts ($p = .004$)—the numbers show clear differences based on how many earning people are in a household. Since all of these p -values are under 0.05, the assumption that Earning Members of the family have no influence was set aside. In contrast, the results for Overconfidence ($p = .758$) and Familiarity ($p = .076$) didn't show much variation, so the original assumption was kept. That suggests family size doesn't strongly affect these two areas.

To examine the effect of the number of earning members in a family on behavioral 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.

4.5.5 Objective 4: To measure the Levels of Different Behavioural Biases among Individual Equity Investors of Selected cities of the Saurashtra Region.

4.5.5.1 Behavioural Bias Impact Index (BBII)

Introduction

Equity investment decision-making is rarely a perfectly rational process. People often rely on mental shortcuts, emotional reactions, and cognitive patterns that unintentionally influence their decision-making process. In financial settings, these psychological tendencies—commonly known as behavioural biases—can significantly alter investment behaviour. Such biases may cause investors to take on unnecessary risks, avoid profitable opportunities, trade excessively, or construct poorly diversified investment portfolios, resulting in losses. Overconfidence is one of the biases that researchers have identified most frequently, where individuals place unwarranted faith or overestimate their own knowledge or future forecasting abilities. Other important biases include familiarity, confirmation, regret aversion, loss aversion, narrow framing, herd behaviour, and anchoring to past experiences; all of these Behavioural Biases have a direct impact on equity investment outcomes.

Examining these biases helps researchers, financial advisors, and regulators understand how investors behave under uncertainty and market pressure. Measuring behavioural tendencies sheds light on the psychological foundations behind investment choices, highlighting why investors may deviate from rational financial theories.

To study these tendencies, the present study formulates a Behavioural Bias Index that includes eight key investors' Behavioural biases among respondents from Junagadh, Rajkot, and Jamnagar. The index is based on 1061 participants' responses to 27 statements rated on a five-point Likert scale (from 1 = Strongly Disagree to 5 = Strongly Agree). To convert the qualitative responses into numbers, a weighted scoring method was employed. Each statement received its own weighted score, and these were subsequently grouped and combined based on the relevant bias category to generate individual bias indices. This method is widely accepted for summarizing attitude-based data in a quantifiable manner (Bozorg-Haddad, et al., 2021)

Research Design for formulating Index

The study adopts a descriptive and quantitative research approach, as the objective was to measure and compare several behavioural biases among investors. The Present study's primary data were acquired with the help of a structured questionnaire from the 1,061 respondents across three districts of the Saurashtra region: Junagadh (306), Rajkot (372), and Jamnagar (384).

The questionnaire consisted of 27 statements, each designed to capture one dimension of investor behaviour linked to eight behavioural biases. Respondents evaluated each statement on a five-point Likert scale, ranging from “Strongly Disagree” (1) to “Strongly Agree” (5). This type of scale is widely used in behavioural and social research because it allows respondents to express the intensity of their opinions while still providing data appropriate for numerical analysis.

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 = ...Equation 4.1

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

Explanation of the Sigma (Σ) Symbol

The summation sign (Σ) 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. This is sometimes called the Simple Additive Weighting (SAW) method:

Table 4.29: Explanation of equation with Frequency and weight

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

(Source: Authors' Compilation)

Table 4.30: 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:

$$(78 \times 1) + (164 \times 2) + (263 \times 3) + (357 \times 4) + (199 \times 5) = 3618$$

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)

$$\text{Bias Index} = \frac{\sum_{j=1}^k S_j}{k} \dots\dots\dots \text{Equation 4.2}$$

Where:

- S_j = weighted score of statement j
- **k** = number of items used to measure the bias

Example: Overconfidence Index

Table 4.31: 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:

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

4

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 $\times$ 1
= 1061 $\times$ 1 = **1061**
- **Maximum** possible score = total respondents $\times$ 5
= 1061 $\times$ 5 = **5305**

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

Table 4.32: 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 4.33: Results of the Study

Behavioural Bias	Index Value	Interpretation
Overconfidence	3699.25	Biased
Familiarity	4123	Biased
Confirmation	3881.2	Biased
Regret Aversion	3696.66	Biased
Narrow Framing	4061.13	Biased
Shadow of the Past	3971.5	Biased
Loss Aversion	3843.4	Biased
Herd Instincts	3530.66	Biased

(Source: Authors' Compilation)

Interpretation

The findings of this study show that all eight assessed behavioural biases lie within the 'Biased' interval (3184–4244), indicating a significant influence of psychological factors on investment decisions. For reference, the Unbiased range is 1061–2122, and the Neutral range is 2123–3183. All indices remained above the lower thresholds, indicating that investors' decisions are heavily shaped by cognitive and emotional biases rather than being neutral or objective.

Overconfidence Bias (3699.25)

The index of overconfidence is 3699.25, within the Biased range, which shows that investors tend to overrate their own abilities, believing They tend to believe they can forecast market trends or identify winning stocks with greater accuracy than is supported by actual evidence. This often leads to higher risk-taking and more frequent trading compared to a neutral or unbiased investor.

Familiarity Bias (4123)

The Index of Familiarity Scoring the highest at 4123, also within the Biased range, this index shows a strong preference for familiar companies or investment options. Investors favour what they know, reducing diversification and increasing exposure to specific risks. It means they would invest based purely on familiarity rather than fundamentals.

Confirmation Bias (3881.2)

The Index of Confirmation, with a score of 3881.2, This Biased Index indicates that investors tend to favour information that supports their existing beliefs while disregarding evidence that challenges them. Neutral or Unbiased ranges would indicate a more balanced evaluation of information without selectively reinforcing beliefs.

Regret Aversion (3696.66)

The index of Regret Aversion is 3696.66 within the Biased range, suggesting that fear of regret significantly impacts investor behaviour. Investors may hold losing assets or postpone difficult financial decisions.

Narrow Framing (4061.13)

The index of Narrow Framing is 4061.13, in the Biased range, which highlights that investors often treat each investment in isolation rather than as part of a diversified portfolio. Neutral scores would reflect occasional compartmentalization, while Unbiased scores would reflect fully integrated portfolio thinking.

Shadow of the Past (3971.5)

The Index score of Shadow of the Past is 3971.5, in the Biased range, which describes that investors depend heavily on previous outcomes, letting past negative experiences affect current decisions. Neutral or Unbiased indices would suggest a more objective assessment based on current market conditions.

Loss Aversion (3843.4)

The Loss Aversion Index is defined as 3843.4, Biased, indicating that the unpleasant feeling from losing outweighs the satisfaction of gains, leading to risk-avoidance or premature selling. In the Neutral range, investors would balance risk and reward more evenly, while in the Unbiased range, loss aversion would minimally influence decisions.

Herd Instincts (3530.66)

The Herd Instinct bias, the lowest index, 3530.66, is within the Biased range, reflecting that social influence still plays a notable role in decisions.

Overall Insight:

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.

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.

Conclusion

This study 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.

Table 4.34: Weighted Likert Scale Scoring of Behavioural Biases: City-wise Calculation and Interpretation

Behavioural Bias	No.	Statement	Location	Strongly Disagree (n/%)	Disagree (n/%)	Neutral (n/%)	Agree (n/%)	Strongly Agree (n/%)	Total	Interpretation
Overconfidence Bias	1	I have sufficient knowledge of Indian stock market. (Prosad, 2014)	Junagadh	14 (4.6%)	30 (9.8%)	115 (37.6%)	115 (37.6%)	32 (10.5%)	306	Out of 306 responses, 147 People were Biased and only 44 People were Unbiased.
			Rajkot	28 (7.5%)	75 (20.2%)	96 (25.8%)	158 (42.5%)	15 (4%)	372	Out of 372 responses, 173 People were Biased and only 103 People were Unbiased.
			Jamnagar	12 (3.1%)	90 (23.5%)	76 (19.8%)	152 (39.7%)	53 (13.8%)	383	Out of 383 responses, 205 People were Biased and only 102 People were Unbiased.
		Weighted Likert Scale Scoring		$54 \times 1 = 54$	$195 \times 2 = 390$	$287 \times 3 = 861$	$425 \times 4 = 1700$	$100 \times 5 = 500$	3505	
	2	I am confident of my ability to pick better stocks than others. (Prosad, 2014)	Junagadh	8 (2.6%)	37 (12.1%)	108 (35.3%)	131 (42.8%)	22 (7.2%)	306	Out of 306 responses, 153 People were Biased and only 45 People were Unbiased.

		Rajkot	24 (6.5%)	79 (21.2%)	81 (21.8%)	142 (38.2%)	46 (12.4%)	372	Out of 372 responses, 188 People were Biased and only 103 People were Unbiased.
		Jamnagar	12 (3.1%)	64 (16.7%)	63 (16.4%)	149 (38.9%)	95 (24.8%)	383	Out of 383 responses, 244 People were Biased and only 76 People were Unbiased.
	Weighted Likert Scale Scoring		$44 \times 1 = 44$	$180 \times 2 = 360$	$252 \times 3 = 756$	$422 \times 4 = 1688$	$163 \times 5 = 815$	3663	
	3	Junagadh	25 (8.2%)	58 (19.0%)	109 (35.6%)	90 (29.4%)	24 (7.8%)	306	Out of 306 responses, 114 People were Biased and only 83 People were Unbiased.
		Rajkot	39 (10.5%)	59 (15.9%)	95 (25.5%)	108 (29.0%)	71 (19.1%)	372	Out of 372 responses, 179 People were Biased and only 98 People were Unbiased.
		Jamnagar	14 (3.7%)	47 (12.3%)	59 (15.4%)	159 (41.5%)	104 (27.2%)	383	Out of 383 responses, 263 People were Biased and only 61 People were Unbiased.
	I take more risks because I have confidence in my abilities. (Malik, 2020)								

		Weighted Likert Scale Scoring		$78 \times 1 = 78$	$164 \times 2 = 328$	$263 \times 3 = 789$	$357 \times 4 = 1428$	$199 \times 5 = 995$	3618	
	4	I trust my ability to start and manage the investments. (Parvathy, 2022)	Junagadh	5 (1.6%)	17 (5.6%)	73 (23.9%)	166 (54.2%)	45 (14.7%)	306	Out of 306 responses, 211 People were Biased and only 22 People were Unbiased.
			Rajkot	28 (7.5%)	41 (11.0%)	77 (20.7%)	159 (42.7%)	67 (18.0%)	372	Out of 372 responses, 226 People were Biased and only 69 People were Unbiased.
			Jamnagar	3 (0.8%)	18 (4.7%)	54 (14.1%)	189 (49.3%)	119 (31.1%)	383	Out of 383 responses, 308 People were Biased and only 21 People were Unbiased.
		Weighted Likert Scale Scoring		$36 \times 1 = 36$	$76 \times 2 = 152$	$204 \times 3 = 612$	$514 \times 4 = 2056$	$231 \times 5 = 1155$	4011	
Familiarity Bias	5	I have a tendency to make investment in only those avenues in which I am familiar with. (Sukanya, 2019)	Junagadh	7 (2.3%)	32 (10.5%)	78 (25.5%)	122 (39.9%)	67 (21.9%)	306	Out of 306 responses, 189 People were Biased and only 39 People were Unbiased.
			Rajkot	14 (3.8%)	40 (10.8%)	78 (21.0%)	140 (37.6%)	100 (26.9%)	372	Out of 372 responses, 240 People were Biased and only

									54 People were Unbiased.
		Jamnagar	5 (1.3%)	27 (7.0%)	35 (9.1%)	185 (48.3%)	131 (34.2%)	383	Out of 383 responses, 316 People were Biased and only 32 People were Unbiased.
	Weighted Likert Scale Scoring		$26 \times 1 = 26$	$99 \times 2 = 198$	$191 \times 3 = 573$	$447 \times 4 = 1788$	$298 \times 5 = 1490$	4075	
6	I select the Shares of companies which I already know. (Sudarshan, 2022)	Junagadh	12 (3.9%)	24 (7.8%)	52 (17.0%)	128 (41.8%)	90 (29.4%)	306	Out of 306 responses, 218 People were Biased and only 36 People were Unbiased.
		Rajkot	12 (3.2%)	41 (11.0%)	46 (12.4%)	155 (41.7%)	118 (31.7%)	372	Out of 372 responses, 273 People were Biased and only 53 People were Unbiased.
		Jamnagar	5 (1.3%)	22 (5.7%)	53 (13.8%)	172 (44.9%)	131 (34.2%)	383	Out of 383 responses, 303 People were Biased and only 27 People were Unbiased.
	Weighted Likert Scale Scoring		$29 \times 1 = 29$	$87 \times 2 = 174$	$151 \times 3 = 453$	$455 \times 4 = 1820$	$339 \times 5 = 1695$	4171	

Confirmation Bias	7	I hold into securities that I have inherited, regardless of whether retaining those securities is financially wise or not. (Sukanya, 2019)	Junagadh	25 (8.2%)	56 (18.3%)	111 (36.3%)	86 (28.1%)	28 (9.2%)	306	Out of 306 responses, 114 People were Biased and only 81 People were Unbiased.
			Rajkot	23 (6.2%)	63 (16.9%)	114 (30.6%)	116 (31.2%)	56 (15.1%)	372	Out of 372 responses, 172 People were Biased and only 86 People were Unbiased.
			Jamnagar	24 (6.3%)	77 (20.1%)	45 (11.7%)	156 (40.7%)	81 (21.1%)	383	Out of 383 responses, 237 People were Biased and only 101 People were Unbiased.
		Weighted Likert Scale Scoring		$72 \times 1 = 72$	$196 \times 2 = 392$	$270 \times 3 = 810$	$358 \times 4 = 1432$	$165 \times 5 = 825$	3531	
	8	I collect maximum information from experts about Equities to confirm my investment decisions. (Sudarshan, 2022)	Junagadh	7 (2.3%)	29 (9.5%)	78 (25.5%)	120 (39.2%)	72 (23.5%)	306	Out of 306 responses, 192 People were Biased and only 36 People were Unbiased.
			Rajkot	15 (4.0%)	54 (14.5%)	68 (18.3%)	145 (39.0%)	90 (24.2%)	372	Out of 372 responses, 235 People were Biased and only 69 People were Unbiased.

		Jamnagar	11 (2.9%)	27 (7.0%)	47 (12.3%)	171 (44.6%)	127 (33.2%)	383	Out of 383 responses, 298 People were Biased and only 38 People were Unbiased.
	Weighted Likert Scale Scoring		$33 \times 1 = 33$	$110 \times 2 = 220$	$193 \times 3 = 579$	$436 \times 4 = 1744$	$289 \times 5 = 1445$	4021	
9	I hold the Equities when the price decreases, even if it increases the loss. (Sudarshan, 2022)	Junagadh	15 (4.9%)	68 (22.2%)	74 (24.2%)	99 (32.4%)	50 (16.3%)	306	Out of 306 responses, 149 People were Biased and only 83 People were Unbiased.
		Rajkot	33 (8.9%)	68 (18.3%)	72 (19.4%)	125 (33.6%)	74 (19.9%)	372	Out of 372 responses, 199 People were Biased and only 101 People were Unbiased.
		Jamnagar	20 (5.2%)	64 (16.7%)	57 (14.9%)	168 (43.9%)	74 (19.3%)	383	Out of 383 responses, 242 People were Biased and only 84 People were Unbiased.
	Weighted Likert Scale Scoring		$68 \times 1 = 68$	$200 \times 2 = 400$	$203 \times 3 = 609$	$392 \times 4 = 1568$	$198 \times 5 = 990$	3635	
10	I study the nature of Equity and search for	Junagadh	5 (1.6%)	7 (2.3%)	48 (15.7%)	156 (51.0%)	90 (29.4%)	306	Out of 306 responses, 246 People were Biased and only

	information while making investments. (Sudarshan, 2022)								12 People were Unbiased.
		Rajkot	27 (7.3%)	43 (11.6%)	49 (13.2%)	172 (46.2%)	81 (21.8%)	372	Out of 372 responses, 253 People were Biased and only 70 People were Unbiased.
		Jamnagar	3 (0.8%)	24 (6.3%)	34 (8.9%)	188 (49.1%)	134 (35.0%)	383	Out of 383 responses, 322 People were Biased and only 27 People were Unbiased.
	Weighted Likert Scale Scoring		$35 \times 1 = 35$	$74 \times 2 = 148$	$131 \times 3 = 393$	$516 \times 4 = 2064$	$305 \times 5 = 1525$	4165	
	11	I seek market news that confirms my investment decision as correct. (Sudarshan, 2022)	Junagadh	7 (2.3%)	20 (6.5%)	65 (21.2%)	169 (55.2%)	45 (14.7%)	306
		Rajkot	22 (5.9%)	48 (12.9%)	59 (15.9%)	168 (45.2%)	75 (20.2%)	372	Out of 372 responses, 243 People were Biased and only 70 People were Unbiased.

			Jamnagar	2 (0.5%)	13 (3.4%)	47 (12.3%)	205 (53.5%)	116 (30.3%)	383	Out of 383 responses, 321 People were Biased and only 15 People were Unbiased.
		Weighted Likert Scale Scoring		$31 \times 1 = 31$	$81 \times 2 = 162$	$171 \times 3 = 513$	$542 \times 4 = 2168$	$236 \times 5 = 1180$	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)	Junagadh	9 (2.9%)	52 (17.0%)	101 (33.0%)	96 (31.4%)	48 (15.7%)	306	Out of 306 responses, 144 People were Biased and only 61 People were Unbiased.
			Rajkot	32 (8.6%)	45 (12.1%)	88 (23.7%)	126 (33.9%)	81 (21.8%)	372	Out of 372 responses, 207 People were Biased and only 77 People were Unbiased.
			Jamnagar	11 (2.9%)	46 (12.0%)	58 (15.1%)	159 (41.5%)	109 (28.5%)	383	Out of 383 responses, 268 People were Biased and only 57 People were Unbiased.
		Weighted Likert Scale Scoring		$52 \times 1 = 52$	$143 \times 2 = 286$	$247 \times 3 = 741$	$381 \times 4 = 1524$	$238 \times 5 = 1190$	3793	
	13	While selling a stock, you become emotionally	Junagadh	14 (4.6%)	62 (20.3%)	104 (34.0%)	97 (31.7%)	29 (9.5%)	306	Out of 306 responses, 126 People were Biased and only

	affected by the price at which you purchased the stock. (Swati, 2021)								76 People were Unbiased.
		Rajkot	38 (10.2%)	67 (18.0%)	61 (16.4%)	101 (27.2%)	105 (28.2%)	372	Out of 372 responses, 206 People were Biased and only 105 People were Unbiased.
		Jamnagar	14 (3.7%)	41 (10.7%)	55 (14.4%)	153 (39.9%)	120 (31.3%)	383	Out of 383 responses, 273 People were Biased and only 55 People were Unbiased.
	Weighted Likert Scale Scoring	$66 \times 1 = 66$	$170 \times 2 = 340$	$220 \times 3 = 660$	$351 \times 4 = 1404$	$254 \times 5 = 1270$	3740		
	14	I avoid selling a stock to avoid the regret of having made a bad investment. (Swati, 2021)	Junagadh	16 (5.2%)	67 (21.9%)	87 (28.4%)	117 (38.2%)	19 (6.2%)	306
Rajkot			52 (14.0%)	62 (16.7%)	82 (22.0%)	127 (34.1%)	49 (13.2%)	372	Out of 372 responses, 176 People were Biased and only 114 People were Unbiased.

			Jamnagar	18 (4.7%)	50 (13.1%)	55 (14.4%)	175 (45.7%)	85 (22.2%)	383	Out of 383 responses, 260 People were Biased and only 68 People were Unbiased.
		Weighted Likert Scale Scoring		$86 \times 1 = 86$	$179 \times 2 = 358$	$224 \times 3 = 672$	$419 \times 4 = 1676$	$153 \times 5 = 765$	3557	
Narrow Framing	15	I tend to treat each element of my investment portfolio separately. (Sudarshan, 2022)	Junagadh	10 (3.3%)	21 (6.9%)	74 (24.2%)	152 (49.7%)	49 (16.0%)	306	Out of 306 responses, 201 People were Biased and only 31 People were Unbiased.
			Rajkot	9 (2.4%)	44 (11.8%)	91 (24.5%)	144 (38.7%)	84 (22.6%)	372	Out of 372 responses, 228 People were Biased and only 53 People were Unbiased.
			Jamnagar	3 (0.8%)	15 (3.9%)	37 (9.7%)	203 (53.0%)	125 (32.6%)	383	Out of 383 responses, 328 People were Biased and only 18 People were Unbiased.
		Weighted Likert Scale Scoring		$22 \times 1 = 22$	$80 \times 2 = 160$	$202 \times 3 = 606$	$499 \times 4 = 1996$	$258 \times 5 = 1290$	4074	
	16	I save a part of my income for investing in the stock market.	Junagadh	8 (2.6%)	18 (5.9%)	45 (14.7%)	137 (44.8%)	98 (32.0%)	306	Out of 306 responses, 235 People were Biased and only

	(Sudarshan, 2022)								26 People were Unbiased.	
		Rajkot	26 (7.0%)	45 (12.1%)	63 (16.9%)	145 (39.0%)	93 (25.0%)	372	Out of 372 responses, 238 People were Biased and only 71 People were Unbiased.	
		Jamnagar	16 (4.2%)	18 (4.7%)	34 (8.9%)	161 (42.0%)	154 (40.2%)	383	Out of 383 responses, 315 People were Biased and only 34 People were Unbiased.	
		Weighted Likert Scale Scoring	$50 \times 1 = 50$	$81 \times 2 = 162$	$142 \times 3 = 426$	$443 \times 4 = 1772$	$345 \times 5 = 1725$	4135		
	17	I classify my money into different accounts based on investment objectives, like money kept aside for insurance, money kept aside for investing in	Junagadh	8 (2.6%)	16 (5.2%)	70 (22.9%)	144 (47.1%)	68 (22.2%)	306	Out of 306 responses, 212 People were Biased and only 24 People were Unbiased.
			Rajkot	16 (4.3%)	57 (15.3%)	80 (21.5%)	147 (39.5%)	72 (19.4%)	372	Out of 372 responses, 219 People were Biased and only 73 People were Unbiased.

		retirement schemes, Equity shares, etc. (Sukanya, 2019)	Jamnagar	11 (2.9%)	42 (11.0%)	47 (12.3%)	160 (41.8%)	123 (32.1%)	383	Out of 383 responses, 283 People were Biased and only 53 People were Unbiased.
		Weighted Likert Scale Scoring		$35 \times 1 = 35$	$115 \times 2 = 230$	$197 \times 3 = 591$	$451 \times 4 = 1804$	$263 \times 5 = 1315$	3975	
Shadow Of The Past	18	I avoid investing in Equity that have performed poorly in the recent past. (Sudarshan, 2022)	Junagadh	17 (5.6%)	57 (18.6%)	75 (24.5%)	93 (30.4%)	64 (20.9%)	306	Out of 306 responses, 157 People were Biased and only 74 People were Unbiased.
			Rajkot	29 (7.8%)	40 (10.8%)	62 (16.7%)	145 (39.0%)	96 (25.8%)	372	Out of 372 responses, 241 People were Biased and only 69 People were Unbiased.
			Jamnagar	11 (2.9%)	45 (11.7%)	44 (11.5%)	197 (51.4%)	86 (22.5%)	383	Out of 383 responses, 283 People were Biased and only 56 People were Unbiased.
		Weighted Likert Scale Scoring		$57 \times 1 = 57$	$142 \times 2 = 284$	$181 \times 3 = 543$	$435 \times 4 = 1740$	$246 \times 5 = 1230$	3854	
	19	I tend to invest more when I am successful in my previous	Junagadh	9 (2.9%)	29 (9.5%)	73 (23.9%)	121 (39.5%)	74 (24.2%)	306	Out of 306 responses, 195 People were Biased and only

		Equity investments. (Sudarshan, 2022)								38 People were Unbiased.
			Rajkot	13 (3.5%)	32 (8.6%)	60 (16.1%)	177 (47.6%)	90 (24.2%)	372	Out of 372 responses, 267 People were Biased and only 45 People were Unbiased.
			Jamnagar	2 (0.5%)	21 (5.5%)	58 (15.1%)	194 (50.7%)	108 (28.2%)	383	Out of 383 responses, 302 People were Biased and only 23 People were Unbiased.
		Weighted Likert Scale Scoring	$24 \times 1 = 24$	$82 \times 2 = 164$	$191 \times 3 = 573$	$492 \times 4 = 1968$	$272 \times 5 = 1360$	4089		
Loss Aversion	20	The pain of financial loss is greater than the pleasure of financial gain. (Sudarshan, 2022)	Junagadh	10 (3.3%)	31 (10.1%)	78 (25.5%)	111 (36.3%)	76 (24.8%)	306	Out of 306 responses, 187 People were Biased and only 41 People were Unbiased.
			Rajkot	23 (6.2%)	41 (11.0%)	62 (16.7%)	126 (33.9%)	120 (32.3%)	372	Out of 372 responses, 246 People were Biased and only 64 People were Unbiased.

		Jamnagar	4 (1.0%)	28 (7.3%)	60 (15.7%)	178 (46.5%)	113 (29.5%)	383	Out of 383 responses, 291 People were Biased and only 32 People were Unbiased.
	Weighted Likert Scale Scoring		$37 \times 1 = 37$	$100 \times 2 = 200$	$200 \times 3 = 600$	$415 \times 4 = 1660$	$309 \times 5 = 1545$	4042	
21	I tend to hold onto losing Equity too long, hoping for a reversal. (Sudarshan, 2022)	Junagadh	18 (5.9%)	50 (16.3%)	101 (33.0%)	100 (32.7%)	37 (12.1%)	306	Out of 306 responses, 137 People were Biased and only 68 People were Unbiased.
		Rajkot	29 (7.8%)	43 (11.6%)	81 (21.8%)	147 (39.5%)	72 (19.4%)	372	Out of 372 responses, 219 People were Biased and only 72 People were Unbiased.
		Jamnagar	13 (3.4%)	48 (12.5%)	61 (15.9%)	157 (41.0%)	104 (27.2%)	383	Out of 383 responses, 261 People were Biased and only 61 People were Unbiased.
	Weighted Likert Scale Scoring		$60 \times 1 = 60$	$141 \times 2 = 282$	$243 \times 3 = 729$	$404 \times 4 = 1616$	$213 \times 5 = 1065$	3752	
22	I feel more sorrow about holding onto losing Equity	Junagadh	10 (3.3%)	58 (19.0%)	96 (31.4%)	115 (37.6%)	27 (8.8%)	306	Out of 306 responses, 142 People were Biased and only

	too long than about selling winning Equity too soon. (Sudarshan, 2022)								68 People were Unbiased.
		Rajkot	28 (7.5%)	69 (18.5%)	86 (23.1%)	118 (31.7%)	71 (19.1%)	372	Out of 372 responses, 189 People were Biased and only 97 People were Unbiased.
		Jamnagar	12 (3.1%)	40 (10.4%)	74 (19.3%)	166 (43.3%)	91 (23.8%)	383	Out of 383 responses, 257 People were Biased and only 52 People were Unbiased.
	Weighted Likert Scale Scoring		$50 \times 1 = 50$	$167 \times 2 = 334$	$256 \times 3 = 768$	$399 \times 4 = 1596$	$189 \times 5 = 945$	3693	
	23	Junagadh	12 (3.9%)	38 (12.4%)	72 (23.5%)	132 (43.1%)	52 (17.0%)	306	Out of 306 responses, 184 People were Biased and only 50 People were Unbiased.
		Rajkot	18 (4.8%)	56 (15.1%)	65 (17.5%)	149 (40.1%)	84 (22.6%)	372	Out of 372 responses, 233 People were Biased and only 74 People were Unbiased.

			Jamnagar	7 (1.8%)	35 (9.1%)	65 (17.0%)	175 (45.7%)	101 (26.4%)	383	Out of 383 responses, 276 People were Biased and only 42 People were Unbiased.
		Weighted Likert Scale Scoring		$37 \times 1 = 37$	$129 \times 2 = 258$	$202 \times 3 = 606$	$456 \times 4 = 1824$	$237 \times 5 = 1185$	3910	
	24	I am willingly remain in a risky stock position, hoping the price will bounce back. (Swati, 2021)	Junagadh	14 (4.6%)	42 (13.7%)	92 (30.1%)	118 (38.6%)	40 (13.1%)	306	Out of 306 responses, 158 People were Biased and only 56 People were Unbiased.
			Rajkot	27 (7.3%)	53 (14.2%)	62 (16.7%)	158 (42.5%)	72 (19.4%)	372	Out of 372 responses, 230 People were Biased and only 80 People were Unbiased.
			Jamnagar	11 (2.9%)	42 (11.0%)	60 (15.7%)	162 (42.3%)	108 (28.2%)	383	Out of 383 responses, 270 People were Biased and only 53 People were Unbiased.
		Weighted Likert Scale Scoring		$52 \times 1 = 52$	$137 \times 2 = 274$	$214 \times 3 = 642$	$438 \times 4 = 1752$	$220 \times 5 = 1100$	3820	
Heard Instincts	25	Other investors' decisions of buying and	Junagadh	27 (8.8%)	92 (30.1%)	98 (32.0%)	70 (22.9%)	19 (6.2%)	306	Out of 306 responses, only 89 People were Biased, and 119

26	selling stocks have impact on my investment decisions. (Swati, 2021)								People were Unbiased.
		Rajkot	39 (10.5%)	74 (19.9%)	67 (18.0%)	130 (34.9%)	62 (16.7%)	372	Out of 372 responses, 192 People were Biased and only 113 People were Unbiased.
		Jamnagar	13 (3.4%)	54 (14.1%)	66 (17.2%)	165 (43.1%)	85 (22.2%)	383	Out of 383 responses, 250 People were Biased and only 67 People were Unbiased.
	Weighted Likert Scale Scoring		$79 \times 1 = 79$	$220 \times 2 = 440$	$231 \times 3 = 693$	$365 \times 4 = 1460$	$166 \times 5 = 830$	3502	
	I usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market. (Swati, 2021)	Junagadh	45 (14.7%)	91 (29.7%)	76 (24.8%)	74 (24.2%)	20 (6.5%)	306	Out of 306 responses, only 94 People were Biased and 136 People were Unbiased.
		Rajkot	39 (10.5%)	87 (23.4%)	75 (20.2%)	112 (30.1%)	59 (15.9%)	372	Out of 372 responses, 171 People were Biased and only 126 People were Unbiased.

		Jamnagar	21 (5.5%)	58 (15.1%)	67 (17.5%)	158 (41.3%)	79 (20.6%)	383	Out of 383 responses, 237 People were Biased and only 79 People were Unbiased.
	Weighted Likert Scale Scoring		$105 \times 1 = 105$	$236 \times 2 = 472$	$218 \times 3 = 654$	$344 \times 4 = 1376$	$158 \times 5 = 790$	3397	
27	Discussing my investment decisions with colleagues reduces my pressure of being successful. (Prosad, 2014)	Junagadh	28 (9.2%)	54 (17.6%)	72 (23.5%)	110 (35.9%)	42 (13.7%)	306	Out of 306 responses, 152 People were Biased and only 82 People were Unbiased.
		Rajkot	41 (11.0%)	66 (17.7%)	76 (20.4%)	104 (28.0%)	85 (22.8%)	372	Out of 372 responses, 189 People were Biased and only 107 People were Unbiased.
		Jamnagar	20 (5.2%)	42 (11.0%)	49 (12.8%)	162 (42.3%)	110 (28.7%)	383	Out of 383 responses, 272 People were Biased and only 62 People were Unbiased.
	Weighted Likert Scale Scoring		$89 \times 1 = 89$	$162 \times 2 = 324$	$197 \times 3 = 591$	$376 \times 4 = 1504$	$237 \times 5 = 1185$	3693	

(Source: Authors' Compilation)

Table 4.35: Weighted Likert Scale Scoring of Behavioural Biases Model of Junagadh, Rajkot, and Jamnagar cities**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	$54 \times 1 = 54$	$195 \times 2 = 390$	$287 \times 3 = 861$	$425 \times 4 = 1700$	$100 \times 5 = 500$	3505	Overconfidence Bias 3699.25
	2	I am confident of my ability to pick better stocks than others. (Prosad, 2014)	1061	$44 \times 1 = 44$	$180 \times 2 = 360$	$252 \times 3 = 756$	$422 \times 4 = 1688$	$163 \times 5 = 815$	3663	
	3	I take more risks because I have confidence in my abilities. (Malik, 2020)	1061	$78 \times 1 = 78$	$164 \times 2 = 328$	$263 \times 3 = 789$	$357 \times 4 = 1428$	$199 \times 5 = 995$	3618	
	4	I trust my ability to start and manage the	1061	$36 \times 1 = 36$	$76 \times 2 = 152$	$204 \times 3 = 612$	$514 \times 4 = 2056$	$231 \times 5 = 1155$	4011	

		investments. (Parvathy, 2022)								
Familiarity Bias	5	I have a tendency to make investment in only those avenues in which I am familiar with. (Sukanya, 2019)	1061	$26 \times 1 = 26$	$99 \times 2 = 198$	$191 \times 3 = 573$	$447 \times 4 = 1788$	$298 \times 5 = 1490$	4075	Familiarity Bias 4123
	6	I select the Shares of companies which I already know. (Sudarshan, 2022)	1061	$29 \times 1 = 29$	$87 \times 2 = 174$	$151 \times 3 = 453$	$455 \times 4 = 1820$	$339 \times 5 = 1695$	4171	
Confirmation Bias	7	I hold into securities that I have inherited, regardless of whether retaining those securities is financially wise or not. (Sukanya, 2019)	1061	$72 \times 1 = 72$	$196 \times 2 = 392$	$270 \times 3 = 810$	$358 \times 4 = 1432$	$165 \times 5 = 825$	3531	Confirmation Bias 3881.2

8	I collect maximum information from experts about Equities to confirm my investment decisions. (Sudarshan, 2022)	1061	$33 \times 1 = 33$	$110 \times 2 = 220$	$193 \times 3 = 579$	$436 \times 4 = 1744$	$289 \times 5 = 1445$	4021
9	I hold the Equities when the price decreases, even if it increases the loss. (Sudarshan, 2022)	1061	$68 \times 1 = 68$	$200 \times 2 = 400$	$203 \times 3 = 609$	$392 \times 4 = 1568$	$198 \times 5 = 990$	3635
10	I study the nature of Equity and search for information while making investments. (Sudarshan, 2022)	1061	$35 \times 1 = 35$	$74 \times 2 = 148$	$131 \times 3 = 393$	$516 \times 4 = 2064$	$305 \times 5 = 1525$	4165
11	I seek market news that confirms my investment decision as	1061	$31 \times 1 = 31$	$81 \times 2 = 162$	$171 \times 3 = 513$	$542 \times 4 = 2168$	$236 \times 5 = 1180$	4054

		correct. (Sudarshan, 2022)								
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	$52 \times 1 = 52$	$143 \times 2 = 286$	$247 \times 3 = 741$	$381 \times 4 = 1524$	$238 \times 5 = 1190$	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	$66 \times 1 = 66$	$170 \times 2 = 340$	$220 \times 3 = 660$	$351 \times 4 = 1404$	$254 \times 5 = 1270$	3740	
	14	I avoid selling a stock to avoid the regret of having made a bad investment. (Swati, 2021)	1061	$86 \times 1 = 86$	$179 \times 2 = 358$	$224 \times 3 = 672$	$419 \times 4 = 1676$	$153 \times 5 = 765$	3557	
Narrow Framing	15	I tend to treat each element of my investment portfolio separately.	1061	$22 \times 1 = 22$	$80 \times 2 = 160$	$202 \times 3 = 606$	$499 \times 4 = 1996$	$258 \times 5 = 1290$	4074	Narrow Framing 4061.13

		(Sudarshan, 2022)							
	16	I save a part of my income for investing in the stock market. (Sudarshan, 2022)	1061	$50 \times 1 = 50$	$81 \times 2 = 162$	$142 \times 3 = 426$	$443 \times 4 = 1772$	$345 \times 5 = 1725$	4135
	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	$35 \times 1 = 35$	$115 \times 2 = 230$	$197 \times 3 = 591$	$451 \times 4 = 1804$	$263 \times 5 = 1315$	3975
Shadow Of The Past	18	I avoid investing in Equity that have performed poorly in the recent past.	1061	$57 \times 1 = 57$	$142 \times 2 = 284$	$181 \times 3 = 543$	$435 \times 4 = 1740$	$246 \times 5 = 1230$	3854
									Shadow Of The Past 3971.5

		(Sudarshan, 2022)								
	19	I tend to invest more when I am successful in my previous Equity investments. (Sudarshan, 2022)	1061	$24 \times 1 = 24$	$82 \times 2 = 164$	$191 \times 3 = 573$	$492 \times 4 = 1968$	$272 \times 5 = 1360$	4089	
Loss Aversion	20	The pain of financial loss is greater than the pleasure of financial gain. (Sudarshan, 2022)	1061	$37 \times 1 = 37$	$100 \times 2 = 200$	$200 \times 3 = 600$	$415 \times 4 = 1660$	$309 \times 5 = 1545$	4042	Loss Aversion 3843.4
	21	I tend to hold onto losing Equity too long, hoping for a reversal. (Sudarshan, 2022)	1061	$60 \times 1 = 60$	$141 \times 2 = 282$	$243 \times 3 = 729$	$404 \times 4 = 1616$	$213 \times 5 = 1065$	3752	
	22	I feel more sorrow about holding onto losing Equity too long than about selling winning Equity too soon.	1061	$50 \times 1 = 50$	$167 \times 2 = 334$	$256 \times 3 = 768$	$399 \times 4 = 1596$	$189 \times 5 = 945$	3693	

		(Sudarshan, 2022)							
	23	I would feel very bad if I buy something and it goes down. (Parvathy, 2022)	1061	$37 \times 1 = 37$	$129 \times 2 = 258$	$202 \times 3 = 606$	$456 \times 4 = 1824$	$237 \times 5 = 1185$	3910
	24	I am willingly remain in a risky stock position, hoping the price will bounce back. (Swati, 2021)	1061	$52 \times 1 = 52$	$137 \times 2 = 274$	$214 \times 3 = 642$	$438 \times 4 = 1752$	$220 \times 5 = 1100$	3820
Heard Instincts	25	Other investors' decisions of buying and selling stocks have impact on my investment decisions. (Swati, 2021)	1061	$79 \times 1 = 79$	$220 \times 2 = 440$	$231 \times 3 = 693$	$365 \times 4 = 1460$	$166 \times 5 = 830$	3502
	26	I usually react quickly to the changes of other investors' decisions and follow their	1061	$105 \times 1 = 105$	$236 \times 2 = 472$	$218 \times 3 = 654$	$344 \times 4 = 1376$	$158 \times 5 = 790$	3397
									Heard Instincts 3530.66

		reactions to the stock market. (Swati, 2021)							
	27	Discussing my investment decisions with colleagues reduces my pressure of being successful. (Prosad, 2014)	1061	$89 \times 1 = 89$	$162 \times 2 = 324$	$197 \times 3 = 591$	$376 \times 4 = 1504$	$237 \times 5 = 1185$	3693

(Source: Authors' Compilation)

Table 4.36: Behavioural Bias Impact Index (BBII) (All Statements)

Behavioural Bias	No.	Statement	1061– 2122 = Unbiased	2123– 3183 = Neutral	3184– 4244 = Biased	4245– 5305 = Highly Biased
Overconfidence Bias	1	I have sufficient knowledge of Indian stock market. (Prosad, 2014)	-	-	3505	-
	2	I am confident of my ability to pick better stocks than others. (Prosad, 2014)	-	-	3663	-
	3	I take more risks because I have confidence in my abilities. (Malik, 2020)	-	-	3618	-
	4	I trust my ability to start and manage the investments. (Parvathy, 2022)	-	-	4011	-
Familiarity Bias	5	I have a tendency to make investment in only those avenues in which I am familiar with. (Sukanya, 2019)	-	-	4075	-
	6	I select the Shares of companies which I already know. (Sudarshan, 2022)	-	-	4171	-
Confirmation Bias	7	I hold into securities that I have inherited, regardless of whether retaining those securities is financially wise or not. (Sukanya, 2019)	-	-	3531	-

	8	I collect maximum information from experts about Equities to confirm my investment decisions. (Sudarshan, 2022)	-	-	4021	-
	9	I hold the Equities when the price decreases, even if it increases the loss. (Sudarshan, 2022)	-	-	3635	-
	10	I study the nature of Equity and search for information while making investments. (Sudarshan, 2022)	-	-	4165	-
	11	I seek market news that confirms my investment decision as correct. (Sudarshan, 2022)	-	-	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)	-	-	3793	-
	13	While selling a stock, you become emotionally affected by the price at which you purchased the stock. (Swati, 2021)	-	-	3740	-

	14	I avoid selling a stock to avoid the regret of having made a bad investment. (Swati, 2021)	-	-	3557	-
Narrow Framing	15	I tend to treat each element of my investment portfolio separately. (Sudarshan, 2022)	-	-	4074	-
	16	I save a part of my income for investing in the stock market. (Sudarshan, 2022)	-	-	4135	-
	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)	-	-	3975	-
Shadow Of The Past	18	I avoid investing in Equity that have performed poorly in the recent past. (Sudarshan, 2022)	-	-	3854	-
	19	I tend to invest more when I am successful in my previous Equity investments. (Sudarshan, 2022)	-	-	4089	-
Loss Aversion	20	The pain of financial loss is greater than the	-	-	4042	-

		pleasure of financial gain. (Sudarshan, 2022)				
	21	I tend to hold onto losing Equity too long, hoping for a reversal. (Sudarshan, 2022)	-	-	3752	-
	22	I feel more sorrow about holding onto losing Equity too long than about selling winning Equity too soon. (Sudarshan, 2022)	-	-	3693	-
	23	I would feel very bad if I buy something and it goes down. (Parvathy, 2022)	-	-	3910	-
	24	I am willingly remain in a risky stock position, hoping the price will bounce back. (Swati, 2021)	-	-	3820	-
Heard Instincts	25	Other investors' decisions of buying and selling stocks have impact on my investment decisions. (Swati, 2021)	-	-	3502	-
	26	I usually react quickly to the changes of other investors' decisions and follow their reactions to the stock market. (Swati, 2021)	-	-	3397	-
	27	Discussing my investment	-	-	3693	-

		decisions with colleagues reduces my pressure of being successful. (Prosad, 2014)				
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(Source: Authors' Compilation)

Table 4.37: 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)

4.5.5.2 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: $27 \times 5 = 135$
- Behavioural Bias percentage is calculated using the formula:

$$\text{Behavioural Bias (\%)} = \frac{\text{Respondent's Total Score}}{\text{Maximum Possible Score (135)}} \times 100 \quad \dots\dots\dots \text{Equation 4.3}$$

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

$$4 + 4 + 4 + 4 + 2 + 4 + 2 + 4 + 2 + 4 + 4 + 3 + 4 + 2 + 4 + 4 + 4 + 3 + 4 + 2 + 4 + 2 + 3 + 4 + 3 + 4 + 4 = 92$$

$$\text{Behavioural Bias (\%)} = \frac{\text{Respondent's Total Score}}{\text{Maximum Possible Score (135)}} \times 100 = \frac{92}{135} \times 100 = 68.15$$

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 4.38: 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)

Interpretation:

- **0–40% (Unbiased):** This range shows very little to no bias. The data or responses are mostly neutral and balanced.

- **41–60% (Moderate Bias):** Values in this range suggest some bias exists. The data may lean slightly toward one side, but the effect of Behavioural Biases is not strong.
- **61–80% (High Bias):** Scores here indicate noticeable bias. The responses or data clearly favour that the investor is affected by Behavioural Biases.
- **81–100% (Very High Bias):** This range represents extreme bias. The data or responses are heavily affected by Behavioural Biases

Table 4.39: Bias Level Evaluation Based on Percentages

Respondent No.	Total Score	% of Biasedness	Interpretation
1	92	68.15%	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.

4.5.5.3 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.

General 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:

$$\text{Bias Score} = \sum (\text{responses for that bias}) \dots\dots\dots \text{Equation 4.4}$$

The maximum possible score for each bias was determined as:

$$\text{Maximum Score} = \text{Number of Items} \times 5 \dots\dots\dots \text{Equation 4.5}$$

The percentage of each bias was then calculated using:

$$\text{Bias\%} = \frac{\text{Bias Score}}{\text{Maximum Score}} \times 100 \dots\dots\dots \text{Equation 4.6}$$

Bias-Wise Calculation:**1. Overconfidence (Q1-Q4)**

$$\text{OC Score} = Q1 + Q2 + Q3 + Q4 = 4 + 4 + 4 + 4 = 16$$

$$\text{Maximum Score} = 4 \times 5 = 20$$

$$\text{OC\%} = \frac{16}{20} \times 100 = 80\%$$

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

2. Familiarity Bias (Q5-Q6)

$$\text{FB Score} = Q5 + Q6 = 2 + 4 = 6$$

$$\text{Maximum Score} = 2 \times 5 = 10$$

$$\text{FB\%} = \frac{6}{10} \times 100 = 60\%$$

Interpretation: Moderate Bias – respondent moderately prefers familiar investments.

3. Confirmation Bias (Q7-Q11)

$$\text{CB Score} = Q7 + Q8 + Q9 + Q10 + Q11 = 2 + 4 + 2 + 4 + 4 = 16$$

$$\text{Maximum Score} = 5 \times 5 = 25$$

$$\text{CB\%} = \frac{16}{25} \times 100 = 64\%$$

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

4. Regret Aversion (Q12-Q14)

$$\text{RA Score} = Q12 + Q13 + Q14 = 3+4+2 = 9$$

$$\text{Maximum Score} = 3 \times 5 = 15$$

$$\text{RA\%} = \frac{9}{15} \times 100 = 60\%$$

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

5. Narrow Framing (Q15-Q17)

$$\text{NF Score} = \text{Q15} + \text{Q16} + \text{Q17} = 4 + 4 + 4 = 12$$

$$\text{Maximum Score} = 3 \times 5 = 15$$

$$\text{NF\%} = \frac{12}{15} \times 100 = 80\%$$

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

6. Shadow of the Past (Q18-Q19)

$$\text{SOP Score} = \text{Q18} + \text{Q19} = 3 + 4 = 7$$

$$\text{Maximum Score} = 2 \times 5 = 10$$

$$\text{SO P\%} = \frac{7}{10} \times 100 = 70\%$$

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

7. Loss Aversion (Q20-Q24)

$$\text{LA Score} = \text{Q20} + \text{Q21} + \text{Q22} + \text{Q23} + \text{Q24} = 2 + 4 + 2 + 3 + 4 = 15$$

$$\text{Maximum Score} = 5 \times 5 = 25$$

$$\text{LA\%} = \frac{15}{25} \times 100 = 60\%$$

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

8. Herd Instinct (Q25-Q27)

$$\text{HI Score} = \text{Q25} + \text{Q26} + \text{Q27} = 3 + 4 + 4 = 11$$

$$\text{Maximum Score} = 3 \times 5 = 15$$

$$\text{HI\%} = \frac{11}{15} \times 100 \approx 73.33\%$$

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

Table 4.40: 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)

Table 4.41: Summary of Behavioural Bias Scores and Levels for a Single Equity Investor

Bias	%	Level
Overconfidence	80%	High
Familiarity	60%	Moderate
Confirmation	64%	High
Regret Aversion	60%	Moderate
Narrow Framing	80%	High
Shadow of the Past	70%	High
Loss Aversion	60%	Moderate
Herd Instinct	73.33%	High

(Source: Authors' Compilation)

The assessment of behavioural biases shows that the respondent's investment decisions are influenced to varying degrees across eight key areas. High levels of bias are seen in Overconfidence (80%), Confirmation Bias (64%), Narrow Framing (80%), Shadow of the Past (70%), and Herd Instinct (73.33%), reflecting a strong reliance on personal judgment, selective information, previous experiences, and social influences when making investment choices. Moderate bias is observed in Familiarity Bias (60%), Regret Aversion (60%), and Loss Aversion (60%), indicating that familiarity, emotional reactions to potential regret, and sensitivity to losses play a noticeable but less dominant role. Overall, the results suggest that the respondent's decisions are shaped by a combination of cognitive, emotional, and social factors, with particular tendencies toward overestimating abilities, narrowly evaluating investments, and being influenced by others' actions. These insights help in understanding the psychological drivers behind the respondent's investment behaviour.

4.5.6 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 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 account for variations in investment choices. These features make it a strong and appropriate statistical tool for fulfilling this objective.

Hypothesis 9

- **H0:** Different Behavioural Biases do not significantly affect the Investment Experience of equity investors of the selected cities of the Saurashtra Region
- **H1:** Different Behavioural Biases significantly affect the Investment Experience of equity investors of the selected cities of the Saurashtra Region

Table 4.42: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.419 ^a	.175	.169	1.03326	1.444
a. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion					
b. Dependent Variable: How much Experience do you have in equity investment?					

(Source: IBM SPSS-2022 Output)

The Model summary of the multiple linear regression shows a moderate positive relationship between the set of behavioural biases and the experience in equity investment, as indicated by an R value of 0.419. The R Square value of 0.175 reveals that about 17.5% of the variation in investment experience can be attributed to the combined influence of the predictor variables. When adjusted for the number of

predictors, the adjusted R Square stands at 0.169, offering a more refined estimate of the model's explanatory power. The standard error of the estimate is 1.033, suggesting that, on average, the actual data points deviate from the predicted values by roughly this amount. Additionally, the Durbin-Watson statistic is 1.444, which points to a slight presence of positive autocorrelation in the residuals because values near 2 are generally considered acceptable.

Table 4.43: ANOVA Test- Behavioural Biases and the Investment Experience.

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	238.839	8	29.855	27.964	.000 ^b
	Residual	1123.137	1052	1.068		
	Total	1361.975	1060			
a. Dependent Variable: How much Experience do you have in equity investment?						
b. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion						

(Source: IBM SPSS-2022 Output)

The above ANOVA table shows that the regression model is statistically significant overall. With an F-value of 27.964 and a significance level (p-value) of .000, the results indicate that the group of behavioural bias variables collectively have a meaningful impact on predicting the investors of the Saurashtra region's experience in equity investment. Since the p-value is well below the conventional threshold of 0.05, it can be concluded that the model is effective in explaining a significant portion of the variation in the dependent variable.

Table 4.44: Coefficient Table of Multiple Regression Analysis of Behavioural Biases and Investment Experience.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.818	.235		-3.483	.001
	Overconfidence	.201	.040	.150	5.081	.000
	Familiarity	.006	.041	.005	.141	.888
	Confirmation Bias	.020	.058	.012	.348	.728
	Regret Aversion	.250	.045	.202	5.561	.000

	Narrow Framing	.236	.046	.166	5.132	.000
	Shadow Of The Past	.053	.043	.041	1.218	.224
	Loss Aversion	.028	.058	.018	.472	.637
	Heard Instincts	.038	.038	.033	1.009	.313
a. Dependent Variable: How much Experience do you have in equity investment?						

(Source: IBM SPSS-2022 Output)

Y = a + b.....Equation 4.7

The regression equation based on this coefficient table:

$$Y = (\text{Experience in Equity Investment}) - 818 + 0.201 \times (\text{Overconfidence}) + 0.006 \times (\text{Familiarity}) + 0.020 \times (\text{Confirmation Bias}) + 0.250 \times (\text{Regret Aversion}) + 0.236 \times (\text{Narrow Framing}) + 0.053 \times (\text{Shadow of the Past}) + 0.028 \times (\text{Loss Aversion}) + 0.038 \times (\text{Heard Instincts})$$

The coefficient table shows that the regression analysis among the behavioural biases studied, Overconfidence, Regret Aversion, and Narrow Framing, significantly affect the level of experience in equity investment. Notably, Regret Aversion has the largest standardised effect (Beta = 0.202), followed by Narrow Framing (Beta = 0.166) and Overconfidence (Beta = 0.150). These findings indicate that individuals who display these tendencies are more likely to report greater experience with equity investment. On the other hand, variables such as Familiarity, Confirmation Bias, Shadow of the Past, Loss Aversion, and Heard Instincts do not show a meaningful statistical relationship with investment experience in this analysis. The intercept is negative and statistically significant, representing the expected baseline experience when all behavioural biases are at zero.

Here, the Discussion shows that the Null hypothesis is rejected, because behavioural biases significantly influence the investment experience of equity investors in the selected cities of the Saurashtra region.

Hypothesis 10

- **H0:** Different Behavioural Biases do not significantly affect the Trading Frequency of equity investors of the selected cities of the Saurashtra Region
- **H1:** Different Behavioural Biases significantly affect the Trading Frequency of equity investors of the selected cities of the Saurashtra Region

Table 4.45: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.302 ^a	.091	.084	1.38979	1.935
a. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion					
b. Dependent Variable: Please specify your trading frequency.					

(Source: IBM SPSS-2022 Output)

The regression results indicate a modest relationship between behavioural biases and trading frequency. The model shows an R value of 0.302, suggesting a weak to moderate correlation. The R Square value of 0.091 reveals that around 9.1% of the variation in trading frequency can be explained by the behavioural factors included in the analysis. After adjusting for the number of predictors, the adjusted R Square drops slightly to 0.084. The standard error of estimate, measured at 1.38979, reflects the average distance of actual data points from the regression line. Additionally, the Durbin-Watson statistic of 1.935 suggests that there is no concerning autocorrelation present in the residuals, as values close to 2 are considered acceptable.

Table 4.46: ANOVA Test- Behavioural Biases and the Trading Frequency

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	203.544	8	25.443	13.172	.000 ^b
	Residual	2031.966	1052	1.932		
	Total	2235.510	1060			
a. Dependent Variable: Please specify your trading frequency.						

b. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion

(Source: IBM SPSS-2022 Output)

The above ANOVA table shows that the regression model is statistically significant. The model produced an F-value of 13.172, and the corresponding p-value is .000, which falls well below the standard threshold of 0.05. This outcome leads to the rejection of the null hypothesis, indicating that the combined influence of the behavioural biases in the model has a statistically meaningful effect on predicting trading frequency.

Table 4.47: Coefficient Table of Multiple Regression Analysis of Behavioural Biases and Trading Frequency of equity investors

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.160	.316		16.333	.000
	Overconfidence	-.468	.053	-.273	-8.780	.000
	Familiarity	.140	.056	.084	2.510	.012
	Confirmation Bias	-.086	.078	-.040	-1.106	.269
	Regret Aversion	-.084	.060	-.053	-1.395	.163
	Narrow Framing	.017	.062	.009	.276	.782
	Shadow Of The Past	.012	.058	.007	.209	.834
	Loss Aversion	-.123	.078	-.061	-1.565	.118
	Heard Instincts	.004	.051	.003	.088	.930
a. Dependent Variable: Please specify your trading frequency.						

(Source: IBM SPSS-2022 Output)

$$Y = a + bx \dots \dots \dots \text{Equation 4.8}$$

The regression equation based on this coefficient table:

$$Y = 5.160(\text{Trading Frequency}) - 0.468 \times (\text{Overconfidence}) + 0.140 \times (\text{Familiarity}) - 0.086 \times (\text{Confirmation Bias}) - 0.084 \times (\text{Regret Aversion}) + 0.017 \times (\text{Narrow Framing}) + 0.012 \times (\text{Shadow of the Past}) - 0.123 \times (\text{Loss Aversion}) + 0.004 \times (\text{Heard Instincts})$$

The coefficient table shows that the regression analysis among the behavioural biases studied, Overconfidence, shows a significant negative relationship with trading frequency ($B = -0.468$, $p = .000$), suggesting that individuals with higher levels of overconfidence tend to trade less frequently.

Familiarity is positively associated with trading activity ($B = 0.140$, $p = .012$), implying that investors who feel more comfortable or knowledgeable about investments are likely to trade more often.

The remaining variables—Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Heard Instincts—did not show statistically significant effects, as their p-values exceeded the standard threshold of 0.05.

Here, the Discussion shows that the Null hypothesis is rejected, because behavioural biases significantly influence the Trading Frequency of equity investors in the selected cities of the Saurashtra region.

Hypothesis 11

- **H0:** Different Behavioural Biases do not significantly affect the Amount of Single trade invested by equity investors of the selected cities of the Saurashtra Region
- **H1:** Different Behavioural Biases significantly affect the Amount of Single trade invested by equity investors of the selected cities of the Saurashtra Region

Table 4.48: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.329 ^a	.109	.102	1.44324	1.598
a. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion					
b. Dependent Variable: How much amount of single trade do you execute?					

(Source: IBM SPSS-2022 Output)

The Model summary of the multiple linear regression shows that behavioural biases have a relatively minor impact on how much individuals invest per trade. The

correlation coefficient is **0.329**, which shows a weak to moderate relationship. The R Square value of 0.109 means that just over 10% of the variation in trade size is explained by the biases included in the model. Once adjusted for the number of predictors, the value slightly decreases to 0.102, which still indicates low explanatory power. The standard error, at 1.44324, shows how much the actual trade amounts differ from the predicted ones on average. Lastly, the Durbin-Watson score of 1.598 doesn't raise major concerns about autocorrelation, though it does lean slightly toward positive correlation.

Table 4.49: ANOVA Test- Behavioural Biases and the Amount of Single Trade

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	266.784	8	33.348	16.010	.000 ^b
	Residual	2191.242	1052	2.083		
	Total	2458.026	1060			
a. Dependent Variable: How much amount of single trade do you execute?						
b. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion						

(Source: IBM SPSS-2022 Output)

The above ANOVA table shows that the regression model is statistically significant. The F-value of 16.010 with a significance level (p-value) of .000 shows that the set of behavioural biases included in the model has a meaningful impact on the amount invested in a single trade. Since the p-value is well below the conventional threshold of 0.05, it can be concluded that the model is effective in explaining a significant portion of the variation in the dependent variable.

Table 4.50: Coefficient Table of Multiple Regression Analysis of Behavioural Biases and Amount of Single Trade

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.255	.328		.778	.437
	Overconfidence	.455	.055	.253	8.215	.000
	Familiarity	.005	.058	.003	.088	.930
	Confirmation Bias	-.024	.081	-.011	-.296	.768

	Regret Aversion	-.104	.063	-.062	-1.653	.099
	Narrow Framing	.348	.064	.182	5.412	.000
	Shadow Of The Past	-.057	.060	-.033	-.944	.345
	Loss Aversion	-.048	.081	-.023	-.591	.554
	Heard Instincts	-.046	.053	-.030	-.875	.382
a. Dependent Variable: How much amount of single trade do you execute?						

(Source: IBM SPSS-2022 Output)

$$Y = a + bx \dots\dots\dots \text{Equation 4.9}$$

The regression equation based on this coefficient table:

$$Y = (\text{Amount of Single Trade})0.255 + 0.455(\text{Overconfidence}) + 0.005(\text{Familiarity}) - 0.024(\text{Confirmation Bias}) - 0.104(\text{Regret Aversion}) + 0.348(\text{Narrow Framing}) - 0.057(\text{Shadow of the Past}) - 0.048(\text{Loss Aversion}) - 0.046(\text{Heard Instincts})$$

The coefficient table shows that the regression analysis among the behavioural biases and the Amount of single trade studied. Among the predictors, Overconfidence (Beta = 0.253, $p < .001$) and Narrow Framing (Beta = 0.182, $p < .001$) have a statistically significant positive effect, indicating that higher levels of these biases are associated with larger trade amounts. Other variables, including Familiarity, Confirmation Bias, Regret Aversion, Shadow of the Past, Loss Aversion, and Heard Instincts, do not show statistically significant relationships, as their p -values exceed the conventional threshold of 0.05. The constant term is also not significant, suggesting that without the influence of these biases, the predicted trade amount is not meaningfully different from zero.

Here, the Discussion shows that the Null hypothesis is rejected, because behavioural biases significantly influence the Amount of Single trades of equity investors invested in the selected cities of the Saurashtra region.

Hypothesis 12

- **H0:** Different Behavioural Biases do not significantly affect the Number of Companies in which investments are made by equity investors of the selected cities of the Saurashtra Region
- **H1:** Different Behavioural Biases significantly affect the Number of Companies in which investments are made by equity investors of the selected cities of the Saurashtra Region

Table 4.51: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.426 ^a	.182	.176	1.31867	1.439
a. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion					
b. Dependent Variable: The number of companies in which investments are made?					

(Source: IBM SPSS-2022 Output)

The Model summary of the multiple linear regression shows a moderate positive relationship between behavioural biases and the number of companies in which investments are made, as indicated by an R value of 0.426. The R Square of 0.182 suggests that approximately 18.2% of the variation in the number of invested companies can be explained by the predictors in the model. The Adjusted R-Square, slightly lower at 0.176, adjusts for the number of variables considered, providing a more accurate measure of the model's explanatory strength. The standard error of the estimate is 1.319, describing the typical deviation between the actual and predicted values. A Durbin-Watson value of 1.439 suggests a slight positive autocorrelation in the residuals, which may require attention in further analysis.

Table 4.52: ANOVA Test- Behavioural Biases and the Number of Companies in which investments are made

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	406.735	8	50.842	29.238	.000 ^b
	Residual	1829.305	1052	1.739		

	Total	2236.040	1060			
a. Dependent Variable: The number of companies in which investments are made?						
b. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion						

(Source: IBM SPSS-2022 Output)

The above ANOVA table shows that the regression model is statistically significant overall. With an F-value of 29.238 and a significance level (p-value) of .000, the results show that the set of behavioural biases included in the model has a meaningful impact on the number of companies in which investments are made by the investors of the Saurashtra region. Since the p-value is well below the conventional threshold of 0.05, it can be concluded that the model is effective in explaining a significant portion of the variation in the dependent variable.

Table 4.53: Coefficient Table of Multiple Regression Analysis of Behavioural Biases and Number of Companies in which investments are made

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.487	.300		-4.961	.000
	Overconfidence	.511	.051	.298	10.092	.000
	Familiarity	.017	.053	.010	.328	.743
	Confirmation Bias	-.020	.074	-.009	-.265	.791
	Regret Aversion	.194	.057	.123	3.394	.001
	Narrow Framing	.214	.059	.117	3.641	.000
	Shadow Of The Past	-.032	.055	-.019	-.585	.559
	Loss Aversion	.150	.074	.075	2.015	.044
	Heard Instincts	.023	.048	.016	.481	.631
a. Dependent Variable: The number of companies in which investments are made?						

(Source: IBM SPSS-2022 Output)

$$Y = a + bx \text{ Equation 4.10}$$

The regression equation based on this coefficient table:

$$Y = (\text{Number of companies in which investments are made}) - 1.487 + 0.511(\text{Overconfidence}) + 0.017(\text{Familiarity}) - 0.020(\text{Confirmation Bias}) + 0.194(\text{Regret Aversion}) + 0.214(\text{Narrow Framing}) - 0.032(\text{Shadow of the Past}) + 0.150(\text{Loss Aversion}) + 0.023(\text{Heard Instincts})$$

The coefficient table shows that among the behavioural biases studied, overconfidence, regret aversion, narrow framing, and loss aversion significantly influence the number of companies in which investors from the Saurashtra region invest. Overconfidence shows the strongest positive impact ($\beta = 0.511$, $p = .000$), suggesting that overconfident investors tend to diversify more. Regret aversion ($p = .001$), narrow framing ($p = .000$), and loss aversion ($p = .044$) also positively affect investment diversification. In contrast, biases such as familiarity, Confirmation bias, shadow of the past, and heard instincts do not show a statistically significant relationship, indicating they have little to no influence on the number of investments made.

Here, the Discussion shows that the Null hypothesis is rejected, because behavioural biases significantly influence the Number of companies in which equity investors invested in the selected cities of the Saurashtra region.

Hypothesis 13

- **H0:** Different Behavioural Biases do not significantly affect the Objective of the Regular Return of equity investors of the selected cities of the Saurashtra Region
- **H1:** Different Behavioural Biases significantly affect the Objective of the Regular Return of equity investors of the selected cities of the Saurashtra Region

Table 4.54: Model summary

Model Summary^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.342 ^a	.117	.110	1.19223	1.756
a. Predictors: (Constant), Heard_Instincts, Overconfidence, Familiarity, Narrow_Framing, Shadow_Of_The_Past, Confirmation_Bias, Regret_Aversion, Loss Aversion					
b. Dependent Variable: Regular Returns					

(Source: IBM SPSS-2022 Output)

The Model summary of the multiple linear regression shows a moderate positive relationship between the set of behavioural biases and the Objective of the Regular Return of equity investors. The R Square is 0.117, meaning that about 11.7% of the variation in the Objective of the Regular Return of equity investors can be explained by the behavioural biases included in the model. The Adjusted R Square of 0.110 accounts for the number of predictors and confirms a similar level of explanatory power. The standard error of 1.19223 reflects the average distance between the observed values and the predicted values from the model. while the Durbin-Watson statistic of 1.756 indicates no major issue with autocorrelation. Overall, the model explains only a small portion of the variability in regular returns.

Table 4.55: ANOVA Test- Behavioural Biases and the Objective of the Regular Return

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	197.463	8	24.683	17.365	.000 ^b
	Residual	1495.337	1052	1.421		
	Total	1692.799	1060			
a. Dependent Variable: Regular Returns						
b. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion						

(Source: IBM SPSS-2022 Output)

The above ANOVA table shows that the regression model is statistically significant overall. With an F-value of 17.365 and a significance level (p-value) of .000, the results indicate that the group of behavioural bias variables collectively have a meaningful impact on the Objective of the Regular Return of investors of the Saurashtra

region. Since the p-value is well below the conventional threshold of 0.05, it can be concluded that the model is effective in explaining a significant portion of the variation in the dependent variable.

Table 4.56: Coefficient Table of Multiple Regression Analysis of Behavioural Biases and Objective of the Regular Return of Equity Investors

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.639	.271		2.358	.019
	Overconfidence	.178	.046	.119	3.891	.000
	Familiarity	.169	.048	.117	3.540	.000
	Confirmation Bias	.122	.067	.065	1.826	.068
	Regret Aversion	-.052	.052	-.038	-1.013	.311
	Narrow Framing	.141	.053	.089	2.645	.008
	Shadow Of The Past	.114	.050	.079	2.296	.022
	Loss Aversion	.176	.067	.101	2.623	.009
	Heard Instincts	-.012	.044	-.009	-.275	.783
a. Dependent Variable: Regular Returns						

(Source: IBM SPSS-2022 Output)

$$Y = a + bx \dots \dots \dots \text{Equation 4.11}$$

The regression equation based on this coefficient table:

$$Y = (\text{Objective of Regular Return}) 0.639 + 0.178(\text{Overconfidence}) + 0.169(\text{Familiarity}) + 0.122(\text{Confirmation Bias}) - 0.052(\text{Regret Aversion}) + 0.141(\text{Narrow Framing}) + 0.114(\text{Shadow of the Past}) + 0.176(\text{Loss Aversion}) - 0.012(\text{Heard Instincts})$$

The coefficient table shows that the regression analysis among the behavioural biases studied, several behavioural biases have a significant influence on the objective of earning regular returns among equity investors. Overconfidence, familiarity, narrow framing, shadow of the past, and loss aversion all show positive and statistically significant effects ($p < 0.05$), suggesting that investors displaying these traits are more likely to aim for steady income from their investments. On the other hand, regret aversion, Confirmation bias, and heard instincts are not significant predictors ($p > 0.05$), indicating they do not have a meaningful impact on this investment objective.

Here, the Discussion shows that the Null hypothesis is rejected, because behavioural biases significantly influence the Objective of the Regular Return of investors in the selected cities of the Saurashtra region.

Hypothesis 14

- **H0:** Different Behavioural Biases do not significantly affect the Objective of the Safety of the Principal Amount of equity investors of the selected cities of the Saurashtra Region
- **H1:** Different Behavioural Biases significantly affect the Objective of the Safety of the Principal Amount of equity investors of the selected cities of the Saurashtra Region

Table 4.57: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.320 ^a	.103	.096	1.05968	1.906
a. Predictors: (Constant), Heard_Instincts, Overconfidence, Familiarity, Narrow_Framing, Shadow_Of_The_Past, Confirmation_Bias, Regret_Aversion, Loss Aversion					
b. Dependent Variable: Safety of the Principal Amount					

(Source: IBM SPSS-2022 Output)

The Model summary of the multiple linear regression shows a moderate positive relationship between the set of behavioural biases the objective of ensuring the safety of the principal amount, indicated by the R value of 0.320. The R Square value of 0.103 shows that about 10.3% of the variation in this investment objective can be explained by the behavioural biases included in the model. The Adjusted R Square of 0.096 confirms the model's explanatory power after accounting for the number of predictors. The standard error of 1.05968 reflects the average difference between the observed and predicted values. Additionally, the Durbin-Watson statistic is 1.906, which points to no significant autocorrelation in the residuals.

Table 4.58: ANOVA Test- Behavioural Biases and the Objective of the Safety of the Principal Amount

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	135.108	8	16.888	15.040	.000 ^b
	Residual	1181.320	1052	1.123		
	Total	1316.428	1060			
a. Dependent Variable: Safety of the Principal Amount						
b. Predictors: (Constant), Heard Instincts, Overconfidence, Familiarity, Narrow Framing, Shadow Of The Past, Confirmation Bias, Regret Aversion, Loss Aversion						

(Source: IBM SPSS-2022 Output)

The above ANOVA table shows that the regression model is statistically significant overall. With an F-value of 15.040 and a significance level (p-value) of .000, the results indicate that the group of behavioural bias variables collectively have a meaningful impact on the Objective of the Safety of the Principal Amount of the investors of the Saurashtra region. Since the p-value is well below the conventional threshold of 0.05, it can be concluded that the model is effective in explaining a significant portion of the variation in the dependent variable.

Table 4.59: Coefficient Table of Multiple Regression Analysis of Behavioural Biases and Objective of the Safety of the Principal Amount

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.390	.241		5.771	.000
	Overconfidence	.056	.041	.043	1.389	.165
	Familiarity	.107	.042	.084	2.515	.012
	Confirmation Bias	.148	.060	.089	2.483	.013
	Regret Aversion	-.063	.046	-.052	-1.370	.171
	Narrow Framing	.237	.047	.169	5.013	.000
	Shadow Of The Past	.043	.044	.034	.964	.335
	Loss Aversion	.155	.060	.101	2.592	.010
	Heard Instincts	-.019	.039	-.017	-.495	.621
a. Dependent Variable: Safety of the Principal Amount						

(Source: IBM SPSS-2022 Output)

$$Y = a + bx \dots \dots \dots \text{Equation 4.12}$$

The regression equation based on this coefficient table:

$$Y = (\text{Safety of their principal amount}) \ 1.390 + 0.056(\text{Overconfidence}) + 0.107(\text{Familiarity}) + 0.148(\text{Confirmation Bias}) - 0.063(\text{Regret Aversion}) + 0.237(\text{Narrow Framing}) + 0.043(\text{Shadow of the Past}) + 0.155(\text{Loss Aversion}) - 0.019(\text{Heard Instincts})$$

The coefficient table shows that the regression analysis among the behavioural biases studied, some behavioural biases significantly influence the importance individuals place on the safety of their principal amount. Notably, Narrow Framing (Beta = 0.237, $p = .000$), Loss Aversion (Beta = 0.155, $p = .010$), Confirmation Bias (Beta = 0.148, $p = .013$), and Familiarity (Beta = 0.107, $p = .012$) show significant positive effects, suggesting that individuals influenced by these biases are more likely to prioritize preserving their original investment. In contrast, Overconfidence ($p = .165$), Regret Aversion ($p = .171$), Shadow of the Past ($p = .335$), and Heard Instincts ($p = .621$) do not show a statistically significant impact in this aspect.

Here, the Discussion shows that the Null hypothesis is rejected, because behavioural biases significantly influence the Safety of their principal amount of investors in the selected cities of the Saurashtra region.

Hypothesis 15

- **H0:** Different Behavioural Biases do not significantly affect the Broking Apps as a source of information for equity investors of the selected cities of the Saurashtra Region
- **H1:** Different Behavioural Biases significantly affect the Broking Apps as a source of information for equity investors of the selected cities of the Saurashtra Region

Table 4.60: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.336 ^a	.113	.106	.47114	1.837
a. Predictors: (Constant), Heard_Instincts, Overconfidence, Familiarity, Narrow_Framing, Shadow_Of_The_Past, Confirmation_Bias, Regret_Aversion, Loss Aversion					
b. Dependent Variable: Your source of information for equity investment. (Broking apps)					

(Source: IBM SPSS-2022 Output)

The Model summary of the multiple linear regression shows a moderate positive relationship between the set of behavioural biases and Broking Apps as a source of information for equity investors, as indicated by an R value of 0.336. The R Square value of 0.113 suggests that behavioural biases approximately 11.3% of the variation in broking app usage. An adjusted R-squared of 0.106. The standard error of 0.471 reflects a reasonable average difference between the observed and predicted values. Moreover, the Durbin-Watson statistic of 1.837 suggests no significant autocorrelation in the residuals, indicating that the model's estimates are reliable.

Table 4.61: ANOVA Test- Behavioural Biases and the Broking Apps as a source of information for equity investors

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	29.699	8	3.712	16.725	.000 ^b
	Residual	233.513	1052	.222		
	Total	263.212	1060			
a. Dependent Variable: Your source of information for equity investment. (Broking apps)						
b. Predictors: (Constant), Heard_Instincts, Overconfidence, Familiarity, Narrow_Framing, Shadow_Of_The_Past, Confirmation_Bias, Regret_Aversion, Loss Aversion						

(Source: IBM SPSS-2022 Output)

The above ANOVA table shows that the regression model is statistically significant overall. With an F-value of 16.725 and a significance level (p-value) of .000, the results indicate that the group of behavioural bias variables collectively have a

meaningful impact on Broking Apps as a source of information for equity investors of the Saurashtra region. Since the p-value is well below the conventional threshold of 0.05, it can be concluded that the model is effective in explaining a significant portion of the variation in the dependent variable.

Table 4.62: Coefficient Table of Multiple Regression Analysis of Behavioural Biases and the Broking Apps as a source of information for equity investors

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.622	.107		24.485	.000
	Overconfidence	-.053	.018	-.090	-2.932	.003
	Familiarity	-.048	.019	-.085	-2.562	.011
	Confirmation_Bias	-.034	.026	-.046	-1.291	.197
	Regret_Aversion	-.049	.020	-.091	-2.412	.016
	Narrow_Framing	-.054	.021	-.086	-2.557	.011
	Shadow_Of_The_Past	2.340E-5	.020	.000	.001	.999
	Loss Aversion	-.084	.027	-.122	-3.162	.002
	Heard_Instincts	.004	.017	.008	.241	.810
a. Dependent Variable: Your source of information for equity investment. (Broking apps)						

(Source: IBM SPSS-2022 Output)

$$Y = a + bx \dots\dots\dots \text{Equation 4.13}$$

The regression equation based on this coefficient table:

$$Y = (\text{Broking Apps as a source of information for equity investors}) \ 2.622 - 0.053(\text{Overconfidence}) - 0.048(\text{Familiarity}) - 0.034(\text{Confirmation Bias}) - 0.049(\text{Regret Aversion}) - 0.054(\text{Narrow Framing}) + 0.0000234(\text{Shadow of the Past}) - 0.084(\text{Loss Aversion}) + 0.004(\text{Heard Instincts})$$

The coefficient table shows that the regression analysis among the behavioural biases studied shows that some behavioural biases significantly influence the use of broking apps for equity investment information. Overconfidence (Beta = -0.053, p = .003), Familiarity (Beta = -0.048, p = .011), Regret Aversion (Beta = -0.049, p = .016), Narrow Framing (Beta = -0.054, p = .011), and Loss Aversion (Beta = -0.084, p = .002) all have significant negative effects, suggesting that as these biases increase, the tendency to rely on broking apps decreases. Meanwhile, Confirmation Bias (Beta = -

0.034, $p = .197$), Shadow of the Past (Beta = 0.0000234, $p = .999$), and Heard Instincts (Beta = 0.004, $p = .810$) do not show a significant relationship, indicating little to no impact on the use of broking apps.

Here, the Discussion shows that the Null hypothesis is rejected, because behavioural biases significantly influence the Broking Apps as a source of information for equity investors in the selected cities of the Saurashtra region.

4.5.7 PLS- SEM Analysis

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a powerful multivariate technique used to examine complex relationships between observed indicators and latent constructs. It is particularly suitable for studies with predictive objectives, exploratory research, or models involving multiple interrelated constructs (Hair et al., 2017; Hair et al., 2019)

In this research, PLS-SEM is employed to investigate the impact of eight behavioural biases—Overconfidence (OC), Familiarity (FAM), Confirmation Bias (CONF), Regret Aversion (RA), Narrow Framing (NF), Shadow of the Past (SOP), Loss Aversion (LA), and Herd Instincts (HI)—on equity investment decisions (IDM) among investors in selected cities of the Saurashtra region.

Several factors justify the selection of PLS-SEM for this study:

- **Complex Model Structure:** The study examines multiple direct and indirect relationships among behavioural biases and investment decisions. PLS-SEM efficiently models such complex interconnections.
- **Predictive Objective:** The primary goal is to predict the influence of behavioural biases on investment decisions, making PLS-SEM more suitable than covariance-based SEM.
- **Data Characteristics:** With a large sample of 1,061 respondents, PLS-SEM effectively accommodates data that may not fully meet normality assumptions.
- **Simultaneous Measurement and Structural Assessment:** PLS-SEM allows evaluation of both the measurement model (assessing reliability and validity of constructs) and the structural model (testing hypothesized relationships) in a single framework.
- **Bootstrapping for Statistical Significance:** To test the significance of path coefficients, the study employs bootstrapping with 5,000 resamples in SmartPLS. Bootstrapping is a non-parametric resampling technique that does not assume normality of data and provides t-values, standard errors, and confidence intervals for each path coefficient, enabling rigorous hypothesis testing (Hair et al., 2017)

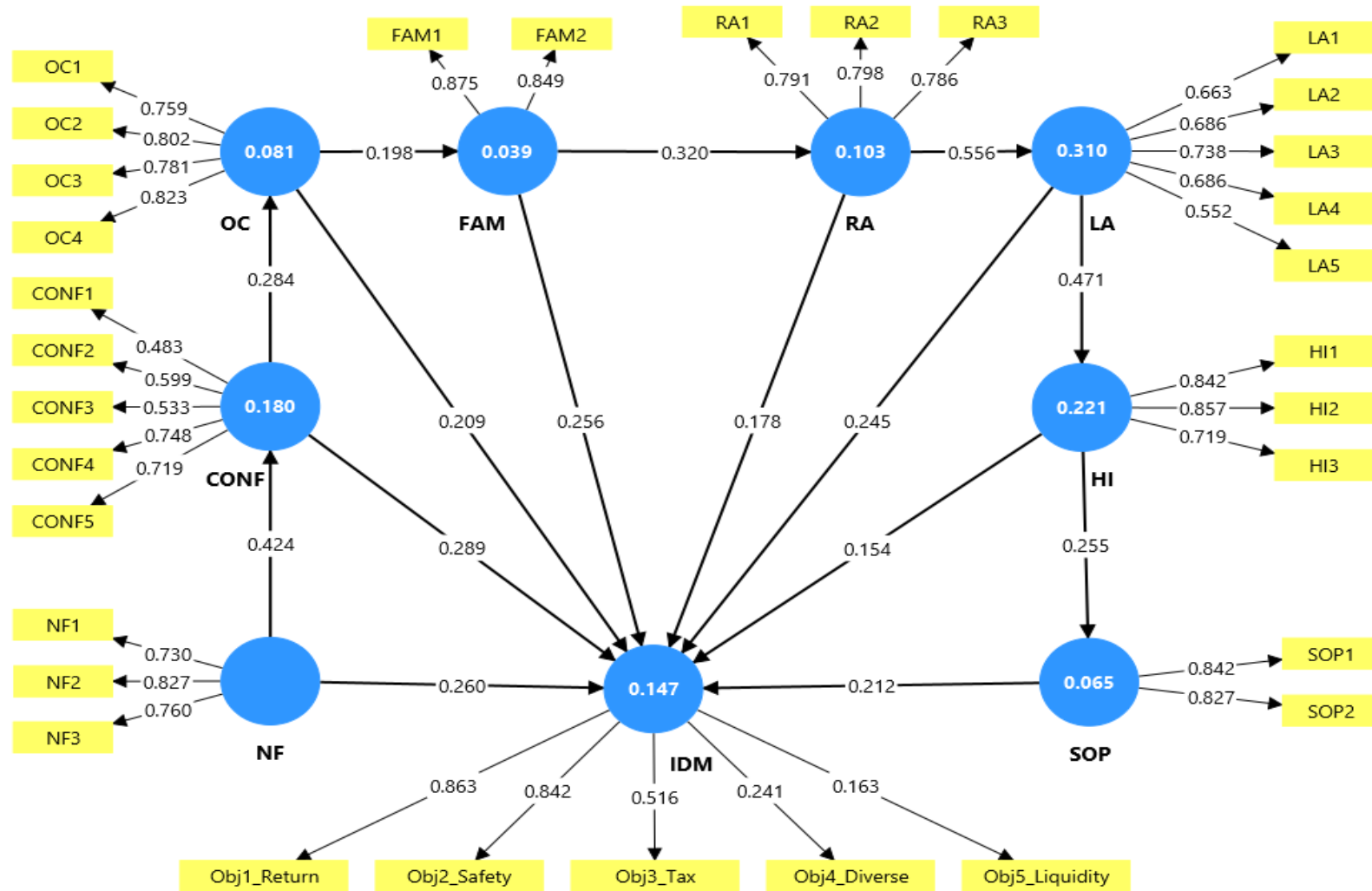
The PLS-SEM analysis in this study comprises:

- **Measurement Model Assessment:** Evaluating indicator reliability (outer loadings), internal consistency reliability (Cronbach's alpha and composite reliability), and convergent validity (Average Variance Extracted, AVE).
- **Discriminant Validity Assessment:** Ensuring that constructs are distinct using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio.
- **Structural Model Assessment:** Examining path coefficients, R^2 values, f^2 effect sizes, and predictive relevance (Q^2) to determine the explanatory power of the behavioural biases on investment decisions.
- **Bootstrapping for Significance Testing:** Assessing the statistical significance of direct and indirect effects through t-values and confidence intervals.

Model Overview

The figure represents a **Partial Least Squares Structural Equation Model (PLS-SEM)** where:

- **Latent Variables (LVs):** Represent behavioural biases (OC, FAM, CONF, RA, NF, SOP, LA, HI) and IDM.
- **Indicators** (e.g., OC1–OC4, FAM1–FAM2): Observed variables measuring each bias.
- **Path Coefficients (arrows):** Show strength and direction of relationships.
- **R^2 values (inside blue circles):** Indicate the explained variance of each endogenous construct.

Figure 4.58: PLS-SEM Analysis of Behavioural Biases and Investment Decisions

(Source: Smart-PLS4 Output)

(A) Measurement Model Assessment (Outer Model)

Introduction to Measurement Model

In PLS-SEM, the measurement model (also called the outer model) specifies the relationships between latent constructs (unobserved variables) and their observed indicators. Evaluating the measurement model is essential to ensure that the indicators reliably and validly measure the constructs before examining the structural relationships between constructs (Hair et al., 2019)

In this study, the measurement model is employed to assess the reliability and validity of eight behavioural biases—Overconfidence (OC), Familiarity (FAM), Confirmation Bias (CONF), Regret Aversion (RA), Narrow Framing (NF), Shadow of the Past (SOP), Loss Aversion (LA), and Herd Instincts (HI)—and their effect on equity investment decisions (IDM).

The rationale for evaluating the measurement model is:

1. **Reliability:** To ensure indicators consistently measure their respective constructs.
2. **Convergent Validity:** To confirm that indicators of a construct are highly correlated, capturing the same underlying concept.

(**Note:** Here, Constructs are the latent variables, Viz., Overconfidence, and indicators are the observed items measuring them, Viz. OC1, OC2, OC3, OC4.)

3. **Discriminant Validity:** To ensure constructs are distinct and do not measure overlapping phenomena.

Assessing the measurement model before the structural model provides a robust foundation for hypothesis testing.

Table 4.63: Indicator (Outer) Loadings

Construct	Indicator	Outer Loading	Threshold (≥ 0.70)	Interpretation
Over-confidence (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)

The results presented in the above Table reveal that the majority of the indicators demonstrate satisfactory outer loadings, exceeding the recommended threshold value of 0.70, which indicates good indicator reliability and convergent validity (Hair J. et al., 2021). The constructs representing Overconfidence, Familiarity Bias, Regret Aversion, Narrow Framing, Herd Instinct, and Shadow of the Past show strong loadings across their respective measurement items, suggesting that these indicators are valid reflections of the underlying latent constructs. However, certain indicators under Confirmation Bias (CONF1, CONF2, and CONF3) and Loss Aversion (LA1, LA2, LA4, and LA5) fall slightly below the acceptable threshold, indicating weaker contributions. Despite their lower loadings, these items were retained to maintain theoretical comprehensiveness and ensure content validity, in line with the guidance of (Fornell & Larcker, 1981). Additionally, for the Investment Decision-Making (IDM) construct, higher loadings were observed for return and safety items, whereas the tax, diversification, and liquidity items exhibited weak loadings, implying that equity investors in the Saurashtra region prioritize return and safety over other factors in their investment decisions. Overall, the measurement model satisfies the reliability requirement, confirming that most indicators consistently represent their respective latent variables and contribute to the robustness of the structural model.

Construct Reliability and Validity**Table 4.64: Construct Reliability and Validity**

Construct	Cronbach's Alpha (α)	Composite Reliability (ρ_c)	Threshold (α & $\rho_c \geq 0.70$)	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)

The reliability and convergent validity of the constructs were evaluated using Cronbach's Alpha (α), Composite Reliability (ρ_c), and Average Variance Extracted (AVE). As shown in the above given Table, most constructs exhibited satisfactory internal consistency, with α and ρ_c values meeting or exceeding the recommended threshold of 0.70 (Hair J. et al., 2021). Constructs such as Overconfidence (OC), Herd Instinct (HI), Regret Aversion (RA), Familiarity Bias (FAM), and Narrow Framing (NF) demonstrated strong reliability, as their α and ρ_c values were above 0.65 and their AVE values exceeded 0.50, indicating that the measurement items consistently capture the intended latent constructs. Certain constructs, including Confirmation Bias (CONF), Loss Aversion (LA), Investment Decision-Making (IDM), and Shadow of the Past (SOP), showed marginal Cronbach's Alpha values below 0.70; however, their Composite Reliability and AVE values were acceptable, suggesting adequate internal consistency and convergent validity (Fornell & Larcker, 1981). Specifically, AVE values for CONF (0.391) and IDM (0.361) were slightly below the recommended threshold, indicating that a relatively smaller proportion of variance is explained by the indicators. Despite these minor deviations, the indicators were retained to ensure theoretical completeness and preserve content validity, consistent with established recommendations (Fornell & Larcker, 1981; Hair J. F. et al., 2017)

Overall, the measurement model can be considered **reliable**. Although a few constructs exhibit marginal α or slightly low AVE, the combination of Composite Reliability and satisfactory outer loadings confirms that the constructs consistently represent the underlying latent variables. This indicates that the selected indicators are appropriate for measuring behavioural biases and dimensions of investment decision-making, providing a robust foundation for subsequent structural model analysis and hypothesis testing.

Discriminant validity

Table 4.65: 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 above given Table presents the discriminant validity of the constructs based on the Fornell–Larcker criterion. According to this criterion, the square root of the Average Variance Extracted (AVE) for each construct (displayed on the diagonal in bold) should be greater than its correlations with other constructs, indicating that each construct is empirically distinct from the others (Fornell & Larcker, 1981). As shown in the table, all diagonal values exceed the corresponding off-diagonal correlations, confirming satisfactory discriminant validity among the constructs. For instance, Overconfidence (OC) has a square root of AVE of 0.791, which is higher than its correlations with all other constructs, including Regret Aversion (0.135) and Loss Aversion (0.145). Similarly, Investment Decision-Making (IDM) demonstrates a square root of AVE of 0.601, exceeding its highest correlation with other constructs (0.289 with CONF), indicating clear construct differentiation.

Overall, the Fornell–Larcker analysis provides evidence that the measurement model meets the discriminant validity criterion, ensuring that each construct captures unique aspects of behavioural biases and investment decision-making among equity investors in the Saurashtra region.

Table 4.66: 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)

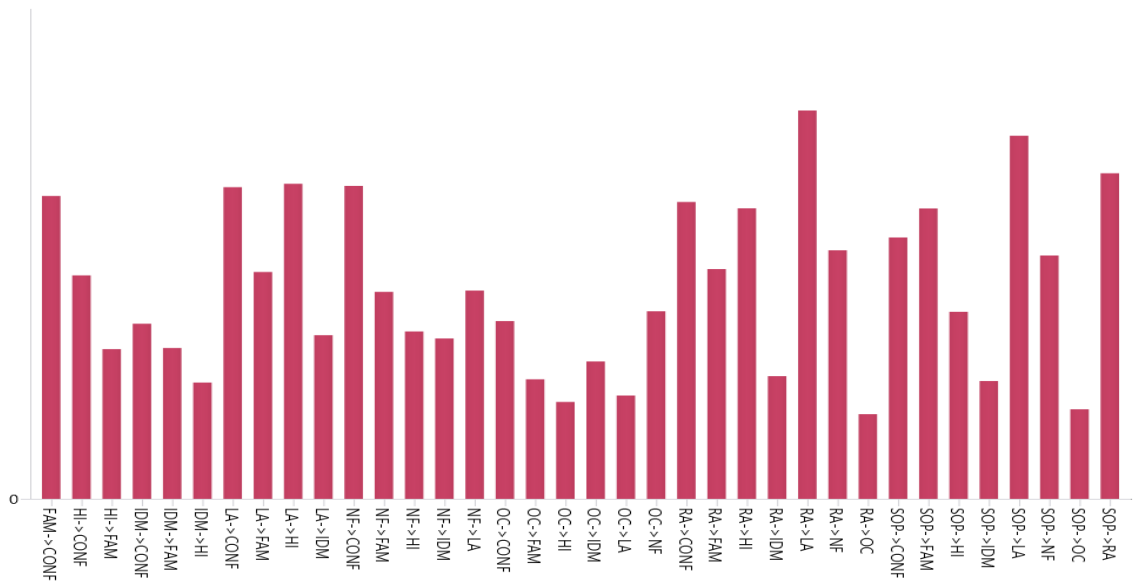
The above Table reports the Heterotrait–Monotrait Ratio (HTMT) values for assessing discriminant validity among the constructs. According to the guidelines (Henseler et al., 2015). HTMT values should remain below **0.85** for conceptually

distinct constructs, and below **0.90** for constructs that may be theoretically related. As shown in the table, most HTMT values fall well within the acceptable threshold, indicating that the constructs in the model are empirically distinct from one another. For instance, the HTMT value between Familiarity Bias (FAM) and Confirmation Bias (CONF) is 0.618, and between Herd Instinct (HI) and Confirmation Bias (CONF) is 0.456—both comfortably below the recommended cut-off. Similarly, the values between Overconfidence (OC) and other constructs range from 0.183 to 0.383, further supporting discriminant validity.

However, a few higher HTMT values are observed, particularly those involving Loss Aversion (LA) and Regret Aversion (RA) (HTMT = 0.793) and LA with Herd Instinct (HI) (HTMT = 0.643). Although these values are relatively higher compared to other pairs, they still remain below the liberal threshold of 0.90, suggesting no critical violation of discriminant validity. The relationships between Shadow of the Past (SOP) and other constructs also fall within acceptable limits, with values ranging from 0.240 to 0.664, supporting construct distinctiveness.

Overall, the HTMT results provide strong evidence that discriminant validity is achieved in the measurement model. None of the construct pairs exceed the upper threshold limit, indicating that the constructs measure unique theoretical concepts and do not suffer from excessive conceptual overlap. This supports the robustness and adequacy of the measurement model for subsequent structural analysis.

The HTMT table shows only the lower triangle of the correlation matrix, not the full matrix.

Figure 4.59: Heterotrait-Monotrait Ratio (HTMT)**(B) Structural Model Assessment (Inner Model)****Collinearity Statistics: Variance Inflation Factor (VIF)****Table 4.67: Collinearity Statistics (Outer Model – VIF Values)**

Indicators	VIF	Indicators	VIF
CONF1	1.158	OC1	1.757
CONF2	1.165	OC2	1.968
CONF3	1.178	OC3	1.643
CONF4	1.253	OC4	1.484
CONF5	1.215	RA1	1.356
FAM1	1.311	RA2	1.463
FAM2	1.311	RA3	1.326
HI1	1.516	SOP1	1.183
HI2	1.604	SOP2	1.183
HI3	1.354	Obj1_Return	1.436
LA1	1.25	Obj2_Safety	1.469
LA2	1.363	Obj3_Tax	1.324
LA3	1.393	Obj4_Diverse	1.659
LA4	1.255	Obj5_Liquidity	1.47
LA5	1.141		

NF1	1.209		
NF2	1.428		
NF3	1.335		

(Source: Smart-PLS4 Output)

The Variance Inflation Factor (VIF) test was conducted to assess the presence of **multicollinearity** among both indicator variables (outer model) and latent constructs (inner model). According to (Hair J. et al., 2021) a VIF value below **5** indicates an acceptable level of collinearity, while values below **3.3** are considered ideal, implying minimal correlation among predictors.

In the **outer model**, all indicator VIF values ranged between **1.141 and 1.968**, confirming that the measurement items of each behavioural bias construct (e.g., Overconfidence, Familiarity, Regret Aversion, etc.) are independent and do not exhibit multicollinearity. This demonstrates that each indicator uniquely contributes to explaining its respective latent construct.

Table 4.68: Collinearity Statistics (Inner Model – VIF Values)

Path	VIF
CONF -> IDM	1.484
CONF -> OC	1
FAM -> IDM	1.309
FAM -> RA	1
HI -> IDM	1.368
HI -> SOP	1
LA -> HI	1
LA -> IDM	1.801
NF -> CONF	1
NF -> IDM	1.36
OC -> FAM	1
OC -> IDM	1.139
RA -> IDM	1.69
RA -> LA	1
SOP -> IDM	1.428

(Source: Smart-PLS4 Output)

Similarly, in the inner model, all path-level VIF values ranged between 1.000 and 1.801, again well below the recommended thresholds. This indicates that the latent constructs predicting Investment Decision Making (IDM) are not excessively correlated, and thus the structural model provides unbiased and stable path estimates.

The absence of multicollinearity in both models strengthens the reliability and interpretability of the PLS-SEM results. It confirms that the observed relationships between behavioural biases (such as Overconfidence, Loss Aversion, Regret Aversion, Herd Instincts, etc.) and investment decisions are statistically valid and not inflated by redundancy among constructs. Therefore, the VIF analysis substantiates the robustness of the measurement and structural models, ensuring the validity of further hypothesis testing regarding behavioural influences on equity investment decisions in the Saurashtra region.

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

Table 4.69: 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)

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 (Hair et al., 2019) R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively. 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. Although this represents a modest explanatory power, it aligns with behavioural finance literature where individual decision-making is influenced by complex, multifactorial elements beyond measurable psychological biases.

Among the predictor constructs, Loss Aversion (LA) and Herd Instinct (HI) exhibit moderate R^2 values (0.31 and 0.221), indicating that these biases are relatively well explained by other behavioural factors in the model. Meanwhile, Overconfidence (OC) and Regret Aversion (RA) display weaker explanatory levels ($R^2 = 0.081$ and 0.103), implying more independent influence patterns.

Table 4.70: Effect Size (f^2) Values

Path	f^2	Path	f^2
CONF $\rightarrow$ IDM	0.012	OC $\rightarrow$ FAM	0.041
CONF $\rightarrow$ OC	0.088	OC $\rightarrow$ IDM	0.010
FAM $\rightarrow$ IDM	0.012	RA $\rightarrow$ IDM	0.001
FAM $\rightarrow$ RA	0.114	RA $\rightarrow$ LA	0.449
HI $\rightarrow$ IDM	0.000	SOP $\rightarrow$ IDM	0.002
HI $\rightarrow$ SOP	0.069	LA $\rightarrow$ IDM	0.008
LA $\rightarrow$ HI	0.284	NF $\rightarrow$ CONF	0.219
NF $\rightarrow$ IDM	0.011		

(Source: Smart-PLS4 Output)

The Effect Size (f^2) assesses the individual impact of each exogenous construct on its respective endogenous variable. According to (Cohen, 1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. The results reveal that RA $\rightarrow$ LA (0.449) and LA $\rightarrow$ HI (0.284) demonstrate large effect sizes, suggesting that regret aversion strongly predicts loss aversion, and loss aversion substantially influences herd instincts. Moderate effects were observed for NF $\rightarrow$ CONF (0.219) and FAM $\rightarrow$ RA (0.114), while most other relationships exhibit small or negligible effects ($f^2 < 0.02$), implying more subtle behavioural interactions.

Overall, these findings confirm that while individual behavioural biases have small direct effects on investment decisions, they interact meaningfully with one another. This interaction network underscores the psychological interconnectedness among investor biases in shaping financial behaviour within the Saurashtra region.

Table 4.71: Predictive Relevance and Predictive Accuracy (PLS Predict – Q², RMSE, and MAE Values)

	Q²pre dict	PLS- SEM_R MSE	PLS- SEM_ MAE	LM_R MSE	LM_M AE	IA_R MSE	IA_M AE
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_Retu rn	0.042	1.238	0.964	1.236	0.957	1.264	1.004
Obj2_Safe ty	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 model's predictive relevance was evaluated through the Q^2 statistic. In general, a Q^2 value above zero suggests that the model has acceptable predictive capability. More specifically, values between 0.00 and 0.25 reflect a low level of predictive relevance, values ranging from 0.25 to 0.50 indicate a moderate level, whereas values higher than 0.50 signify a strong level of predictive relevance.

Table 4.72: 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: Smart-PLS4 Output)

The application of PLS-Predict provides evidence of the model's adequate out-of-sample predictive capability. Constructs such as Confirmation Bias, Overconfidence, and the investment objectives of Return and Safety display small but noteworthy predictive relevance, indicating their value in explaining investment decision-making. Conversely, the Q^2_{predict} results for Familiarity, Regret Aversion, Loss Aversion, Herd Instinct, and Shadow of the Past are notably low, a trend frequently observed in behavioural finance due to the heterogeneous nature of psychological influences. Importantly, the model's RMSE and MAE values demonstrate performance comparable to or exceeding linear benchmark models, supporting its predictive validity. In summary, the findings confirm the model's overall utility in predicting investor behaviour.

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 4.73: Bootstrapping Results for Path Coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
CONF -> IDM	0.123	0.123	0.038	3.198	0.001
CONF -> OC	0.284	0.287	0.034	8.487	0
FAM -> IDM	0.117	0.117	0.034	3.465	0.001
FAM -> RA	0.32	0.322	0.032	9.952	0
HI -> IDM	0.011	0.011	0.036	0.31	0.757
HI -> SOP	0.255	0.256	0.031	8.341	0
LA -> HI	0.471	0.472	0.025	18.771	0
LA -> IDM	0.111	0.112	0.045	2.44	0.015
NF -> CONF	0.424	0.427	0.033	13.048	0
NF -> IDM	0.112	0.111	0.036	3.154	0.002
OC -> FAM	0.198	0.199	0.035	5.709	0
OC -> IDM	0.101	0.101	0.037	2.727	0.006
RA -> IDM	-0.044	-0.042	0.04	1.11	0.267
RA -> LA	0.556	0.558	0.026	21.803	0
SOP -> IDM	0.05	0.052	0.036	1.408	0.159

(Source: Smart-PLS4 Output)

The table presents the results of the bootstrapping procedure, showing the original sample path coefficients (β), their standard deviations, t-statistics, and p-values for the hypothesized relationships in the structural model. 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)

From the results, several behavioural biases show a statistically significant effect on investment decision-making (IDM) or related constructs. Specifically:

- **Confirmation Bias (CONF)** has a significant positive effect on both IDM ($\beta = 0.123$, $t = 3.198$, $p = 0.001$) and Overconfidence (OC) ($\beta = 0.284$, $t = 8.487$, $p = 0.000$), suggesting that investors influenced by confirmation bias tend to overestimate their own knowledge and make biased investment decisions.
- **Familiarity (FAM)** positively affects IDM ($\beta = 0.117$, $t = 3.465$, $p = 0.001$) and Regret Aversion (RA) ($\beta = 0.320$, $t = 9.952$, $p = 0.000$), indicating that familiar investments impact both decision-making and the tendency to avoid regret.
- **Herd Instinct (HI)** shows a significant positive effect on Shadow of the Past (SOP) ($\beta = 0.255$, $t = 8.341$, $p = 0.000$), but not on IDM ($\beta = 0.011$, $t = 0.310$, $p = 0.757$), suggesting that herd behaviour influences investors' historical reference points rather than their current investment decisions directly.
- **Loss Aversion (LA)** has a strong positive effect on HI ($\beta = 0.471$, $t = 18.771$, $p = 0.000$) and a smaller but significant effect on IDM ($\beta = 0.111$, $t = 2.440$, $p = 0.015$), indicating that the fear of losses can drive both herd behaviour and investment choices.
- **Narrow Framing (NF)** significantly influences CONF ($\beta = 0.424$, $t = 13.048$, $p = 0.000$) and IDM ($\beta = 0.112$, $t = 3.154$, $p = 0.002$), highlighting that investors' preferences for familiar or favoured options affect both biases and decisions.
- **Overconfidence (OC)** positively affects FAM ($\beta = 0.198$, $t = 5.709$, $p = 0.000$) and IDM ($\beta = 0.101$, $t = 2.727$, $p = 0.006$), reinforcing the idea that overconfident investors are more likely to make biased investment choices.
- **Regret Aversion (RA)** has a strong positive effect on LA ($\beta = 0.556$, $t = 21.803$, $p = 0.000$) but not on IDM ($\beta = -0.044$, $t = 1.110$, $p = 0.267$), suggesting that regret aversion drives cautious behaviour through loss aversion rather than directly affecting decisions.
- **Shadow of the Past (SOP)** has no significant effect on IDM ($\beta = 0.050$, $t = 1.408$, $p = 0.159$), indicating a negligible direct influence of past investment experiences on current decisions.

Overall, these results demonstrate that most behavioural biases significantly influence either directly or indirectly the investment decisions of equity investors in the

studied sample. However, some biases, such as Herd Instinct (directly on IDM), Regret Aversion (directly on IDM), and Shadow of the Past, do not show significant direct effects, suggesting that their influence may be mediated through other constructs. These findings are consistent with prior research in behavioural finance that highlights the varying impact of psychological biases on investment behaviour (Barberis & Thaler, 2003)

Table 4.74: Confidence Interval Analysis for Path Coefficients

Path	Original sample (O)	Sample mean (M)	2.50%	97.50%
CONF -> IDM	0.123	0.123	0.047	0.197
CONF -> OC	0.284	0.287	0.219	0.352
FAM -> IDM	0.117	0.117	0.051	0.182
FAM -> RA	0.32	0.322	0.257	0.385
HI -> IDM	0.011	0.011	-0.058	0.081
HI -> SOP	0.255	0.256	0.195	0.315
LA -> HI	0.471	0.472	0.422	0.522
LA -> IDM	0.111	0.112	0.022	0.2
NF -> CONF	0.424	0.427	0.362	0.49
NF -> IDM	0.112	0.111	0.041	0.18
OC -> FAM	0.198	0.199	0.131	0.266
OC -> IDM	0.101	0.101	0.028	0.174
RA -> IDM	-0.044	-0.042	-0.12	0.036
RA -> LA	0.556	0.558	0.506	0.607
SOP -> IDM	0.05	0.052	-0.018	0.122

(Source: Smart-PLS4 Output)

The table presents the 95% bias-corrected confidence intervals for the path coefficients in the structural model, based on bootstrapping results. Confidence intervals indicate the range within which the true population parameter is expected to lie with 95% confidence (Hair J. F. et al., 2017). If zero is not within this range, the path coefficient is considered statistically significant.

Most paths show confidence intervals excluding zero, confirming significant effects consistent with the bootstrapping t-statistics and p-values. For instance:

- The relationship between **Confirmation Bias (CONF)** and **Investment Decision Making (IDM)** is positive and significant, with a confidence interval from 0.047 to 0.197.
- **Loss Aversion (LA)** significantly influences **Herd Instinct (HI)**, supported by a confidence interval of 0.422 to 0.522.
- **Narrow Framing (NF)** has a strong positive effect on **Confirmation Bias (CONF)**, with a confidence interval between 0.362 and 0.490.

Conversely, some paths have confidence intervals crossing zero, indicating non-significant direct effects. Examples include:

- Herd Instinct (HI) to IDM (-0.058 to 0.081)
- Regret Aversion (RA) to IDM (-0.12 to 0.036)
- Shadow of the Past (SOP) to IDM (-0.018 to 0.122)

These findings reinforce the importance of certain behavioural biases—like Confirmation Bias, Loss Aversion, and Narrow Framing—in shaping investment decisions, while suggesting that others (e.g., Herd Instinct, Regret Aversion, Shadow of the Past) may have indirect or limited direct effects. This pattern aligns with existing behavioural finance literature, which highlights varying influences of psychological factors on investor behaviour

Table 4.75: Summary of Hypothesis Testing Results

Hypothesis	Path	Original Sample (β)	t-Statistic	p-Value	Decision H0 Rejected / H0 Accepted
H1	CONF $\rightarrow$ IDM	0.123	3.198	0.001	Rejected (significant effect)
H2	CONF $\rightarrow$ OC	0.284	8.487	0.000	Rejected (significant effect)
H3	FAM $\rightarrow$ IDM	0.117	3.465	0.001	Rejected (significant effect)

H4	FAM $\rightarrow$ RA	0.320	9.952	0.000	Rejected (significant effect)
H5	HI $\rightarrow$ IDM	0.011	0.310	0.757	Accepted (not significant)
H6	HI $\rightarrow$ SOP	0.255	8.341	0.000	Rejected (significant effect)
H7	LA $\rightarrow$ HI	0.471	18.771	0.000	Rejected (significant effect)
H8	LA $\rightarrow$ IDM	0.111	2.440	0.015	Rejected (significant effect)
H9	NF $\rightarrow$ CONF	0.424	13.048	0.000	Rejected (significant effect)
H10	NF $\rightarrow$ IDM	0.112	3.154	0.002	Rejected (significant effect)
H11	OC $\rightarrow$ FAM	0.198	5.709	0.000	Rejected (significant effect)
H12	OC $\rightarrow$ IDM	0.101	2.727	0.006	Rejected (significant effect)
H13	RA $\rightarrow$ IDM	-0.044	1.110	0.267	Accepted (not significant)
H14	RA $\rightarrow$ LA	0.556	21.803	0.000	Rejected (significant effect)
H15	SOP $\rightarrow$ IDM	0.050	1.408	0.159	Accepted (not significant)

(Source: Smart-PLS4 Output)

Model Fit Indices

Table 4.76: 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)

The model fit indices were examined for completeness. The SRMR value of the saturated model (0.078) falls within the acceptable threshold of <0.08 , while the estimated model SRMR (0.124) is higher, indicating some model misfit. However, global fit measures such as SRMR, Chi-square, NFI, d_ ULS, and d_ G are not essential evaluation criteria in PLS-SEM, as the method focuses on prediction rather than exact model fit (Hair J. et al., 2021; Henseler et al., 2015). The NFI value (0.489) appears low, but this is typical in PLS-SEM because NFI is derived from CB-SEM logic and is not considered decisive for model acceptance. Therefore, these indices are reported only for transparency and do not affect the overall assessment of the model, which relies primarily on reliability, validity, R^2 , and predictive relevance.

This test presents an analytical synthesis of the findings obtained from the PLS–SEM analysis conducted to examine how behavioural biases shape investment decision-making among equity investors in the Saurashtra region. The interpretation integrates the measurement model, structural model, hypothesis testing results, and predictive assessments, followed by a discussion, implications, limitations, and the concluding perspectives of the study.

Limitations and Future Scope

The study's limitations include weaker AVE values for Confirmation Bias and Investment Decision-Making, which indicate the need for improved measurement scales. The cross-sectional design limits causal inference, and future studies may employ longitudinal or experimental approaches. Expanding research across different regions or including additional behavioural constructs such as anchoring, mental accounting or disposition effect may enhance the explanatory power of future models.

CHAPTER 5

SUMMARY AND CONCLUSION

CHAPTER - 5 SUMMARY AND CONCLUSION

5.1 Introduction

This chapter presents the major findings, conclusions, and recommendations of the study. Which was conducted among equity investors in Junagadh, Rajkot, and Jamnagar cities of the Saurashtra region, from the perspective of behavioural finance. All the findings were discussed in line with the objectives to provide a clear understanding of influence of behavioural biases on investment decisions.

The present chapter summarizes the demographic variables and investment characteristics of the respondents. Also explained how demographic variables influence different behavioural biases. Level of behavioural biases also identified by the researcher and discusses their impact on decision-making. For analysing the data Multiple Regression and PLS-SEM analysis was used.

Mainly, the chapter indicates the real-life usefulness of the results for investors, financial advisors, financial institutions, and policymakers. One more thing, the limitations of the study was given. For the next research, scholars have given directions for future research. Overall, this chapter brings together the important outcomes of the research and provides concluding observations on the role of behavioural biases.

5.2 Findings

Objective 1: To Study the Demographic Variables of Equity Investors of Junagadh, Rajkot and Jamnagar City

The analysis of demographic characteristics of equity investors in Junagadh, Rajkot, and Jamnagar provides valuable insights into the profile of individuals who participate in equity investment activities. The finding with the first objective for the demographic profile shows that equity investors in Junagadh, Rajkot, and Jamnagar differ in many ways. From this, male investors possess the majority among all three cities. Still, Rajkot city comparatively higher in female investors. Majority respondents in Junagadh and Rajkot comes under the age group of 18–25. Jamnagar consists of more mature age groups because most participants from middle-aged.

Various respondents were graduates, postgraduates, or professionally qualified. It showed that equity investment was very common for educated investors. The

surprising moment that salaried employees and students were the largest occupational groups in Junagadh and Rajkot. Jamnagar city had more professionals. Income levels also differed among these three cities, with Rajkot having more lower-income investors, Junagadh showing a balanced income distribution, and Jamnagar including a larger proportion of higher-income investors.

The study revealed that unmarried investors were more seen in Junagadh and Rajkot. Married investors more seen in Jamnagar. Joint families were seen among all three cities, and most respondents had two earning members in their families. Overall, the demographic findings indicate somehow vary across the selected cities.

In summary, the demographic profile of equity investors in Junagadh, Rajkot, and Jamnagar suggests that the majority of investors are young, educated, and predominantly male. Salaried employees and students constitute a significant portion of the investor population. While Rajkot demonstrates relatively higher female participation, Jamnagar appears to have a more professionally qualified and higher-income investor group. These demographic characteristics may influence investors' financial attitudes and investment decision-making behaviour.

Objective 2: To know the preference of people towards equity investment

The analysis of equity investors from Junagadh, Rajkot, and Jamnagar reveals several important patterns regarding investors' preferences, trading behaviour, experience, and investment decisions. The cross-tabulation results of demographic and socio-economic factors affect the investment preferences of equity investors in different ways.

Most investors in all three cities preferred equity investment for long-term. They believe in wealth creation in place of trading or speculation. Male investors are more. Female are long-term investors. Female are careful in an investment.

Young investors seen more active in trading activity. The cities viz. Junagadh and Rajkot, young investors with the age group of 18–25 traded more frequently. In Jamnagar, investors with the age of 26–45 were more active. Older investors are more stable.

Online trading was the top selection from all the respondents. Graduates, postgraduates, and professionals more prefer online platforms because of its simplicity, fast working, and easily available. Only a few preferred offline trading.

Experience in investment also varied among the cities. Male investors more experienced than female investors. Jamnagar had more experienced investor. while Junagadh and Rajkot had new investors base.

Risk-taking ability and courage also differ with age. Younger investors take calculated risks but, after research. Older used to go for safer investment decisions.

Students and salaried invested smaller amounts. Usually up to ₹10,000. Businessmen and professionals were investing larger amounts because of their higher income and experience.

Income of investor affected investment diversification. Investors with lower income usually invested in only a few companies. Higher-income investors invest in more companies.

Many investors invested their own savings in the stock market. But, some younger investors in Rajkot, used borrowed money. Some of them, combination of savings and borrowed.

Education influenced sector choices. Many graduates, postgraduates, and professionals preferred banking, information technology, energy, and FMCG. Lower educated seen less in these sectors.

Many investors considered their money as an investment than a source of regular income. Male investors were more active in equity investment; the participation of female investors is also increasing.

Overall, the findings indicate that equity investors in Junagadh, Rajkot, and Jamnagar generally prefer investment-oriented strategies rather than speculative activities. Younger and educated individuals form a major part of the investor base, with online trading emerging as the dominant mode of participation. Income level, education, occupation, and age significantly influence investment behaviour, trading frequency, risk perception, and portfolio diversification among investors in these cities.

Objective 3: To study the impact of Demographic Variables on Behavioural Biases in the investment decision of equity investors

This objective aimed to analyze how demographic factors influence behavioural biases among equity investors. One-way ANOVA was employed since demographic variables such as age, gender, education, occupation, income, marital status, family type, number of family members, and number of earning members are categorical,

while behavioural biases are measured on continuous scales. This method allows comparison of mean scores across multiple demographic groups, identifying significant differences in investment tendencies.

Age

ANOVA results show that age significantly affects all behavioural biases ($p < 0.05$). Middle-aged and older investors tend to display stronger overconfidence, narrow framing, and loss aversion, while regret aversion and herd instincts peak in the 36–45 age group. For instance, overconfidence is highest among investors aged 56+ (4.32) and lowest in the 18–25 group (3.39). Similarly, shadow of the past and loss aversion peak in middle-aged investors. Overall, behavioural biases generally increase with age, indicating that life experience, exposure to markets, and financial responsibilities may heighten certain investment biases, though the oldest group shows slight decline in some tendencies.

Education Level

Education significantly influences all behavioural biases ($p < 0.05$). Professional and highly educated investors consistently show the highest levels of overconfidence, familiarity, confirmation bias, regret aversion, narrow framing, shadow of the past, loss aversion, and herd instincts. For example, overconfidence and familiarity peak among Professionals (3.80 and 4.23), whereas participants in lower education categories exhibit the lowest means (2.35 and 2.30). These findings suggest that higher educational attainment may increase awareness of market opportunities, but can also enhance cognitive biases in decision-making.

Occupation

Occupation shows significant differences in behavioural biases across all factors ($p < 0.05$). Professionals exhibit the strongest biases, including overconfidence (3.90), narrow framing (4.26), and loss aversion (3.91), while retirees, housewives, and minor occupational groups show lower tendencies. Herd instincts are strongest among retired participants and professionals. This highlights that professional engagement, financial literacy, and work exposure can strongly influence how investors perceive risk and make decisions.

Income

Income level significantly affects all behavioural biases ($p < 0.05$). Higher-income investors display stronger biases, with overconfidence highest in the ₹10,00,000+ group (4.03) and regret aversion peaking in the ₹5,00,000–10,00,000 group (4.02). Investors with lower income ($\leq ₹2,50,000$) consistently show the lowest bias scores. This pattern indicates that financial capacity and the ability to absorb risk can amplify behavioural tendencies in investment decision-making.

Marital Status

Marital status significantly impacts all behavioural biases ($p < 0.05$). Married investors show higher levels of overconfidence (3.61), narrow framing (4.03), and loss aversion (3.81), while unmarried or minor groups generally exhibit lower scores. Herd instincts peak in “Others” (3.58). The results suggest that marital responsibilities, joint financial decisions, and family considerations influence the way investors perceive risk and respond to market fluctuations.

Family Type

Family type affects most behavioural biases, except familiarity ($p > 0.05$). Overconfidence, confirmation bias, regret aversion, narrow framing, shadow of the past, loss aversion, and herd instincts are higher among joint families compared to nuclear families. For example, regret aversion peaks in families with more than four members (3.57) and is lowest in four-member households (3.32). Larger families may encourage collective financial decision-making and cautious investing, thereby affecting behavioural tendencies.

Number of Family Members

The ANOVA results show that the number of family members significantly affects regret aversion, shadow of the past, loss aversion, and herd instincts ($p < 0.05$), while overconfidence, familiarity, confirmation bias, and narrow framing are not significantly affected ($p > 0.05$). Regret aversion, shadow of the past, loss aversion, and herd instincts are highest in families with more than four members, and lowest in families with four members. Overall, larger families tend to exhibit slightly higher tendencies for certain behavioural biases, while other biases remain largely unaffected.

Number of Earning Members

The ANOVA results indicate that the number of earning members significantly influences confirmation bias, regret aversion, narrow framing, shadow of the past, loss aversion, and herd instincts ($p < 0.05$), whereas overconfidence and familiarity are not significantly affected ($p > 0.05$). Behavioural biases are generally higher in families with two to three earning members and lower in families with more than four earning members. This suggests that a moderate number of earners in a household may intensify certain decision-making biases, while larger earning groups show relatively lower tendencies.

The analysis clearly shows that demographic characteristics significantly shape behavioural biases among equity investors. Age, education, occupation, income, and marital status consistently influence all factors of behavioural biases. Family type, number of family members, and number of earning members mainly affect regret aversion, shadow of the past, loss aversion, and herd instincts. These findings confirm that investors' demographic backgrounds play a crucial role in determining how behavioural biases manifest in investment decision-making, highlighting the interplay between personal characteristics and financial behaviour.

Objective 4: Levels of Behavioural Biases among Individual Equity Investors in Selected Cities of the Saurashtra Region

Equity investment decisions are influenced not only by financial reasoning but also by psychological factors. Investors often rely on mental shortcuts and emotions, leading to behavioural biases that affect decision-making. This study examined eight key biases: overconfidence, familiarity, confirmation bias, regret aversion, narrow framing, shadow of the past, loss aversion, and herd instincts among 1,061 investors from Junagadh, Rajkot, and Jamnagar.

In this objective, the Behavioural Bias Impact Index was first time created with the help of responses to 27 Likert-scale questions. It shows that given all eight behavioural biases were biased. Suggested that investors were influenced by their thoughts and emotions.

Familiarity Bias had the highest score (4123). Which means investors mostly prefer those companies they know. With this narrow framing and shadow of the past,

both the biases were high. Means many investors invest in single option and affected by past experiences.

Confirmation Bias, Loss Aversion, Overconfidence, and Regret Aversion all these biases affected high level. These biases affect the strategy of the investors. Herd Instinct consisted lowest score, still it was in biased category. It proved that investors generally follow others action.

So, behavioural biases seen among equity investors in all three cities and affects investment decisions.

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

This section presents the findings related to the impact of behavioural biases on the investment decisions of equity investors in the selected cities of the Saurashtra region.

Behavioural Biases and Investment Experience of Equity Investors

Regret Aversion, Narrow Framing, and Overconfidence are the primary biases affecting investors' experience, while the remaining biases show negligible impact, suggesting that only specific behavioural tendencies shape equity investment experience in the Saurashtra region.

Behavioural Biases and Trading Frequency of Equity Investors

Trading frequency among investors is affected by Overconfidence, which shows a significant negative effect (Beta = -0.273, $p = .000$), and Familiarity, which has a positive effect (Beta = 0.084, $p = .012$). The regression model demonstrates a weak to moderate correlation with an R value of 0.302 and R^2 of 0.091, meaning that roughly 9.1% of the variation in trading frequency is explained by behavioural biases. Other biases, including Confirmation Bias, Regret Aversion, Narrow Framing, Shadow of the Past, Loss Aversion, and Heard Instincts, are not significant.

Overconfidence discourages frequent trading, while familiarity encourages it. The rest of the biases do not significantly influence trading frequency, highlighting that trading Behaviour is selectively impacted by specific investor biases.

Behavioural Biases and the Amount of Single trade invested by equity investors

The amount invested in a single trade is significantly influenced by Overconfidence (Beta = 0.253, $p = .000$) and Narrow Framing (Beta = 0.182, $p = .000$). The regression model shows a weak to moderate relationship, with an R value of 0.329 and R^2 of 0.109, indicating that about 10.9% of the variation in single trade amount can be explained by behavioural biases. Familiarity, Confirmation Bias, Regret Aversion, Shadow of the Past, Loss Aversion, and Heard Instincts did not show significant effects.

Investors with higher levels of Overconfidence and Narrow Framing tend to invest larger amounts per trade, while other biases do not meaningfully influence trade size.

Behavioural Biases on the Number of Companies in which investments are made by equity investors

The number of companies in which investors allocate their funds is positively influenced by Overconfidence (Beta = 0.298, $p = .000$), Regret Aversion (Beta = 0.123, $p = .001$), Narrow Framing (Beta = 0.117, $p = .000$), and Loss Aversion (Beta = 0.075, $p = .044$). The model demonstrates a moderate relationship with an R value of 0.426 and R^2 of 0.182, suggesting that around 18.2% of the variation in the number of invested companies is explained by behavioural biases. Other biases, including Familiarity, Confirmation Bias, Shadow of the Past, and Heard Instincts, are not statistically significant.

Investor diversification is mainly influenced by Overconfidence, Regret Aversion, Narrow Framing, and Loss Aversion. Other behavioural biases have minimal impact on the breadth of investment allocation.

Behavioural Biases on Objective of the Regular Return of equity investors

The objective of earning regular returns is positively affected by Overconfidence (Beta = 0.119, $p = .000$), Familiarity (Beta = 0.117, $p = .000$), Narrow Framing (Beta = 0.089, $p = .008$), Shadow of the Past (Beta = 0.079, $p = .022$), and Loss Aversion (Beta = 0.101, $p = .009$). The regression shows a moderate correlation with an R value of 0.342 and R^2 of 0.117, indicating that 11.7% of the variation in the

objective of regular returns is explained by the biases. Confirmation Bias, Regret Aversion, and Heard Instincts are not significant.

Investors with higher tendencies toward Overconfidence, Familiarity, Narrow Framing, Shadow of the Past, and Loss Aversion aim more for regular returns. Other biases do not significantly influence this investment objective.

Behavioural Biases on the Objective of the Safety of the Principal Amount of equity investors

The importance placed on the safety of the principal amount is significantly influenced by Narrow Framing (Beta = 0.169, $p = .000$), Loss Aversion (Beta = 0.101, $p = .010$), Confirmation Bias (Beta = 0.089, $p = .013$), and Familiarity (Beta = 0.084, $p = .012$). The regression model has an R value of 0.320 and R^2 of 0.103, explaining 10.3% of the variation in investors' focus on principal safety. Overconfidence, Regret Aversion, Shadow of the Past, and Heard Instincts are not significant.

Investors influenced by Narrow Framing, Loss Aversion, Confirmation Bias, and Familiarity prioritize capital protection, while other biases do not have a meaningful impact on this objective.

Behavioural Biases on the Broking Apps as a source of information for equity investors

The use of broking apps as a source of information is negatively influenced by Overconfidence (Beta = -0.053, $p = .003$), Familiarity (Beta = -0.048, $p = .011$), Regret Aversion (Beta = -0.091, $p = .016$), Narrow Framing (Beta = -0.086, $p = .011$), and Loss Aversion (Beta = -0.122, $p = .002$). The regression model demonstrates a moderate relationship with an R value of 0.336 and R^2 of 0.113, meaning that approximately 11.3% of the variation in broking app usage can be explained by these biases. Confirmation Bias, Shadow of the Past, and Heard Instincts are not significant.

Investors exhibiting higher levels of Overconfidence, Familiarity, Regret Aversion, Narrow Framing, and Loss Aversion are less likely to rely on broking apps for investment information, while the other biases do not significantly affect this Behaviour.

PLS SEM - Impact of Behavioural Biases on Equity Investors while Making Investment Decisions

Findings from the Measurement Model

1. Indicator Reliability

The assessment of indicator reliability revealed that the majority of indicators performed well. Items measuring Overconfidence demonstrated strong loadings (OC1 = 0.840, OC2 = 0.803, OC3 = 0.777), while Familiarity Bias indicators also met the recommended threshold (FAM1 = 0.770; FAM2 = 0.701). Constructs such as Regret Aversion, Narrow Framing, Herd Instinct, and Shadow of the Past similarly showed stable loading patterns. However, some indicators exhibited weaker loadings. Confirmation Bias items loaded between 0.458 and 0.591, and several Loss Aversion items—including LA1 (0.477), LA2 (0.582), LA4 (0.621) and LA5 (0.553)—fell below the 0.70 threshold. Investment Decision-Making items related to tax benefits, diversification and liquidity were notably weak, some below 0.40. These indicators were retained to preserve content coverage and maintain the theoretical scope of the constructs despite their lower statistical strength.

2. Construct Reliability (Cronbach's Alpha & Composite Reliability)

The reliability analysis indicated that Cronbach's Alpha exceeded 0.70 for several constructs, including Overconfidence (0.747), Regret Aversion (0.803), Herd Instinct (0.741), and Narrow Framing (0.799). Composite Reliability values met acceptable standards across all constructs, even for those with lower Alpha coefficients, such as Confirmation Bias (0.663) and Investment Decision-Making (0.645). These results demonstrate adequate internal consistency within the measurement scales.

3. Convergent Validity (Average Variance Extracted - AVE)

Convergent validity was partially established. Constructs such as Overconfidence, Familiarity Bias, Narrow Framing, Regret Aversion, and Herd Instinct achieved AVE values above 0.50, confirming sufficient convergence. However, Confirmation Bias (AVE = 0.399) and Investment Decision-Making (AVE = 0.319) fell below the acceptable threshold, indicating that these constructs require refinement in future research.

4. Discriminant Validity (Fornell–Larcker Criterion)

Discriminant validity was successfully established using the Fornell–Larcker criterion. For each construct, the square root of AVE exceeded all inter-construct correlations, demonstrating that each construct was empirically distinct from the others. This confirms that behavioural biases measured in this study represent independent conceptual dimensions.

5. Discriminant Validity (HTMT Ratio)

The HTMT ratios further reinforced discriminant validity. All values remained below the 0.90 cut-off, with the highest ratios observed between Loss Aversion and Regret Aversion (0.793), still within acceptable limits. This test confirms that measurement items do not overlap excessively across constructs.

6. Collinearity Assessment (Outer and Inner VIF)

Collinearity diagnostics indicated no multicollinearity issues. Outer VIF values ranged between 1.054 and 1.718, while inner VIF values remained below 1.80. These results fall far below the recommended ceiling of 5, confirming that the independent constructs do not distort each other's explanatory capacity within the model.

Findings from the Structural Model

1. Coefficient of Determination (R^2)

The structural model reported that behavioural biases explained 14.7% of the variance ($R^2 = 0.147$) in Investment Decision-Making, which is modest but consistent with behavioural finance research, where decisions are influenced by multiple psychological and situational factors. Loss Aversion exhibited an R^2 value of 0.310, indicating moderate explanatory power, while Herd Instinct recorded an R^2 of 0.221, also reflecting moderate predictive capability. Other endogenous constructs yielded lower R^2 values.

2. Effect Size (f^2)

Effect size analysis demonstrated substantial relationships among key behavioural variables. Regret Aversion showed a strong effect on Loss Aversion ($f^2 =$

0.449), while Loss Aversion exerted a large effect on Herd Instinct ($f^2 = 0.284$). Moderate effects emerged for Narrow Framing on Confirmation Bias ($f^2 = 0.219$) and Familiarity Bias on Regret Aversion ($f^2 = 0.114$). Most other effects were small, which is typical in behavioural studies due to the complexity of psychological processes.

3. Predictive Relevance (Q^2 – Stone–Geisser Test)

The Q^2 values indicated small but meaningful predictive relevance for Confirmation Bias (0.112), Overconfidence (0.124), and the return and safety dimensions of Investment Decision-Making (0.095 and 0.066 respectively). Constructs such as Herd Instinct, Regret Aversion, Loss Aversion and Familiarity Bias displayed negligible predictive relevance, which is expected when psychological variables vary considerably across individuals.

4. PLS-Predict (RMSE, MAE)

The PLS-Predict analysis showed that the error metrics (RMSE and MAE) for the PLS model were comparable to or lower than the linear benchmark model. This suggests that the model has acceptable predictive utility for practical applications.

5. Bootstrapping Results (Path Coefficients & Hypothesis Testing)

Bootstrapping analysis revealed that twelve out of fifteen hypotheses were supported. Significant positive relationships were observed for Confirmation Bias ($\beta = 0.126$; $t = 2.143$), Familiarity Bias ($\beta = 0.181$; $t = 2.520$), Loss Aversion ($\beta = 0.196$; $t = 2.564$), Narrow Framing ($\beta = 0.163$; $t = 2.331$) and Overconfidence ($\beta = 0.225$; $t = 3.076$) on Investment Decision-Making. Three paths—Herd Instinct ($t = 0.548$), Regret Aversion ($t = 0.848$) and Shadow of the Past ($t = 0.496$)—were not significant as their confidence intervals crossed zero. Despite this, these constructs demonstrated important indirect effects, especially via Loss Aversion and Regret Aversion.

The findings highlight that investors rely heavily on their pre-existing beliefs, familiarity with financial instruments, narrow cognitive framing, emotional sensitivity to potential losses and subjective confidence levels when making investment decisions. These results align strongly with behavioural finance theories that emphasise psychological deviations from rational investor behaviour. Although Herd Instinct, Regret Aversion and Shadow of the Past did not directly influence investment choices,

their significant indirect effects underscore their mediating and reinforcing roles within the behavioural framework.

5.3 Major Findings

Objective 1: To Study the Demographic Variables of Equity Investors of Junagadh, Rajkot, and Jamnagar City

The analysis of demographic data from the three cities shows the following key points:

- **Location:** Jamnagar has the largest investor base (383), followed by Rajkot (372) and Junagadh (306).
- **Gender:** Male investors dominate in all cities — Junagadh (81.7%), Jamnagar (72.1%), Rajkot (62.1%). Rajkot has the highest female participation (37.9%).
- **Age:** Young investors (18–25 years) dominate in Junagadh (59.5%) and Rajkot (62.4%), while Jamnagar has a more balanced age distribution, including significant participation from 26–45 years (57.2%).
- **Education:** Jamnagar has the highest proportion of professionals (50.9%), Rajkot leads in undergraduates (44.4%), and Junagadh shows a mix of postgraduates (29.7%), graduates (26.1%), and undergraduates (23.9%).
- **Occupation:** Salaried employees and students form the majority in all cities. Jamnagar stands out with 30% professionals, Junagadh has more businesspeople (19.6%).
- **Annual Income:** Investors in Jamnagar are higher-income (35.8% earn ₹5–10L, 20.1% earn ₹10L+), Junagadh shows balanced income, and Rajkot has more low-income investors (61.3% earn $\leq$ ₹2.5L).
- **Marital Status:** Jamnagar has a more settled investor base (56.9% married), whereas unmarried investors dominate Junagadh (69%) and Rajkot (70.7%).
- **Family Type & Size:** Joint families dominate — Jamnagar (70%), Rajkot (64.8%), Junagadh (64.1%). Most families have more than four members, indicating traditional family structures.

- **Earning Members:** Dual-income families are most common — Jamnagar (54%), Junagadh (45.4%), Rajkot (44.1%), while Rajkot has the highest single-earner families (38.2%).

Equity investors across the three cities are largely young, educated, and male, with salaried employees and students forming a significant share. Jamnagar stands out for higher-income, professional, and married investors, while Rajkot shows greater female participation and Junagadh reflects a youth-oriented and mixed-education investor base. These demographic factors are likely to influence investment decisions and behaviour within the context of Behavioural Finance.

Objective 2: To Know the Preference of People Towards Equity Investment

- **Investment Preference:** Across all three cities, equity investment is preferred over trading or speculation, with women showing a slightly stronger preference for safe or long-term investment.
- **Trading Frequency & Age:** Younger investors (18–25) in Junagadh and Rajkot are more active in trading, while in Jamnagar, 26–45-year-olds trade more regularly, mostly monthly or weekly. Older investors trade less frequently.
- **Mode of Trading: Online trading dominates** in all cities (Junagadh 257, Rajkot 331, Jamnagar 361), across all education levels. Offline trading is rare.
- **Experience in Equity:** Most male investors are experienced, especially in Jamnagar (>6 years), while female investors are largely new entrants (under 3 years).
- **Investor Risk Profile & Age:** Young investors are either careful or research-based risk takers, while older groups adopt a more cautious approach.
- **Investment Amounts:** Small trades (up to ₹10,000) are common among students and salaried employees, while higher-value trades are mainly by salaried and professional investors, particularly in Jamnagar.
- **Diversification & Income:** Lower-income investors mostly invest in 1–5 companies, whereas higher-income investors (₹5–10L & ₹10L+) diversify across 15–20+ companies.

- **Source of Funds:** Most investors rely on personal funds, with younger investors occasionally borrowing or mixing sources.
- **Preferred Sectors:** Highly educated investors prefer Banking, IT, and FMCG, with professionals leading in investments across all sectors.
- **Money Perspective:** Most investors view money primarily as investment, especially highly educated men and professional investors; women and undergraduates also show a growing investment-oriented mindset.

Investors across the three cities favor equity investment, trade mostly online, and show age and income-based differences in trading frequency, investment amount, and diversification. Education, gender, and professional experience strongly influence investment behaviour and risk-taking, highlighting the role of behavioural factors in equity investment decisions in the context of Behavioural Finance.

Objective 3: To Study the Impact of Demographic Variables on Behavioural Biases in Equity Investment Decisions

- **Age:** Behavioural biases generally increase with age. Middle-aged and older investors show stronger overconfidence, narrow framing, and loss aversion, while regret aversion and herd instincts peak in 36–45 years. Younger investors exhibit lower bias scores.
- **Education:** Higher educational attainment amplifies biases. Professionals and highly educated investors display the highest overconfidence, familiarity, confirmation bias, regret aversion, narrow framing, shadow of the past, loss aversion, and herd instincts, while lower-educated investors show the lowest tendencies.
- **Occupation:** Professionals show stronger behavioural biases across all factors, while retirees, housewives, and minor occupational groups exhibit lower tendencies. Herd instincts are strongest among professionals and retirees.
- **Income:** Higher-income investors show more pronounced biases. Overconfidence peaks in the ₹10,00,000+ group, and regret aversion is highest in the ₹5–10 lakh group, while lower-income investors display minimal biases.

- **Marital Status:** Married investors display higher overconfidence, narrow framing, and loss aversion, suggesting that marital and family responsibilities influence investment behaviour.
- **Family Type:** Joint families exhibit higher biases, particularly in regret aversion, loss aversion, shadow of the past, and herd instincts. Larger families promote collective decision-making, affecting behavioural tendencies.
- **Number of Family Members:** Families with more than four members show stronger regret aversion, shadow of the past, loss aversion, and herd instincts, while other biases remain largely unaffected.
- **Number of Earning Members:** Behavioural biases are higher in households with two to three earners, while larger earning groups (>4) show slightly lower tendencies. Overconfidence and familiarity are not significantly affected.

Demographic factors such as age, education, occupation, income, and marital status consistently shape all behavioural biases, while family structure mainly affects specific biases like regret aversion, loss aversion, shadow of the past, and herd instincts. These findings confirm that investors' demographic characteristics play a critical role in determining the manifestation of behavioural biases, highlighting the strong link between personal attributes and investment decision-making in the context of Behavioural Finance.

Objective 4: To Measure the Levels of Different Behavioural Biases Among Individual Equity Investors

The analysis using the Behavioural Bias Impact Index (BBII) shows that all eight behavioural biases among investors in Junagadh, Rajkot, and Jamnagar fall in the “Biased” range (3184–4244), indicating strong psychological influence on investment decisions.

Objective 5: To Study the Impact of Behavioural Biases on Equity Investors While Making Investment Decisions

The multiple regression analysis shows that behavioural biases significantly influence equity investment decisions across various parameters:

- **Investment Experience:** Behavioural biases have a moderate positive effect on investment experience ($R^2 = 0.175$). Regret aversion, narrow framing, and overconfidence are the strongest predictors.
- **Trading Frequency:** Biases show a weak-to-moderate effect ($R^2 = 0.091$). Overconfidence negatively affects trading frequency, while familiarity has a positive effect.
- **Amount of Single Trade:** Biases moderately impact trade amounts ($R^2 = 0.109$). Overconfidence and narrow framing are significant positive predictors.
- **Number of Companies Invested:** Behavioural biases moderately influence diversification ($R^2 = 0.182$). Key predictors include overconfidence, regret aversion, narrow framing, and loss aversion.
- **Objective of Regular Returns:** Biases moderately affect this objective ($R^2 = 0.117$). Overconfidence, familiarity, narrow framing, shadow of the past, and loss aversion are significant predictors.
- **Objective of Safety of Principal:** Behavioural biases have a moderate positive effect ($R^2 = 0.103$). Narrow framing, loss aversion, confirmation bias, and familiarity significantly impact this objective.
- **Usage of Broking Apps & Financial News:** Biases show a weak-to-moderate negative effect ($R^2 = 0.113$). Overconfidence, familiarity, regret aversion, narrow framing, and loss aversion negatively influence the usage of apps and portals.

Behavioural biases such as overconfidence, narrow framing, regret aversion, loss aversion, familiarity, and shadow of the past significantly shape equity investors' experience, trading behaviour, investment amounts, diversification, risk objectives, and usage of financial tools. The findings confirm that cognitive and emotional biases are

strong determinants of investment decisions, highlighting the critical role of behavioural factors in the context of Behavioural Finance.

Impact of Behavioural Biases on Equity Investors while Making Investment Decisions PLS- SEM

The PLS-SEM analysis confirms that behavioural biases significantly influence the investment decisions of equity investors in Junagadh, Rajkot, and Jamnagar.

Results indicate that behavioural biases have good role in investment decisions. Overconfidence, Familiarity Bias, Loss Aversion, Narrow Framing, and Confirmation Bias, all these biases directly affected equity investors.

Herd Instinct, Regret Aversion, and Shadow of the Past indirectly affected.

5.4 Limitations of the Study

- First, the study was carried out only in three cities: Junagadh, Rajkot, and Jamnagar.
- Second, the study was based on a questionnaire survey. So, some respondents may not have shared their actual opinions.
- Third, the study focused only on individual equity investors. Other factors such as market conditions, economic changes, and institutional investors were not included.
- Instead of these limitations, the study gives more useful insights into behavioural biases and investment decisions among equity investors in the Saurashtra region.

5.5 Future Scope for Research

- The future research can be possible considering the other regions of Gujarat and India. Researcher will include rural areas. Also can compare the behaviour of investors from different backgrounds.
- Future researchers may also conduct longitudinal (Time Period Analysis) studies.
- Researcher may also Considering another biases except presenting in this study.
- Further research can be possible like, mutual fund investors, institutional investors, or investors in different financial markets.

- Future studies can use larger samples or different research methods.

5.6 Implications of the Study

- **Implications for Individual Investors**

The findings of the study carried significant implications for investors. Behavioural biases affected the decisions of equity investors. All the investors should understand these biases to make good investment decisions.

- **Implications for Financial Advisors and Intermediaries**

The findings of this research can also help financial advisors. With the help of this study, they can identify investors' behavioural biases and provide better guidance.

- **Implications for Policymakers and Regulatory Bodies**

This research again benefited to policymakers and market regulators. They can design their financial literacy programs and also can add the knowledge regarding behavioural biases in such programs.

- **Theoretical Implications**

The study also had theoretical implications, as it contributed to the understanding of the interplay between demographic factors and behavioural biases in equity investment. By empirically confirming the influence of psychological tendencies on investment choices, the research provided a foundation for future investigations in behavioural finance, enabling scholars to develop more nuanced models of investor behaviour.

- **Practical Implications for Market Efficiency**

Overall, the study demonstrated that incorporating behavioural finance perspectives could improve both practical investment outcomes and the broader efficiency of financial markets.

5.7 Conclusion

The present study investigated the behavioural patterns and decision-making processes of equity investors in Junagadh, Rajkot, and Jamnagar, focusing on the relationship between demographic characteristics, investment preferences, and behavioural biases. The findings revealed several key insights regarding investor behaviour in the Saurashtra region.

The demographic analysis indicated that the majority of investors were young, educated, and predominantly male. Salaried employees, students, and professionals constituted the largest investor groups, with Jamnagar exhibiting a relatively higher-income and professionally qualified population. Female participation had increased, particularly in Rajkot, reflecting a gradual shift toward more inclusive equity investment practices. Family structure and the number of earning members influenced financial decision-making, as joint families and dual-income households demonstrated distinctive patterns in investment behaviour.

The study found that investors showed clear preferences for equity investment over trading or speculative activities. Most investors preferred online trading platforms, invested primarily in familiar sectors such as Banking, IT, and FMCG, and relied mainly on their own funds. Younger investors engaged in higher trading frequency, whereas older and more experienced investors demonstrated greater risk awareness and careful investment approaches.

Demographic variables were found to significantly influence behavioural biases. Age, education, occupation, income, and marital status affected overconfidence, loss aversion, narrow framing, and other biases, while family type, household size, and number of earning members primarily influenced regret aversion, shadow of the past, loss aversion, and herd instincts. These results highlighted the strong role of personal characteristics in shaping investors' psychological tendencies and decision-making processes.

The study confirmed that equity investors were heavily affected by behavioural biases. Familiarity Bias, Narrow Framing, and Shadow of the Past were particularly dominant, while overconfidence, confirmation bias, and loss aversion were also highly prevalent. These biases influenced investment decisions, leading investors to rely on

familiar options, past experiences, and subjective confidence rather than purely rational analyses.

The analysis of the impact of behavioural biases on investment decisions demonstrated that biases significantly affected investment experience, trading frequency, trade size, number of companies invested, and investment objectives such as regular returns and safety of principal. The final conclusion of Multiple Regression and PLS-SEM was that overconfidence, familiarity, narrow framing, regret aversion, and loss aversion affected the investment decisions of equity investors. It clearly indicates that investors do not always rely only on facts. But affected by emotions and biases.

The final conclusion of this study that both demographic variables and behavioural biases influence the investment decision of equity investors of Junagadh, Rajkot and Jamnagar cities of the Saurashtra region.

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APPENDICES

APPENDICES

Appendix- A: Questionnaire

For Office Use Only

City				
Sr. No.				

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	
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2. Gender:

Male		Female		Transgender	
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3. Age:

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

4. Education:

Below HSC		12 th /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	
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8. Family Type:

Nuclear Family		Joint Family	
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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	
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13. Is It Your Source of Income or Investment?

Income		Investment		Both	
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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	☐
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20. Your Preferred Mode of trading?

Online	☐	Offline	☐	Both	☐
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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!!

Appendix- B: Review Paper Publication- 1 Acceptance Letter (Web of Science)



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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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ORIGINAL RESEARCH PAPER

Behavioral finance: A systematic literature review

Vipul Sundavadara^{1*}, Riddhi Sanghvi²

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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Appendix- D: Research Paper Publication- 1 (Peer Review)



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Research Paper / Article / Review

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

¹Vipul Sundavadara, ²Prof. (Dr.) Riddhi Sanghvi

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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

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

Vipul Sundavadara

Riddhi Sanghvi

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

Abstract

This study examines the influence of behavioural finance on equity investment decisions among individual investors in Junagadh and Rajkot. The research is based on primary data collected through structured questionnaires administered to 200 respondents, with an equal representation of 100 investors from each city. The study specifically focuses on key behavioural biases, including overconfidence, familiarity bias, regret aversion, and narrow framing, and further evaluates the impact of demographic factors such as age and education on these biases. Statistical tools such as independent sample t-tests and analysis of variance (ANOVA) were employed to analyse the data and identify significant differences between the two regions. The findings reveal that most behavioural biases do not significantly differ between investors in Junagadh and Rajkot; however, investors in Junagadh demonstrate a relatively higher tendency toward narrow framing in their investment decisions. On the other hand, demographic variables, particularly age and education, exert a more pronounced influence on investor behaviour in Rajkot, indicating notable regional variation. The study highlights the critical role of behavioural biases in shaping investment decisions and underscores the need for enhanced financial literacy and awareness programs to support rational decision-making among investors.

References

Benartzi, S., & Thaler, R. (1995). Myopic Loss Aversion and the Equity Premium Puzzle. *The Quarterly Journal of Economics*, 110(1), 73–92. <https://doi.org/10.2307/2118511>

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Section

Research Paper

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The Certificate of Presentation

Vipul Sundavadara

Has actively participated in the International Multi-disciplinary, Multi-lingual Online Conference on “**From Tradition (IKS) to Tomorrow (NEP 2020): Multidisciplinary Conference for a Viksit Bharat@2047**”, organized by Vedant Knowledge Systems Pvt. Ltd. on **29th September 2024**.

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

The Title of Presentation:
Behavioural Finance: A Systematic Literature Review

Arjun Dave Director, Vedant Knowledge Systems Pvt. Ltd. www.MyVedant.com	R. V. Soni CS Raj Soni Director, Vedant Knowledge Systems Pvt. Ltd. www.MyVedant.com
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Behavioural Bias Impact Index (BBII)

Introduction

Equity investment decision-making is rarely a perfectly rational process. People often rely on mental shortcuts, emotional reactions, and cognitive patterns that unintentionally influence their decision-making process. In financial settings, these psychological tendencies—commonly known as behavioural biases—can significantly alter investment behaviour. Such biases may cause investors to take on unnecessary risks, avoid profitable opportunities, trade excessively, or construct poorly diversified investment portfolios, resulting in losses. Overconfidence is one of the biases that researchers have identified most frequently, where individuals place unwarranted faith or overestimate their own knowledge or future forecasting abilities. Other important biases include familiarity, confirmation, regret aversion, loss aversion, narrow framing, herd behaviour, and anchoring to past experiences; all of these Behavioural Biases have a direct impact on equity investment outcomes.

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Measuring these biases helps researchers, financial advisors, and regulators understand how investors behave under uncertainty and market pressure. Measuring behavioural tendencies sheds light on the psychological foundations behind investment choices, highlighting why investors may deviate from rational financial theories.

To study these tendencies, the present study formulates a **Behavioural Bias Impact Index** that includes eight key investors' Behavioural biases among respondents from Junagadh, Rajkot, and Jamnagar. The index is based on 1061 participants' responses to 27 statements rated on a five-point Likert scale (from 1 = Strongly Disagree to 5 = Strongly Agree). To convert the qualitative responses into numbers, a weighted scoring method was employed. Each statement received its own weighted score, and these were subsequently grouped and combined based on the relevant bias category to generate individual bias indices.

Research Design

The study adopts a **descriptive and quantitative research approach**, as the objective was to measure and compare several behavioural biases among investors. The Present study's primary data were acquired with the help of a structured questionnaire from the 1,061 respondents across three districts of the Saurashtra region: Junagadh (306), Rajkot (372), and Jamnagar (384).

The questionnaire consisted of 27 statements, each designed to capture one dimension of investor behaviour linked to eight behavioural biases. Respondents evaluated each statement on a **five-point Likert scale**, ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). This type of scale is widely used in behavioural and social research because it allows respondents to express the intensity of their opinions while still providing data appropriate for numerical analysis.



Appendix- J: Thesis Plagiarism Report



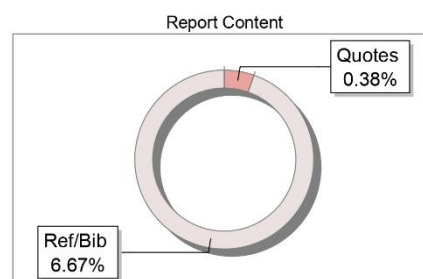
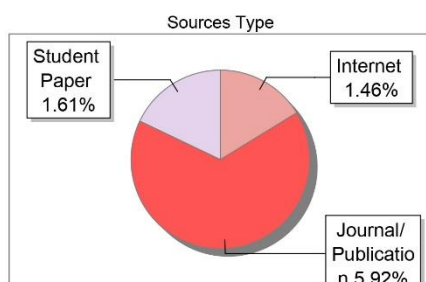
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Appendix- K: Thesis AI Report



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