



**Behavioral Biases and their Impact on Individual
Investors- A Study based in Delhi NCR**

Ph.D. Thesis

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March, 2023

Behavioral Biases and their Impact on Individual Investors- A Study based in Delhi NCR

Thesis

Submitted to

Jamia Millia Islamia



**In partial fulfillment of the requirement of the award of the
Degree of Doctor of Philosophy
Commerce & Business Studies**

By

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Portfolio construction by individual investors has always been a complex activity. It is driven by several factors concerning individual investors including their financial goals, risk appetite, human psychology, financial literacy, the regulatory framework of the country in which they are operating, and the accessibility of investors to financial instruments (Morningstar Manager Research, 2022). While the impact of the regulatory regime, accessibility of financial instruments, and risk appetite on investors' practices and investment patterns are quite apparent and predictable, human psychology works covertly to build or abate the financial success of individual investors. Psychological factors always remain at work in all human interactions, decisions, and functions it is ubiquitous and pertinent, but it wasn't until the late 1970s that behavioral economists and psychologists began to formally underscore the importance of psychological factors in investment decision-making and the disciplines of 'Behavioral Economics' and 'Behavioral Finance' came into existence. According to Shefrin (2007), psychology is the basis for all human desires, goals, and motivations but at the same time, it is also a source for the wide variety of human errors and irrationality. The psychology of the investors can influence the outcomes of the investment process both at a personal and collective scale in financial markets. Marks and Greenwald (2013) famously said that *"The biggest investing errors come not from the factors that are informational or analytical, but from those that are psychological"* (p.98). Mackay (1841) recorded the earliest evidence of the collective impact of investors' irrationality stemming from human psychology in the form of *The Tulip Bubble*, *The South Sea Bubble*, and *The Mississippi Company Scheme* in the sixteenth and seventeenth centuries, where the prices of tulip bulbs, share prices of the South sea company and the Mississippi company rose dramatically and then collapsed ruining thousands of investors and their wealth. In the twentieth century, the stock market crash of 1929 led the way to the Great Depression the most catastrophic economic contraction viewed by the world (White, 1990), the great bull market of the 1950s and early 1960s, the dotcom tech bubble of the late 1990s when several online and technology companies declared bankruptcy (Shiller, 1988; CFI team, 2022). In the 21st century, the Global Financial Crises of 2008-

2009 associated with the housing markets collapse and the major hit faced by financial institutions due to the ultimate default of individuals on subprime mortgages are the major examples of market anomalies across the globe (CFI team, 2022). These bubbles and market anomalies are sufficient to prove that the collective judgment of investors can go wrong in many ways and raised serious doubts about the traditional understanding of financial theories as they were unable to explain the reasons behind the presence of market bubbles and could not provide answers to questions like; what causes the markets to crash? How may these bubbles and crashes be avoided? When exactly do these market bubbles and crashes occur? Behavioral approaches to finance become more prominent in response to these crises and behavioral finance takes up this challenge to understand these bubbles and anomalies by borrowing concepts from psychology. Behavioral finance proposes that the behavior of markets can be better understood through the behavior of the agents participating in those markets. Thus, it goes against both the theory of market efficiency and the premise of investor rationality.

On a personal level, retail investors are constantly required to make several decisions during the cyclical process of investment decision-making right from procuring information from diverse sources to deciding where to invest, what and when to buy and sell, how long to hold, followed by a new selection of investment avenues. Much of the traditional financial theories assume that individuals are capable of considering all available information and can act optimally at all levels of investment decision-making (Waweru et al., 2008). However, behavioral finance studies that have taken place over many decades have empirically proved that the entire process of investment decision-making is full of psychological pitfalls and when individuals are faced with too many decisions the results can be paralyzing (Hens & Meier, 2015). Behavioral finance recognizes that we as humans suffered from many limitations be it, limited information processing capabilities, limited time, limited energy, limited resources, and the influence of emotions over normatively acceptable decisions. One of the main causes of decision failures by individual investors is the psychological or behavioral biases that limit their ability to act impartially when making investment decisions. A behavioral bias is an inclination to feel or think in particular ways that might result in regular departures from a standard of objectivity or good judgment. Behavioral biases are traditional examples of dysfunctional psychology that are specifically applicable to the investment field (Baker and Puttonen 2017). Primarily, three branches of

psychology add depth to the definitions and forms of behavioral biases. First is cognitive behavioral biases, which occur when investors fall victim to errors in their thinking patterns, memory, attention, and judgments. Since attention is a limited resource, investors have to be selective and their minds try to simplify information processing using shortcuts called 'heuristics'. These financial shortcuts or heuristics help investors to lessen the psychological pressure in financial decision-making and to be quick about their judgments but they act as a double-edged sword, greater reliance on these shortcuts and instincts makes investors prone to certain psychological and behavioral biases that can be detrimental to their overall financial wellbeing. The second is emotional reactions to investment decisions, as humans, investors make financial judgments based on their emotional reactions to various events making them prone to certain emotional biases. The third is social psychology, which acknowledges the need to obtain support for our actions, including encouragement, as social beings, investors are also influenced by the behaviors of other investors resulting in social biases. These biases impair reasoning, cause investors to take risks they do not recognize, experience results they did not expect, are prone to unjustified trading, and frequently end up blaming themselves or others if the results are negative (Kahneman & Riepe, 1998). However, according to evolutionary psychologists, a subset of these biases, known as heuristics, are built-in brain processes that were developed for the survival of humans and play a critical role in enhancing a person's sense of well-being. Certainly, these biases do impact the investment decision-making process of an investor (Ullah & Elahi, 2014; Jain et al., 2020; Sukamulja et al., 2019; Rasheed et al., 2018; Shah et al., 2018; Khan, 2017; Irshad et al., 2016; Kisaka, 2015) and the natural outcomes of the investment decision-making process such as investment performance (Akhtar et al., 2018; Alrabadi et al., 2018; Javed et al., 2017; Kumari and Sar, 2017; Kengatharan & Kengatharan, 2014; Le Luong & Thi Thu Ha, 2011) and financial satisfaction of an individual investor (Parmitasri et al., 2018; Sadiq, 2018; Sahi, 2017; Sahi & Kalra, 2013). Therefore to understand the individual investor better, it is important to be aware of the irrationality and psychological biases present in their investment behavior, so that they can ponder about them and, if feasible, make corrections to aid in making better investment decisions. To understand and give some suitable clarifications for investor behavior present study focuses on seven behavioral biases (overconfidence, availability, anchoring, representativeness, mental accounting, loss aversion, and regret aversion) and their impact on the financial well-being of

individual investors. Thus, the major research problem which motivated the present study is to explore whether behavioral aspects of individual investors influence their financial satisfaction in the Indian context. Further, is this relationship between behavioral biases and financial satisfaction mediated by the perceived investment performance and investment satisfaction of Indian individual investors?

The present study will help individual investors in introspecting their financial behaviors and will advise them on how they can make use of behavioral factors to better exploit profitable investment opportunities in the market, it will also assist them to create optimal investment portfolios for themselves depending on their personality. This study will also help stock market policymakers, financial advisors, and regulators better comprehend the mechanism, the role, and the effects that behavioral factors have on investors' decision-making.

1.2 Individual Investors in Indian Financial Markets

The Indian capital markets began to emerge nearly 150 years ago with the establishment of securities exchanges in Mumbai, Ahmedabad, and Kolkata, today it is the finest and fastest-growing of all the financial markets in emerging economies (Akhtar & Das, 2017). Following the economic reforms of 1991, the Indian capital market saw several progressive reforms, which led to its evolution and development. As a result of these economic reforms the Securities and Exchange Board of India (SEBI) was founded in 1992 to supervise functions, bolster infrastructure, and increase awareness and participation in the Indian securities market (Kaur & Pattnaik, 2014). According to the Issue of Capital and Disclosure Requirements Regulation, 2009, of SEBI, a retail individual investor is someone who applies for or bids on securities with a value of no more than Rs 2, 00,000 in an IPO and purchases or retains shares of stock with a value of no more than Rs 2, 00,000. No such threshold exists in commodities to define a retail investor (SEBI, 2016). An individual investor in India can make purchases and sales of equity shares, futures contracts, mutual funds, exchange-traded funds (ETFs), and other types of investment products through conventional or online brokerage houses or other sorts of investment accounts. To attract investors to the market, SEBI adopted a number of steps, such as allocating 35% of share offers to individual investors, granting a 5% discount on share prices, and increasing the value of one lot from INR 5,000 to INR 7,000 to between INR 10,000 and INR 15,000 (Akhtar and Das, 2017). Recently, SEBI

in May 2022 raised the investment cap for payments made using the UPI method for retail investors purchasing debt securities in public issues from Rs 2 lakh to Rs 5 lakh (Press Trust of India, 2022). From these measures, the importance of retail investors for the growth of the economy as a whole as well as for socializing the benefits of corporate profits can be understood.

Yet, despite these efforts, the proportion of individual investors in the Indian capital markets is still quite low, even after more than 70 years of independence, Indian investors prefer to build wealth through non-financial assets that can be passed down through the generations, such as gold and real estate. Within financial assets, annuities, bank accounts, and deposits rule household investments in India, whereas investors in other nations like the USA, Australia, Canada, Hong Kong, and Singapore feel more at ease investing in direct equities and mutual funds. This ease is primarily driven by a system that depends more on personal savings for significant life goals and expenses and less on governmental support (Morningstar Manager Research, 2022). As per the SEBI investors survey 2015, there were a total of 3.37 crore investor households in India investing in capital markets. Mutual funds were the most widely used of these, with roughly 66 percent (2.2 crore households) investing in them. An expected 1.9 crore households made investments in stocks, and 77 lakh households made investments in bonds (public, private, and PSU). There were 30 lakh investors in stock and currency derivatives, and 21 lakh in commodity futures. In the primary (IPO) marketplaces, about 18% of equity investors (or 33 lakh) had made investments. However, the situation is changing rapidly, the trading volumes in these markets have witnessed significant growth over the past few years and covid-19 pandemic has significantly changed investors' attitudes toward the financial markets. The rapid and exceptional spread of the COVID-19 pandemic made financial markets highly volatile as a result investors quickly suffered significant losses, still, investors continue to participate in the markets despite the volatility because they need financial goods and services to profitably use their investable surplus (Talwar et al., 2020). During the pandemic, when investors were confined to their homes under the COVID-19 lockdown restrictions and had plenty of free time, the technology-enabled access to stock trading via the internet interface has added a multitude of first-time investors in India. As the country started recovering from the pandemic there has been an addition of a whopping 142 lakh demat accounts at NSDL and CSDL in the financial year 2021 itself. In comparison to the four

lakh new demat accounts opened on average each month in 2019–20, 26 lakh new demat accounts were opened on average each month in the year concluding March 2022. The total number of investor accounts remained at 7.7 crores as of November 2021 and reached 10 crores in August 2022 both NSDL and CDSL combined (CNBCTV18.com, 2022; ET Contributors, 2022). Even though the number of individual investors in the Indian stock markets is increasing, there is still a sizable population of households from the high to the middle-income range that are educated, and save money (in bank accounts, life insurance policies, or post offices) but do not invest. The main causes of this lack of participation are ignorance of the key financial instruments that are offered in the markets, risk aversion, and inadequate returns. Indian investors lack a thorough understanding of stocks, particularly their advantages in terms of variety and returns when compared to mutual funds. They also face additional challenges in the form of substantially greater fees that they have to pay for their transactions due to their limited purchasing power and the information asymmetry that prevails in the markets.

There have been a lot of research studies on individual investors' behavior in different financial markets around the world. However, very limited research has been conducted in the context of Indian financial markets. It is crucial to keep in mind that retail investors may be biased against some instruments because they are thought to carry greater risks, but they may also be more tolerant of other instruments based only on some visible features, their perception is filled with heuristics and biases that need to be taken care of while deciding about various investment options. In this context of the increasing role and complexity, any lack of awareness about the available investment options and their attributes along with the consequent inability to choose products optimally could have a significant impact on an individual's financial outcomes. Individuals' financial well-being depends on their behaviors, which are influenced by psychological factors or behavioral biases. Understanding the relationship between behavioral biases and the corresponding portfolio performance and financial satisfaction is an increasingly recognized area in behavioral finance.

1.3 Need for the Study

As more people invest in the financial markets, financial instruments are changing to meet the needs of various types of investors based on their unique requirements, which is raising competition and complexity in the Indian financial markets. Nevertheless, investors rely on a few heuristics and biases to speed up the decision-making process and optimize their overall financial well-being because they lack the necessary skills to assess all opportunities that are available (Sahi, 2017). According to the theory of behavioral finance, heuristics and biases are two-edged swords, and disregarding them can harm an investor's ability to make money and their sense of investment decision-making (Tversky & Kahneman, 1974; Barber & Odean, 2000; Le Luong & Thi Thu Ha, 2011; Ahamd & Shah, 2020). However, according to findings from evolutionary psychology heuristics and biases are necessary components of decision-making because they help a person make sense of their surroundings and protect their own well-being (Haselton et al., 2009; Gigerenzer, 2008). Recent developments in behavioral finance literature have also found a positive effect of behavioral biases on investment performance and the financial satisfaction of individual investors, which supports the theory of evolutionary psychology (Oberlechner & Osler, 2008; Khan, 2015; Sahi, 2017; Zouaoui & Bellouma, 2018; Pandey & Jessica, 2019). The behavioral finance literature's mixed evidence indicates that it is still unclear how heuristics and biases affect an individual's financial well-being and investment performance. Consequently, it highlights the urgent need for research into how behavioral biases affect investors' levels of financial satisfaction, investment satisfaction, and performance. Despite the fact that there is a wealth of literature on behavioral finance in western nations, it might not be applicable in the Indian setting. Since India is a country with diverse social and economic profiles, the majority of primary data studies in India are restricted to examining the connections between demographics and behavioral biases. Little emphasis is placed on examining the effects of behavioral biases on financial outcomes, so there is a need to ascertain how these behavioral factors affect the inevitable results of financial choices in the form of perceived investment performance and the perceived satisfaction of individual investors in India.

Furthermore, prior studies that were disseminated in the literature assessed behavioral biases directly through manifest variables without taking into account the antecedents that caused those manifest variables. Besides that, prior studies focused on exploring

direct connections between behavioral biases and financial satisfaction, ignoring the underlying mechanisms behind these connections and their effects. The present study will make an effort to close this research vacuum by deeply investigating the antecedents of behavioral biases and introducing perceived investment performance and investment satisfaction as mediating variables in the relationship between behavioral biases and financial satisfaction in order to gain a better understanding of individual investors' behavior in the Indian stock market. As a result, the current study will attempt to examine all facets of select behavioral biases while also introducing and emphasizing the significance of perceived investment performance and satisfaction as well as their effects on an investor's financial well-being. Since behavioral finance is a new concept in comparison to other financial theories, the study is significant for the field. The present study is a modest attempt to add contextually and conceptually to the field of behavioral finance. It is being conducted with the hope of ensuring its relevance for all types of financial markets.

1.4 Problem Statement and Research Questions

As is evident from the above discussion, previous research studies have already shown that behavioral biases do have an effect on the investment decision-making process of individual investors. However, the impact of behavioral biases on individual investors' perceived financial outcomes and financial satisfaction has received less attention in the field of behavioral finance. We are also aware that these behavioral biases are not universal in all people. They differ depending on a person's personality, demographics, and investor sophistication levels. Therefore, the present study is an attempt to address the following research problems:-

- To analyse the role of demographic variables and investor sophistication measures in determining the behavioral biases of individual investors in India.
- To determine the impact of behavioral biases on financial outcomes in terms of perceived investment performance, investment satisfaction, and overall financial satisfaction of individual investors in India.

Specifically, the present study will provide answers to the following research questions:

- 1) Do demographic variables like gender, age, education, occupation, marital status, and income affect the behavioral biases of individual investors in the Indian context?
- 2) Do Individual investors' sophistication measures influence the behavioral biases of individual investors?
- 3) Which bias is most evident in the Indian context?
- 4) What are the direct effect of behavioral biases on perceived investment performance and investment satisfaction of individual investors?
- 5) What is the direct effect of behavioral biases on the financial satisfaction levels of individual investors in India?
- 6) How do behavioral biases affect the financial satisfaction of individual investors in the presence of perceived investment performance and investment satisfaction?
- 7) How do demographic and investor sophistication variables affect the relationships between behavioral biases and perceived investment success, investment satisfaction, and financial satisfaction?

1.5 Research Objectives

The study covers the following specific objectives according to the specific research questions discussed above:-

- 1) To examine the role of demographic and investor sophistication variables in determining the behavioral biases of individual investors.
- 2) To examine the impact of select behavioral biases on the perceived investment performance of individual investors.
- 3) To examine the impact of select behavioral biases on the investment satisfaction of individual investors.
- 4) To examine the impact of select behavioral biases on the financial satisfaction of individual investors.
- 5) To assess the mediating role of the perceived investment performance and investment satisfaction in the relationship between behavioral biases and financial satisfaction.

- 6) To investigate the moderating effects of key demographic variables and investor sophistication measures on the structural model relationships.

1.6 The rationale for Selecting Behavioral Biases

The present study focuses on seven behavioral biases identified from various academic sources. These biases include three heuristics (representativeness, anchoring, and availability) introduced by Tversky and Kahneman (1974), one heuristic (overconfidence) suggested by Waweru et al. (2008) and three biases derived from prospect theory (loss aversion, regret aversion, and mental accounting). Although the list of behavioral biases is long and steadily expanding, an extensive review of the literature reveals that these seven are the most common behavioral biases that have a greater impact on individual investors' investment decisions worldwide and in India. In the context of Indian research studies Chandra and Kumar (2012) identified eight behavioral biases (overconfidence, anchoring, availability, gambler's fallacy representativeness, loss aversion, regret aversion, and mental accounting) along with five other factors that influence individual investors in India and concluded that anchoring and availability within heuristics and regret aversion bias within prospect factors are the most dominant. Baker et al. (2018) found that overconfidence, representativeness, and mental accounting have the highest impact while anchoring, emotional bias (loss aversion & regret aversion), herding, and disposition effect have a moderate impact on the investment decisions of Indian individuals investors. Isidore and Christie (2018) determined that overconfidence, anchoring, availability, loss aversion, representativeness, and mental accounting are significantly related to the income of individual investors in Chennai. Jain et al. (2020) also described these seven biases along with herding as the main criteria influencing the choices of Indian retail investors. Therefore, overconfidence, availability, anchoring, representativeness, mental accounting, loss aversion, and regret are chosen as the most common behavioral biases influencing the investment decisions of Indian individual investors, with the exception of herding, which can be analysed more appropriately using secondary sources of data.

1.7 Definition of Constructs under Study

1.7.1 Overconfidence Bias

The most researched cognitive bias in the theory of behavioral finance is overconfidence. Different researchers have defined it differently from time to time. According to Odean (1998), overconfident investors overestimate the precision of their knowledge about the value of a financial security. This definition of overconfidence highlights the fact that overconfident investors give more weight to their own beliefs and they are least concerned about the beliefs of others. Daniel Kahneman has termed overconfidence as the most “pervasive” and “catastrophic” among all cognitive biases to which human beings fall victim. Isidore and Christie (2018) have defined overconfidence as the bias that causes investors to be overconfident about their stock-picking ability, their knowledge, their information processing capability, and their skill set.

In view of the above definitions, we can say that in the literature of behavioral finance, there is no precise definition of overconfidence rather it incorporates in itself many psychological aspects such as miscalibration, better than average effect, the illusion of control, self-attribution that are together known as overconfidence.

- *Miscalibration*: It refers to the phenomenon that how often people wrongly estimate the probabilities of occurrence or non-occurrence of an event when they are asked to do so (due to unwarranted faith in their own knowledge and reasoning).
- *Better than the average effect*: Overconfident investors rate their skills better than the skills possessed by other rational investors this is known as the “better than average effect”
- *The illusion of control*: Overconfident people believe that they have control over situations that are actually uncontrollable, this is known as the “illusion of control”
- *Self-attribution*: Another important contributor to overconfidence is “self-attribution”. Self-attribution is the tendency of investors due to in which they give credit to themselves for their success and blame bad luck and other external factors for their failures.

- *Planning Fallacy*: It refers to the phenomenon in which people overestimate their capacity to complete a task and underestimate the time, risk, and cost involved in a future project. Different researchers have shown in their studies how planning fallacy leads to overconfidence.

1.7.2 Availability Bias

Tversky and Kahneman (1974) defined availability bias as a heuristic in which people assess the frequency of an event by the ease with which the instance came to mind. It is a bias in which the decision-makers rely on the information that is readily available and makes investors avoid laborious fact-checking and detailed analysis of information which increases the chance of the decision being flawed.

Availability bias emerges because of the following reasons:-

- *Easy to recall and Retrievability*: Ease of recall suggests that if something is more easily recalled in memory it must occur with a higher probability. Prior research in this domain has shown that *recent occurrences* are easier to recall than earlier experiences and concluded that people assess probabilities by overweighting current information as opposed to processing all relevant information. Investors are found to choose only those stocks that have recently caught their attention from the news, family, friends, and advertising or those trading abnormally or offering extreme returns (Barber and Odean, 2008).
- *Exposure effect/ Narrow range of experience*: Another very important aspect of availability is the exposure effect. People tend to develop a preference for things because they are familiar with them or the things that fit in their narrow range of life experiences. This is called the exposure effect. According to Titchener (1910), People feel warmth, a sense of ownership, and intimacy as a result of the exposure effect. The more we are exposed to something the easier it is to recall it in our minds. The exposure effect influences investors in many ways one of them is investors prefer to invest in local companies with which they are more familiar or where they feel a strong sense of association as compared to international companies. (Waweru et al., 2008).

1.7.3 Anchoring Bias

Forecasting is a part of our everyday life. Likewise, stock market forecasting is a part of investors' daily lives. The success or failure of investors depends very much upon their forecasting abilities. An anchoring and adjustment heuristic is a ubiquitous forecasting bias that most investors fall prey to.

Anchoring bias refers to the human tendency to rely too heavily on the “anchor” while making judgments for which the answer is ambiguous. Anchor here generally refers to one characteristic or piece of information about an event or initial value of an estimate easily available to them. Kahneman and Tversky (1974) argue that people start with a reference point that they adjust upwards or downwards while arriving at final estimates. Such adjustments in the initial value are often insufficient and biased in the direction of the original anchor value giving rise to the popular anchoring and adjustment heuristic. These anchor values are sometimes directly provided by the experimenter or some external agent known as “externally provided” and sometimes they are generated by participants to simplify a complicated assessment known as “incidental anchoring” or “self-generated anchoring” Furnham and Boo (2011) showed that relevant anchors and irrelevant anchors both induce anchoring effects in judgment which illustrates that anchoring effect is independent of the relevancy of information provided by the anchors. Prior research studies have shown that investors frequently use moving averages along with 52-week high or low prices, recent prices, and an initial purchase price as anchors while making investment decisions.

1.7.4 Representativeness Bias

Representativeness is the tendency of individuals to classify things or events into discrete groups only on the basis of some noticeable or visible characteristics and includes overreliance on stereotypes. Tversky and Kahneman (1974) in their seminal work have shown many ways in which representativeness can cause investors to diverge from rational thinking. First is failure to consider base rate probabilities or representativeness, the second is failure to consider sample size and the third is the misconception of chance or Gambler's Fallacy.

- *Base rate neglect:* Representativeness bias cause investors to take decisions on the basis of some stereotypes rather than indulging themselves in tedious calculations of actual probabilities of the occurrence of an event. Investors

prone to base rate neglect take decisions on some representative characteristic of the company this can be recent returns, popularity, or type of management. Investors may consider popular or “glamour stocks” as good investments but many studies have shown this is not the case most of the time.

- *Sample size neglect*: when assessing probabilities under the influence of the representativeness heuristic people often wrongly consider a small sample size as representative of the whole population without paying any regard to basic statistical theory. Investors prone to sample size neglect might consider stocks with abnormal returns in the recent past as “value stocks” and fails to take into account the fundamentals of the company. Most of the time investors base their decisions on the basis of recent past returns because they consider recent returns as the representative of future returns this is also known as “extrapolation bias”.(Chan *et al*, 2002)
- *Gambler’s Fallacy/ Misconception of fairness*: People believe that a sequence generated by random events will always be fair and will represent all characteristics of the process even if the sequence is very short to be fair or self-correcting. This is also known as the law of small numbers. For example, if a fair coin is tossed ten times and it lands on heads each time, an investor who feels that the next flip will result in tails can be said to be suffering from this bias. Investors suffering from Gambler’s fallacy would inappropriately predict that trend will reverse and are drawn into contrarian thinking.

1.7.5 Mental Accounting Bias

Mental accounting is a process that suggests that people code, categorize, and evaluate their financial activities based on a variety of subjective criteria, ignoring the fungible nature of money. Though traditional methods of accounting by businesses and corporations are well established, mental accounting is a psychological or cognitive form of bookkeeping, literature on which is growing every day.

The term “mental accounting” was first introduced by renowned economist Richard Thaler. It is intuitive; it comes naturally for all of us. It explores psychological processes such as how people group incomes and expenses into different categories known as

“mental accounts” and how they establish budgets and perform a cost-benefit analysis for different categories created by them also known as “mental budgeting”.

Therefore, mental accounting is composed of two broad sets of mental activities categorization and mental budgeting.

- *Categorization:* The way of organizing information into different groups or mental accounts based on some commonalities is known as categorization. This grouping process improves cognitive efficiency by facilitating the quick recall and judgment of relevant information (Henderson & Peterson, 1992). Categorization is the starting point of the mental accounting process. Although mental accounts created by individuals are only notional, yet they violate an important economic principle of the fungibility of money.
- *Mental Budgeting:* Budgeting is the process of allocating and keeping track of funds against different mental accounts. Budgets can determine the financial well-being of households. Both short-term (current spending decisions) and long-term (savings and investment decisions) budgets can be created depending on the financial objectives of consumers and investors.

1.7.6 Loss Aversion Bias

Loss aversion is one of the primary psychological biases that emerged from the framework of prospect theory, proposed by Kahneman and Tversky (1979), who described loss aversion as “*the aggravation that one experiences in losing a sum of money appear to be greater than the pleasure associated with gaining the same amount of money*”. The phenomenon that losses loom larger than gains is embedded in the prospect theory in the form of an ‘S-shaped’ shaped utility function passing through a reference point. The idea invoked in the model has formalized several empirical observations in the choice behavior of individuals. One of the important observations that can be drawn from this value function is that people are risk seekers below the reference point and are risk averse above the reference point. This change in behavior of respondents above or below the reference point clearly suggests greater sensitivity to losses than to gains and thus “Loss Aversion”

Based on the above discussion Loss aversion is characterized by these three properties

- Wealth is measured with respect to a given reference point.

- A decrease in marginal utility initiated by a negligible loss is constantly greater than the increase in marginal utility due to a minimal gain.
- People are risk averse in the domain of gains and they are risk lovers in the domain of losses.

1.7.7 Regret Aversion Bias

Regret is one of the most researched emotions in the field of decision making it has been found to affect many behavioral choices of individuals. Regret theory is one of the most popular theories after prospect theory in the discipline of behavioral finance. Loomes and Sugden (1982) and Bell (1982) came up with the idea of **regret theory** as another possible explanation for the failure of the axioms of expected utility theory. Bell (1982) described regret as an emotion caused by comparing a given outcome or state of events with the state of forgone outcomes. He further added that if the outcomes of the forgone alternatives are better than the outcome of the chosen alternative, the decision maker may feel a sense of loss or regret and he would be ready to trade some financial return in order to avoid this regret. This temptation to avoid post-decisional regret gives rise to a decision bias known as regret Aversion Bias.

Anticipated and Experienced Regret.

“Regret is a negative, cognitively bases emotion that we experience when realizing or imagining that our present situation would have been better if we acted differently” (Zeelenberg & Pieters, 2004). This comprehensive definition classifies regret into anticipated and experienced regret and highlights some unique aspects of this emotion.

- First, regret can occur in the future only if we compare the expected outcome of the chosen alternative with imagined outcomes of forgone alternatives in case of anticipated regret.
- Second, regret can occur if we compare the actual or realized outcome with the actual outcomes of the forgone alternatives in case of experienced regret
- Third, this post-decisional comparison of the outcome makes the emotion of regret a counterfactual emotion in the sense that in order to experience or anticipate regret one needs to compare his/her present situation with a better situation that has never happened.

- Lastly, regret is a negative emotion as it brings with it a lot of pain, sadness, and disappointment, therefore people want to avoid this emotional pain as it represents disutility and goes against the basic utility maximization objective of a rational human being.

1.7.8 Perceived investment performance

The self-analysis of the return on stock investment by the individual investor is known as perceived investment performance. The subjective and objective perspectives of individual investors can be used to assess the return rate of stock purchases. The objective evaluation is done by comparing the real return rates and the average return rate of the security market, whereas the subjective assessment of investors is done by asking them to compare their current real return rates to their anticipated return rates or with the profits of their peers or with the market rate of return (Phuoc Luong and Thi Thu Ha, 2011). Perceived investment performance is a subjective assessment of returns in comparison to peers' returns and one's own expectations. Investments are deemed to be well-performing if their real returns exceed their expected returns or those of their peers and market and, underperform otherwise.

1.7.9 Investment satisfaction is the degree to which investors are happy with the outcomes of their investment decisions. It is the subjective assessment of the quality of their choices and performance (Asif, 2016). Return rates and investment satisfaction are closely related. Investors are satisfied with their performance when returns on their investment portfolio are equal to or higher than expected returns; however, when the actual return is lower than anticipated, investors become dissatisfied (Phuoc Luong and Thi Thu Ha, 2011). Investment satisfaction is comparable to, but still distinct from, "financial satisfaction," which refers to the overall subjective assessment of an individual's financial position in contrast investment satisfaction is concerned with assessments of one's investment quality (Hu et al., 2021).

1.7.10 Financial Satisfaction

Financial satisfaction is defined as "satisfaction with one's present financial situation" (Joo & Grable, 2004). When someone thinks their resources are sufficient for achieving their financial objectives, they are said to be financially satisfied. It is a purely arbitrary indicator of financial well-being. As it takes into account both monetary and nonmonetary aspects of one's financial situation, it is usually thought to be a sub-

construct of general well-being or an important constituent of life satisfaction (Campbell, 1981; Williams, 1983). The effect of increasing financial satisfaction can be seen in a person's ability to be happy at home, work, and in general, is a good indicator of how important it is to that person. People develop depression, health issues, and other problems when they have financial problems and are unable to achieve their financial goals (O'Neill et al., 2005). Financial satisfaction results from a cognitive judgment process in which a person compares their level of experienced satisfaction with a personal reference point. This assessment would reveal to the person how satisfied they felt with their financial situation. If in their opinion, they outperformed their indicative reference point, the person would be more financially satisfied, and less financially satisfied if they didn't (Sahi, 2017). According to the theory of subjective well-being (SWB), which was established in the 1970s, a person's satisfaction with their income or level of financial satisfaction is a specific aspect of their satisfaction with their overall quality of life (Toscano et al., 2006).

1.7.11 Investor sophistication

The ability of an investor to avoid making poor investment decisions is a common definition of individual investor sophistication (Stalnacke, 2018). It is a crucial factor to take into account when attempting to understand investor behavior because it has a variety of implications for individual investors. An individual's willingness to participate in the market and the performance of individual investors have both been found to be positively correlated with sophistication in earlier studies (Seru et al., 2010; Grinblatt et al., 2011). However, because sophistication is such a broad concept, it is challenging to quantify and is typically measured using a large number of proxies. Sophistication proxies generally include measures of investment-related information such as perceived financial knowledge of investors, investment experience, trading frequency, number of stocks in the portfolio, and whether traded in derivatives or not. However, broader measures of sophistication can also include information on socio-demographic factors and the cognitive and numerical abilities of a person (Stalnacke, 2018).

1.8 The organization of the Thesis

Chapter 1 (Introduction): This chapter develops a broad understanding of the research problem to be investigated in the present study. It briefly discusses the reasons for choosing the area, the background of behavioral finance, the current state of individual investors in India, the need for the study, research questions, and research objectives. The chapter also covers the justification for choosing the behavioral biases, followed by a comprehensive explanation of each behavioral bias to lay a solid groundwork for the remaining chapters of the study.

Chapter 2 (Theoretical framework of behavioral finance): This chapter provides an introduction to the field of behavioral finance. The shortcomings of traditional finance theories, as well as the evolution of behavioral finance, have been discussed. Behavioral finance concepts and themes have been thoroughly developed. Finally, the chapter sheds light on the various types of behavioral biases identified in the behavioral finance literature.

Chapter 3 (Review of Literature): This chapter aims at providing an in-depth review of the existing studies on relevant aspects of behavioral finance. It aims to update the reader regarding studies both empirical and theoretical in the area of behavioral biases and their impact on natural outcomes of financial decision-making such as investment performance, investment satisfaction, and overall financial satisfaction of an individual.

Chapter 4 (Research Methodology): This chapter deals with the development of a research design for the study. The current chapter outlines specific objectives, develops a conceptual framework, and formulates hypotheses to have a better understanding of the purpose of the study. Additionally, the chapter also explains the questionnaire design and measurements multivariate data analysis techniques used for data analysis.

Chapter 7 (Data analysis and Interpretation): This chapter presents a summary of data collected from individual investors. Subsequently, the data were analysed and interpreted using the appropriate statistical techniques and procedures.

Chapter 6 (Findings and conclusion): The present chapter summarizes the major findings of the study on behavioral biases and their impact on individual investors in the Delhi-NCR region. The answers to all of the research objectives formulated in the first chapter have been incorporated into this chapter.

CHAPTER 2

THEORETICAL FOUNDATIONS OF BEHAVIORAL FINANCE

2.1 Introduction

Behavioral finance is a burgeoning discipline that provides fertile ground for innovative research work in the field of finance. It has emerged out of behavioral economics and seeks to provide explanations for people's economic decisions by incorporating human psychology with conventional economics and finance (Baker and Nofsinger, 2010). Today what we know as behavioral finance started acquiring its form as a distinct discipline merely four decades ago. However, its foundations can be traced back to the eighteenth century i.e. the classical economics period. Later on, economists in the neo-classical period and twentieth century in their ambition and contention to re-shape the discipline parallel to natural sciences kept on distancing themselves from psychology and it became very rare to take human factors into consideration in any theoretical or empirical financial research pursuit. After the 1970s the renaissance of behavioral economics happened because of the development of cognitive psychology that started to define the human brain as an information-processing machine. Psychologists Amos Tversky and Daniel Kahneman apparently made history by putting out the "Prospect theory" in 1979 which became the foundation of modern-day behavioral finance. In the 1980s, behavioral finance started acquiring its formal shape and emerged as a full-fledged academic discipline. As we moved to the 21st-century behavioral finance has made the greatest contributions to the field of investment and portfolio management. Today behavioral finance is helping in ascertaining the behavior of aggregate markets as well as the behavior of market participants through its macro and micro offshoots. It is playing a significant role in the lives of financial market advisors, institutional investors, as well as individual investors in making better financial portfolios. In essence, the behavioral finance paradigm essentially evolved as a result of traditional finance's constraints which argued upon the assumptions of full rationality and normative decision choices. Therefore to understand the need for the emergence of behavioral finance let's have a look at traditional finance theories and the challenges they pose to proponents of behavioral finance.

2.2 Standard Finance and Challenges to Behavioral Finance

In the late 1950s and early 1960s, finance was prevalent in the form of standard finance. Standard finance tries to find out rational solutions to people's economic decisions by developing theories and tools on the premise of how investors should behave (Baker and Nofsinger, 2002). Statman (2000) has defined standard finance as *"the body of knowledge built on the pillars of the arbitrage, principles of Miller and Modigliani, the portfolio principles of Markowitz, the capital asset pricing theory of Sharpe, Lintner, and Black, and the option-pricing theory of Black, Scholes, and Merton."* Thus the unified financial theory presented in the form of standard finance constitutes several theories, hypotheses, and models given by a number of researchers of that time. All these theories and models under the umbrella of standard finance are based on the basic assumptions that markets are efficient and agents participating in those markets are fully rational.

Assumptions of standard finance:

- i) **Homo Economicus/ Rational economic agent:** Homo economicus is an awesome person that always makes rational decisions without getting affected by emotions and situations, possesses mental capabilities to process any amount of available information, and holds preferences with the objective of utility maximization. Market participants in standard finance theories are homo-economicus means they are "rational maximizers". **Rationality** here implies two things first, individuals update their beliefs in a timely and appropriate manner as they receive new information as described by Bayes' Law, and second, investors make choices that are normatively acceptable.
- ii) **Efficient markets:** An efficient market is a market where at any given point in time security prices match the intrinsic value of a security. In an efficient market large number of rational participants compete with each other to maximize their wealth and pertinent information is freely available to all of them this makes competition really intense and suboptimal decision-makers are either thrown out of the market or become better over time leading to market efficiency.

- iii) **Perfect Information:** Decision makers in standard finance theories have access to perfect information that is required to make perfect decisions. This information is available to all the investors at the same time without any cost and is essential for the functioning of an efficient market.
- iv) **Perfect Self-Interest:** Market participants in standard finance theories always act in their own best interests. They are guided by the sole objective of maximizing returns at minimum costs without any additional benefits and considerations.

2.2.1 Theories in Standard Finance

2.2.1.1 Expected Utility Theory

Neo-classical economists used expected utility theory to illustrate the decision maker's choice between risky and uncertain prospects by comparing their expected utility values (Mongin, 1998). Expected utility is the weighted average of levels of utility assigned to each possible outcome at any given point in time. According to the EUT, the decision maker is homo economicus and will always choose a prospect with maximum expected utility based on his/her risk appetite. The concept was first posited by Daniel Bernoulli while solving the St. Petersburg paradox in 1713 and was given an axiomatic foundation by Von-Neumann and Morgenstern in 1944 known as the VNM theorem. The VNM theorem prescribes four axioms of the EUT that defines a rational decision-maker: Completeness, Transitivity, Independence, and Continuity. If these axioms are fulfilled the expected utility of a prospect can be presented in the following form:

$$E(U) = \sum_{i=1}^n P_i \cdot u(x_i)$$

Where; $E(U)$ is the expected utility of the prospect, P_i is the probability associated with the outcome x_i , x_i is the i^{th} possible outcome, and $U(x_i)$ is the utility of x_i .

The curvature of the utility function explains the risk attitude of a decision-maker. The convex, concave and linear utility function represents a risk-seeker, risk-averse, and risk-neutral decision maker respectively. EUT is the normative interpretation of reality but the mathematical correctness of the axioms of EUT is not sufficient to describe

human behavior under uncertain situations and its departure from reality ultimately led to the development of behavioral economics and subsequently behavioral finance.

2.2.1.2 Harry Markowitz Model

In the year 1952, Harry Markowitz published an article named “Portfolio selection” in the journal of finance and for the first time in the history of finance, it was realized that the performance of an individual security is not as important as the performance of the entire portfolio. The importance of systematic diversification to create efficient portfolios was also recognized at the same time. Thus Markowitz’s paper was the first mathematical conceptualization of the ideas of diversification, return, and risk. This conceptualization was the birth moment for the modern portfolio theory or standard finance (Rubinstein, 2002). Basically, Markowitz’s model helps in choosing the most efficient portfolio out of the various portfolios available to an individual investor. To choose among the portfolios investors must know the return and risk of those portfolios. The H-M model defines return on security as the weighted mean of all possible outcomes with different probabilities and risk as the variance of those outcomes around the means. But an individual is interested in the portfolio risk and return and not the risk and return of individual security. Again, the portfolio return was defined as the weighted sum of the return on individual securities ($R_p = \sum_{i=0}^n w_i \cdot r_i$). While the portfolio risk comprised of the weighted average of variance plus twice the weighted sum of covariances [$\sigma_p^2 = \sum_{i=1}^n \sum_{j=1}^n w_i w_j \sigma(R_i, R_j)$] and we have been literally living on these formulas for more than sixty years from now. Given the risk and return of a portfolio, an investor can choose a portfolio with a minimum variance if the expected return is specified or can choose a portfolio with the maximum return if the desired level of risk is specified. Thus, Harry Markowitz’s model developed a way in which investors can achieve their optimal portfolios. Like the expected utility theory, Harry Markowitz’s model is also normative in nature means it also focuses on how an investor should behave and not how he actually behaves.

2.2.1.3 Capital Asset Pricing Model

Sharpe, (1964) and Lintner, (1965) independently took forward the work of Harry Markowitz and tried to establish a quantitative relationship between risk and return on an asset, given that the investors follow the Markowitzian approach to portfolio selection. The CAPM model establishes a linear relationship between the expected return of an individual security to the systematic risk of that security (Galagedera, 2007). The model is an idealized depiction of how capital markets price securities so that the expected returns will compensate for the expected risks (Rossi, 2016). Although CAPM provides valuable insights for evaluating various investment options its application in practical situations has always been controversial since its inception.

Markowitz's "mean-variance" model already had its own assumptions Sharpe and Lintner introduced a few additional assumptions in developing CAPM while building on the Markowitz work. Thus CAPM relies on several assumptions developed by Markowitz, (1952), Sharpe, (1964), and Lintner, (1965) as described below:

- Investors are risk averse and will maximize their utility by trading off between risk and return.
- Investors hold their investments for a single period planning horizon.
- The markets are perfect means that capital markets are in equilibrium, there is no inflation, no change in interest rates, no transaction costs, and no taxes.
- Investors can buy or sell even in portions.
- Investors can borrow or lend any amount of money at a risk-free rate, which remains the same for all investors.
- Expectations of all investors in the market are homogenous regarding risks, returns, and covariances eventually they tend to make the same choices in any given situation.

According to CAPM, the expected return on security $[E(R_i)]$ is the sum of risk-free return (R_f) plus a risk premium ($E(R_m) - R_f$) multiplied by the β of the security. ' β ' refers to the systematic risk that measures the sensitivity of the security's return to the return on the market portfolio.

$$E(R_i) = R_f + \beta_i [E(R_m) - R_f]$$

Although CAPM is widely popular among market professionals as an asset pricing theory due to its simplicity, still it is criticized by many researchers on various grounds. First, it requires investors to compare expected returns on security with the expected returns on the market portfolio with the help of expected β . Unfortunately, this process is not as practical as it seems because investors' expectations are very subjective and inadequate (Chandra, 2020). Second, Roll and Ross, (1983) persuasively argued that an ideal market portfolio consists of all assets in the world; financial, real, and human however in reality, a true market portfolio doesn't exist therefore CAPM can't accurately be tested statistically. Third, the assumptions of the CAPM model are absurdly unrealistic. This artificialness of CAPM has created a gap between theory and reality which can be curtailed by the realistic theories of behavioral finance.

2.2.1.4 Efficient Market Hypothesis

After Markowitz, Sharpe, Lintner, and others Eugene Fama in the mid-1960s introduced the idea of the "Efficient Market Hypothesis" to the literature of standard finance for which he received a Nobel Prize in economics in the year 2013. Fama persuasively illustrated that in the securities market due to a large number of rational investors, investments will always be appropriately priced and will always reflect all available information. The efficient market hypothesis is the assertion that the securities' prices always equal their intrinsic value (Fama, 1965). Intrinsic value refers to the present value of all future cash flows that a person is going to receive by owning that security.

As per Fama, (1970) the efficient market hypothesis distinguishes market efficiency at three levels i.e. the weak, semi-strong, and strong form of market efficiency. The weak form of efficiency implies that all past information is reflected in current prices and hence, technical analysis is useless. Semi-strong form means that the market is efficient to process all publicly available information making the fundamental analysis of securities a futile activity. The strong form of market efficiency implies that all kinds of relevant information are reflected in securities' prices such that even insider information is of no use in such a market.

However, the validity of the EMH has always been questioned over time. Many "anomalies" or significant predictable patterns in the guise of technical anomalies, fundamental anomalies, and calendar anomalies have been uncovered in the literature

in recent years. There exist examples like the “crash of 1987”, and the “internet bubble” which contradict the view of EMH. In present times there are investors like Warren Buffet who have consistently outperformed the market over a long period of time, all these wouldn't have been possible in a perfectly rational market. Malkiel, (2003) concluded that markets are far more efficient and far less predictable than our beliefs.

2.2.1.5 Three-Factor Model

The CAPM developed by Sharpe (1964) and Lintner (1965) explained expected returns on assets, particularly stocks as a function of the systematic risk of those stocks. The popularity of the CAPM can be attributed to its simplicity in facilitating easy comparisons of investment alternatives. However, it has been subject to a huge amount of criticism over time due to its lack of consistency in practical applications. Many authors have tried to improve it and presented their own modified versions of the model. The three-factor model proposed by Fama and French (1992) is an improvised version of the CAPM. They identified two factors *size of the company* and the *Book to Market Equity Ratio* (BE/ME ratio) that play an important role in explaining stock price dynamics in the market. Thus, the three-factor model is an extended version of CAPM with the first factor being the same i.e. “ β ” or systematic risk along with two additional factors SMB and HML where SMB stands for *Small Minus Big Market Capitalization* measuring excess stock returns of small companies over big companies and HML represents *High Book-to-Market Ratio Minus Low book-to- Market Ratio* measuring historical excess return value stocks over growth stocks (Rehnby, 2016).

Mathematically the model can be presented as follows:-

$$r = r_f + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \varepsilon$$

r = Expected return

r_f = risk free rate

β = Factors sensitivity

SMB = Size Premium

HML = Value Premium

ε = residuals of the regression model

Fama and French conducted several studies to validate their model and revealed that the three-factor model could explain more than 90 percent of the variation in the

diversified portfolio returns making it a better tool for assessing portfolios (Hayes, 2022; Taneja, 2010).

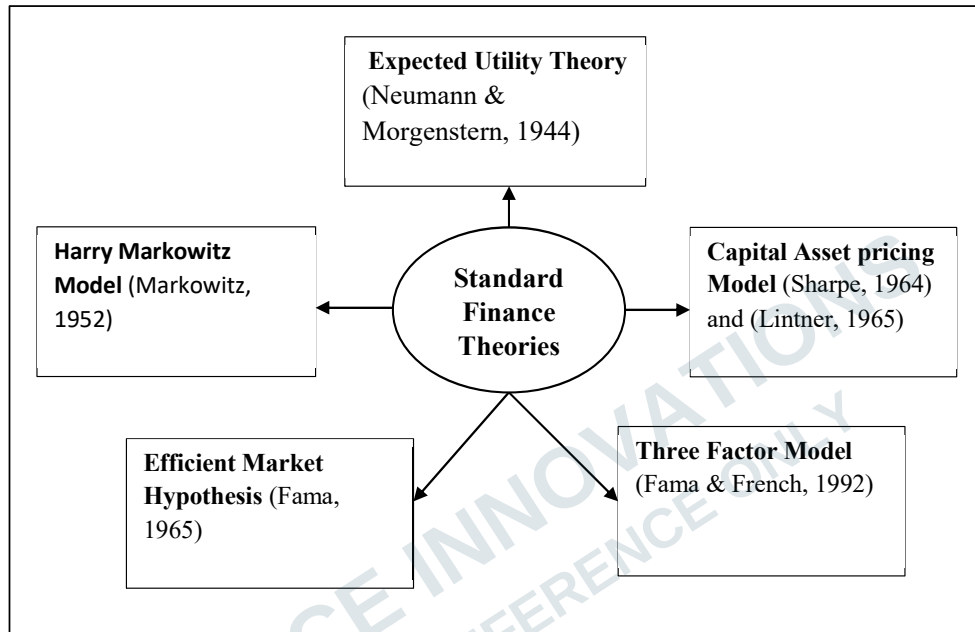


Figure 2.1 Standard finance theories

Source – Compiled by Author

2.3 Behavioral Finance

As we saw in the previous section that standard finance theories assume that how investors are perfect little economic beings taking actions in their own interests, and how efficient the capital markets are, but when we try to apply standard finance theories to real-world investment problems these theories seldom work. Behavioral finance is a new approach that has emerged in response to absurdly unrealistic assumptions and real-world problems not recognized by standard finance. In a sense, it picks up where standard finance theories leave off and thereby completes the circle. Behavioral finance accepts the reality that investors do not always act in a rational manner, sometimes they are perfect economic beings but other times they are just normal human beings. Being normal humans, their decisions are often driven by emotions like hope, greed, and fear.

They allow their decisions to depend upon how questions are framed. Most of the time they are unaware of the fact that how their own psychology is leading them to suboptimal decision-making. Sometimes investors unconsciously apply heuristics and shortcuts to escape tedious mental calculations and sometimes they do unnecessary complex mental accounting without knowing that various asset baskets are interrelated. Thus behavioral finance attempts to understand the financial markets and investor behavior by relaxing the fundamental assumptions of the traditional paradigm and offers the following insights:

- i) **Investors are not fully rational:** While making investment decisions investors form beliefs and opinions about various alternatives based on the available information. These beliefs and opinions are influenced by a number of factors such as their cognitive abilities, predominant emotions, and social influence which leads to biases and prevents them to act in a rational manner.
- ii) **Human intuition is fragile:** Not everyone who invests in financial markets is a student of finance. As decisions become more complex and time grows short the tendency of investors to take decisions on the basis of intuition increases manifold, which makes them prone to psychological biases and fall into predictable error patterns.
- iii) **Markets are not efficient even if they are difficult to beat:** Standard finance theory assumes that financial markets are efficient but in practice there exist financial market anomalies, mispricing persists for longer than normal durations, and partially predictable return patterns provide evidence for the fact that financial markets not efficient in reality however, they are difficult to beat.
- iv) **Investors seek satisfactory rather than optimal solutions:** Market participants in the standard finance theory are “mean-variance” optimizers’ which means they always select the optimal portfolios (portfolios with high returns and low risk). But in reality, in addition to risk and return investors are also guided by other benefits from their investments. Statman (1999, 2011) divided these benefits into three categories utilitarian benefits, expressive benefits, and emotional benefits. Sometimes the objective of beginners is to survive in a highly competitive market rather than thrive in

such a scenario investors often invest in minimally acceptable portfolios instead of optimal portfolios.

- v) **Investors' decisions are not always normatively acceptable:** In standard finance people always make normatively acceptable decisions, but behavioral finance tells us that even after applying Bayes' laws properly, people sometimes make choices that are normatively questionable. These decisions are open to change as they are formed during the decision process itself.

2.3.1 Behavioral finance – The Concept

Currently, there is no precise definition of behavioral finance as the field itself is evolving. Different researchers have defined it differently from time to time as per their own perception. But what is common in all those viewpoints is that they unanimously recognized the interdisciplinary nature of behavioral finance. Mitchell (1995) emphasized that the true merits of interdisciplinary research are attained when the combination of two disciplines emerged into an entirely new field of study. Olsen (1998) defined behavioral finance as *“the application of **psychological and economic principles for the improvement of financial decision-making.**”* (p. 11). Olsen (1998) acknowledged that behavioral finance does not reject sound economic principles it only recognizes the fact that these principles can be true only within specific boundaries. Riccardi and Simon (2000) defined *“behavioral finance as a discipline that attempts to understand the reasoning pattern and emotional processes of investors and their impact on the decision-making process. Thus it attempts to understand what, why, and how of **investing from a human perspective**”* (p.27). Baker and Nofsinger (2010) defined behavioral finance as a *“relatively new but quickly expanding field that seeks to provide explanations for people's economic decisions by combining behavioral and **cognitive psychological theory with conventional economics and finance**”* (p.3)

The above definitions underline the fact that behavioral finance brings together the content, methods, and research studies from various existing fields of study such as economics and behavioral economics from the economics department perspective, finance, investing, accounting, and management from the business school perspective, and finally the psychology, sociology, and anthropology from the point of view of liberal arts (Miller, 1999; Ricciardi & Simon, 2000; Subhash, 2012; Singh, 2019). Similar to the field of economics behavioral finance also looks at the psychology of

investors at two levels first, to identify the impact of broad characteristics and investors' personality types on the aggregate market behavior known as **Macro behavioral finance**, and second to understand the biases that exist within the personality under **Micro behavioral finance**.

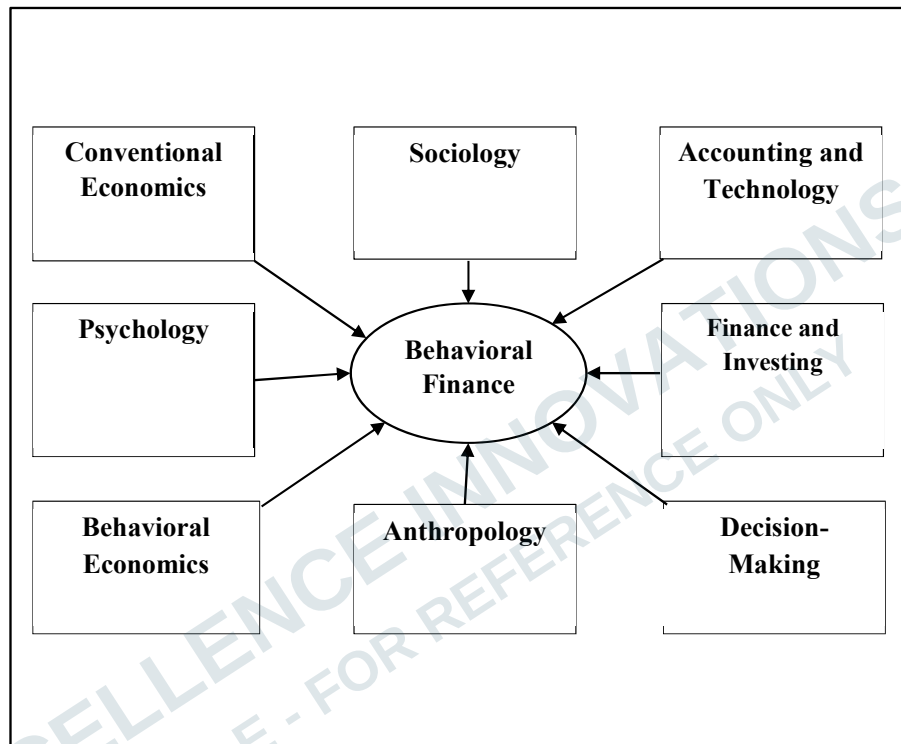


Figure 2.2 Contributing disciplines of behavioral finance

Source- Adapted from Ricciardi (2006)

2.3.2 Evolution of behavioral finance

In the late 1950s and 1960s, two disciplines were simultaneously emerging to contribute to the progress of behavioral finance i.e. cognitive psychology and decision theory. The development of these disciplines allowed researchers in behavioral finance to use the concepts learned in cognitive psychology and decision theory to further refine the concepts of modern behavioral finance. Simon (1955) made the most significant contribution to the field of behavioral finance by publishing an article titled “A behavioral model of rational choice” in the quarterly journal of economics and proposed his “bounded rationality theory” to counter the commonly held belief that the decision

maker is 'homoeconomicus'. The model acknowledged the fact that the rationality of an individual decision-maker is limited by his mental abilities and time constraints. For the first time, bounded rationality theory treated market participants as 'satisfiers' instead of 'optimizers'. Later on, the Nobel Prize Committee recognized the efforts of Herbert A Simon and honored him with Nobel Memorial Prize in Economic Sciences in the year 1978. During the 1960s, professors O.K. Burrell and W. Scott Bauman from the University of Oregon began publishing research articles by combining quantitative investment models with behavioral approaches to finance. Slovic (1972) from the psychology department of the same Oregon University published their first seminal paper on behavioral finance titled "psychological study of human judgment" on the investment decision-making process from a behavioral perspective. Building on this initial work two researchers Kahneman and Tversky (1979) published an article titled "Prospect theory: An analysis of decision under risk" this paper introduced the concept of 'Prospect theory' which is eventually viewed as the intellectual foundation of micro behavioral finance. Prospect theory presents an alternative to 'Expected utility theory' and explains how investors make decisions under the conditions of uncertainty and provide a better account of the observed investor behavior in comparison to traditional theories. Along with Daniel Kahneman and Amos Tversky, the research work of experimental economist Vernon Smith has also inspired modern generations to use laboratory experiments as an essential tool in empirical economic analysis. Daniel Kahneman and Vernon Smith shared the 2002 Nobel Prize in Economic Sciences for their contributions to making behavioral finance and experimental economics a unique academic and professional discipline. Kahneman et al. (1982) published another paper titled "Judgment under uncertainty: heuristics and biases" in which they introduced three heuristics representativeness, anchoring, and availability to the world, and explained how people use these heuristics to assess probabilities without having any knowledge of their detrimental impact on rational decision making. In the same year, two different research studies by Loomes and Sugden (1982), and Bell (1982) independently gave the concept of regret aversion that described how this bias can cause people either to take more than normal risk or no risk at all in order to avoid the feeling of regret. The conceptualization of prospect theory and identification of the first few heuristics stirred the interest of researchers and the decade of the 1980s witnessed major developments in macro behavioral finance in the form of the identification of market anomalies. Questions were raised about the underpinnings of the efficient market

hypothesis and the working of the aggregate stock market and consequently De Bondt and Thaler (1985) came up with the 'overreaction hypothesis' in their paper titled "Does the stock market overreact?" which explained how the psychology of individual investors can cause markets to overreact to news and dramatic events they also expanded on a well-known 'value anomaly' and their work also shed light on the 'January effect' anomaly. It is also worth noting that the year 1985 saw the publication of three more seminal papers; Shefrin and Statman (1985) defined the now well-established 'disposition effect' which suggests that investors tend to sell winning stocks too early to realize gains and hold losing stocks too long to avoid losses. Shefrin (2000) describes the disposition effect as the blend of three main aspects of behavioral finance i.e. the prospect theory, self-control bias, and regret aversion bias. Thaler (1985) published the paper "Mental accounting and consumer choice" and coined the term mental accounting for the first time. Mental accounting refers to the phenomenon that individuals keep their money in separate mental accounts and treat these accounts as non-fungible with different propensities to consume. Mehra and Prescott (1985) uncovered the equity premium puzzle in the same year that explained why historically average return on equity is excessively high in comparison to treasury bills in the U.S. Additionally, the field of behavioral finance starts taking its formal shape in the decade of 1980s with the institutionalization of many societies such as the 'Society for advancement in behavioral economics in 1982', 'Russel sage foundation', and the first-ever conference on behavioral finance titled 'Behavioral foundations of economic theory' were also organized in the same decade. Many new behavioral finance journals were started that acted as catalysts for the development of the field. By the end of the 1980s, too many market anomalies were uncovered and there was little inspiration among the researchers to formulate econometric models for the working of the aggregate stock market and the entire focus of the research shifted to the development of models explaining human psychology and its impact on asset prices and portfolio selection. Shefrin and Statman (1994) postulated their famous 'Behavioral asset pricing model' as an alternative to CAPM and the Three-factor model of standard finance. The BAPM model assumes that the expected return of a security depends on a variety of 'expressive' and 'emotional' factors in addition to the sole 'utilitarian' factors recognized in standard finance. BAPM described expected return on security as a function of market factor, book-to-market factor, market cap factor, momentum effect, social responsibility, and status factor. In the late 1990s and early 2000 behavioral

finance achieved a number of important milestones. Shleifer and Vishny (1997) established the concept of 'Limits to Arbitrage' which explained how and why anomalies and mispricings survive in financial markets. Shleifer and Vishny's model adequately captured the 1998 LTCMs (Long Term Capital Management) arbitrage distress during the Asian Financial Crises (Mackenzie, 2010). Almost at the same time Odean (1999) started a new wave of behavioral finance research by analyzing data from brokerage accounts to track down the most significant cognitive bias i.e. Overconfidence. Kahneman (2011) regarded overconfidence as "*the mother of all psychological biases*". Barber and Odean (2001) provided evidence for the fact that men are more overconfident than women in financial markets which negatively impacts their financial performance. In 2000, Andrei Shleifer released his pioneering book "*Inefficient Markets: An Introduction to Behavioral Finance*" and Robert Shiller published his renowned book "*Irrational Exuberance*" in which he accurately foresaw the burst of the dot-com bubble. Shefrin and Statman (2000) also introduced Behavioral Portfolio Theory parallel to the Modern Portfolio Theory of standard finance. The central feature of the Behavioral Portfolio Theory is that the investors do not view their portfolio as a whole instead they divide it into separate mental accounts, where each mental account can have its own investment goals and risk-return relationships. Briefly said behavioral finance gained acceptance and credibility in the 2000s after years of heated debate with the supporters of orthodox standard finance.

In the last two decades, behavioral finance has become even more diversified and dispersed than it used to be. The field has witnessed an increase in specialization in terms of accepted methods and data. Currently, behavioral finance makes use of text analysis, randomized field experiments, and genetic and neuroimaging data. Today it is addressing a variety of issues from the behavior of corporates to the behavior of households in financial decision-making (Illiasenko, 2017).

Table 2.1 Decade-wise Evolution of Behavioral Finance

Year	Author	Concept	Paper
Prior to 1980s			
1955	Herbert A Simon	Bounded Rationality	A Behavioural Model of Rational Choice
1972	Paul Slovic		Psychological study of human judgment: Implications for investment decision making
1974	Tversky and Kahneman	Heuristics	
1979	Kahneman and Tversky	Prospect Theory	Prospect theory: An analysis of decision under risk
The Decade of 1980s			
1980	Richard Thaler	Endowment effect	
1981	Tversky and Kahneman	Framing Bias	The Framing of Decisions and the Psychology of Choice
1982	Kahneman, slovic, and Tversky	Representativeness, Anchoring, and Availability	Judgment under uncertainty: heuristics and biases
1982	Loomes and Sudgen	Regret aversion Bias	Regret theory: An alternative theory of rational choice under uncertainty
1982	Bell		Regret in decision-making under uncertainty
1984	Kahneman and Tversky	Framing Bias	Choices, values, and Frames
1985	De Bondt and thaler	Overreaction hypothesis	Does the stock market overreact?

1985	Shefrin and Statman	Disposition Effect	The disposition to sell winners too early and ride losers too long: Theory and evidence.
1985	Richard Thaler	Mental Accounting	Mental accounting and consumer choice
1985	Mehra and Prescott	Equity premium puzzle	The equity premium: A puzzle.
1989	Knetsch	Endowment effect	The endowment effect and evidence of non-reversible indifference curves.
The Decade of 1990s			
1990	Kahneman, Knetsch, and, Thaler	Endowment effect	Experimental tests of the endowment effect and the Coase theorem.
1994	Shefrin and Statman	The Behavioral Asset Pricing Model	Behavioral capital asset pricing theory
1997	Shleifer and Vishny	Limits to Arbitrage	The limits of arbitrage
1999	Odean	Overconfidence	Do investors trade too much?
The Decade of the 2000			
2000	Andrei Shleifer	Limits to Arbitrage	Inefficient Markets: An Introduction to Behavioral Finance
2000	Robert Shiller	Insights about Behavioral finance	Irrational Exuberance
2000	Shefrin and Statman	Behavioral Portfolio theory	Behavioral portfolio theory.
2001	Barber and Odean	Overconfidence	Boys will be boys: Gender, overconfidence, and common stock investment.

2.3.3 Themes under Behavioral Finance

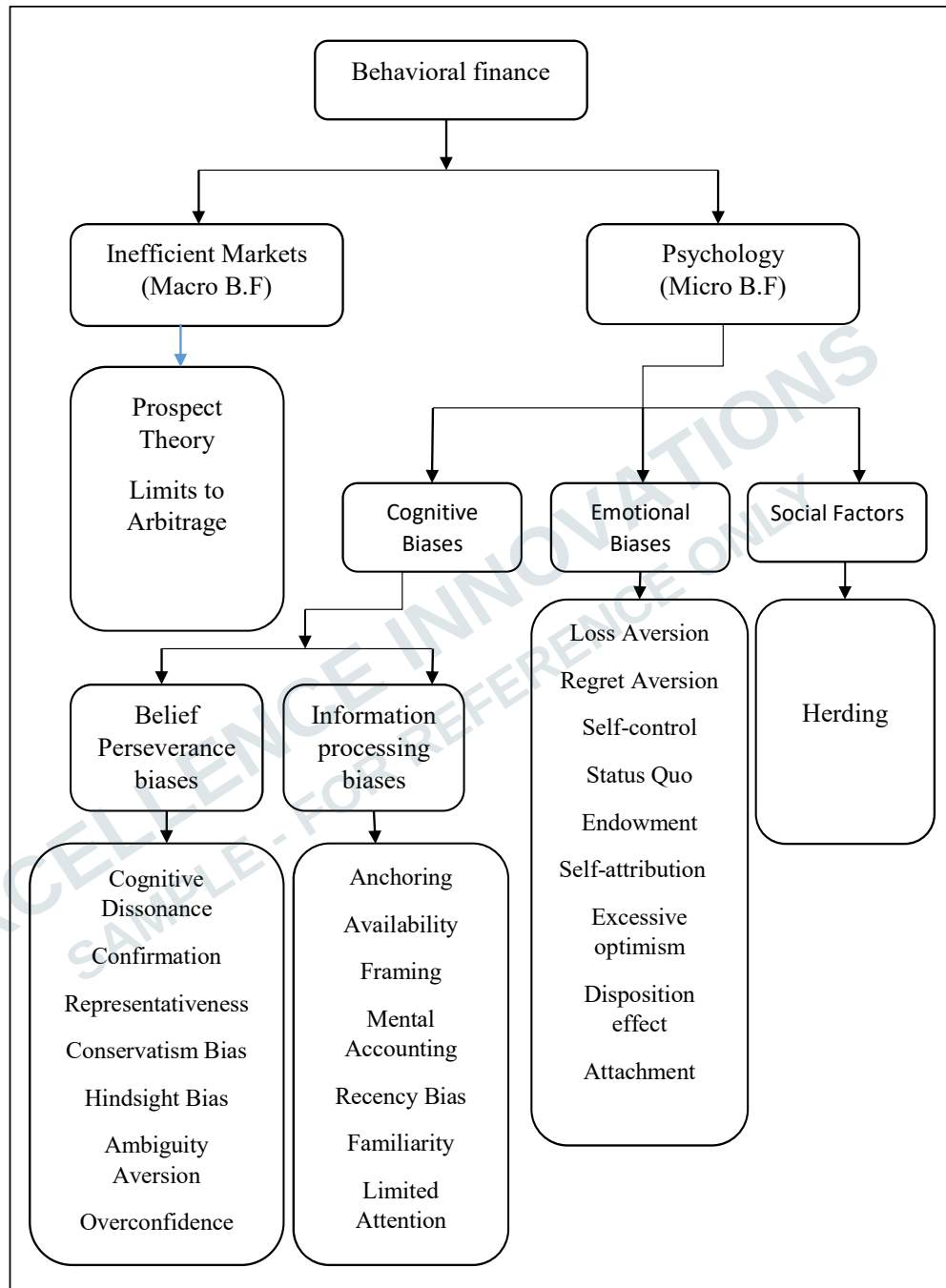


Figure 2.3 Themes under behavioral finance

Source- Compile by Author

2.3.3.1. Prospect Theory

Prior to the advent of the Prospect Theory, Expected Utility Theory used to dominate the analysis of decision-making under risk. The theory was widely accepted as a normative theory of decision-making in which the decision-maker was assumed to be a *homo economicus* i.e. a rational and self-interested person who always chose prospects with maximum expected utility based on his risk appetite. The EUT was given an axiomatic foundation by Neumann and Morgenstern, (1944) however, the mathematical correctness of the theory was not sufficient to describe human behavior under risk and uncertainty. In response to the limitations of EUT Kahneman and Tversky (1979) in their paper titled “*Prospect Theory: An Analysis of Decision under Risk*” presented an alternate theory called the Prospect Theory which later on became a milestone in the development of the field of behavioral finance (Pompian, 2011). Prospect theory through a series of choice problems demonstrated how people’s behavior can systematically violates the axioms of the EUT in laboratory settings and provided an explanation for an individual’s inconsistent behavior through certain psychological biases inbuilt within the theory. The importance of prospect theory can be understood from the fact that many psychological biases such as framing, loss aversion, mental accounting, status quo bias, disposition effect, and reference dependence can be directly derived from this theory. Many other psychological biases such as overconfidence, cognitive dissonance, and optimism can also be derived indirectly from the Prospect Theory.

Key Propositions of the Prospect Theory

- i) **Reference Dependence:** Prospect theory assumes that people value a prospect relative to an initial reference point which is usually their current wealth. This assumption was in contrast with the assumption of EUT that prospects are valued on the basis of their final outcomes or final wealth rather than the current wealth.
- ii) **Diminishing Sensitivity:** People value gains and losses according to the S-shaped value function shown in figure xx. The tenet of diminishing sensitivity suggests that changes in the value function will have a greater impact on an individual’s preferences when he is near the reference point and this impact keeps on diminishing as the individual moves away from

the reference point. In other words, a gain of the first \$500 would be more pleasurable to a person than a gain of the second \$500. Likewise, a loss of the first \$500 would be more painful for a person than a loss of the second \$500. Thus the value function is concave for gains and convex for losses as per the law of diminishing sensitivity (Chiu & Whu, 2010)

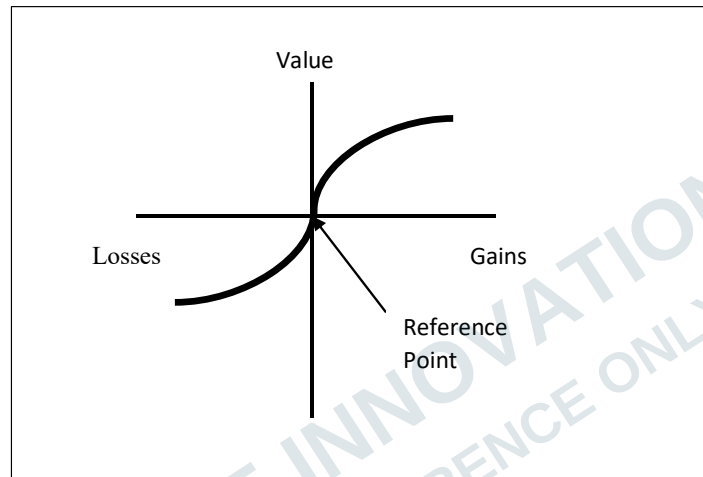


Figure 2.4 Value Function under Prospect Theory

Source: Kahneman and Tversky (2013)

- iii) **Loss Aversion:** The phenomenon that losses loom larger than gains is embedded in the prospect theory in the form of an “S” shaped utility function passing through a reference point. One of the important observations that can be drawn from this value function is that people are risk seekers below the reference point and are risk averse above the reference point. This change in behavior of respondents above or below the reference point clearly suggests greater sensitivity to losses than to gains and thus “Loss Aversion”.
- iv) **Change in Risk Attitude:** According to EUT the decision maker can either be a risk seeker or risk averse, in most cases the decision maker is assumed to be a risk-averse person the EUT does not allow for a change in the risk attitude of a person but the prospect theory suggests that individuals are not universally risk averse, depending on the nature of the prospect same person can display both characteristics of risk aversion and risk seeking.

- v) Decision weights: EUT assumes that people weigh outcomes on the basis of objective probabilities, while prospect theory assumes the use of subjective probabilities for the evaluation of decision outcomes. People are more sensitive to unlikely extreme outcomes and underweight the probabilities of intermediate outcomes consequently, the probability weighting function is convex for larger probabilities and concave for smaller probabilities.

2.3.3.2 Limits to Arbitrage

The Efficient Market Hypothesis says that prices in the financial markets are always right as there are rational investors in the market who will quickly act to correct the price if the price of any of the securities deviates from its fundamental value. This process of taking advantage of mispriced opportunities is called the 'Arbitrage Theory'. The EMH view of standard finance assumes that this comes to investors at absolutely no risk but behavioral finance recognizes the fact that this arbitrage opportunity is not free of cost as perceived by Friedman (1953) and Fama (1965) in their arguments, rather it comes at a risk that limits the ability of the rational investors or traders to take full advantage of this arbitrage opportunity and this phenomenon is known as 'Limits to Arbitrage'. The concept was introduced by Shleifer and Vishny (1997) in their paper titled "Limits to Arbitrage" it answers the most fundamental questions as to why arbitrage opportunities do not disappear quickly and mispricing exist for a longer duration if markets are efficient. Barberis and Thaler (2003) designated Limits to Arbitrage as one of the two building blocks of behavioral finance. They identified four risks and costs which derail the process of automatic price correction and allow mispricing to survive in the market.

- i) Fundamental Risk: If arbitrageurs or rational investors in the market try to correct the mispriced securities in the process they are exposed to the obvious risk of losing all the fundamental value. Fundamental risk is the risk that arises because of the bad news about the security that you had already purchased. Even if investors are aware of the strategies to hedge against this risk by shorting substitute security from the same industry, it still leaves the investor in a vulnerable situation as perfect substitutes do not exist in reality

making it impossible to remove all the fundamental risk (Barberis & Thaler, 2003).

- ii) Noise Trader Risk: The theory of Limits to Arbitrage is based on the notion of the coexistence of rational and irrational traders i.e. arbitrageurs and noise traders. For the sake of argument even if we agree on the availability of perfect substitute securities in the market still rational traders face the risk caused by noise traders if they become more pessimistic about the future. This can drag the prices in opposite direction and arbitrageurs are forced to liquidate their positions early. Thus in the process, they fail to combat the existing mispricing problems and can suffer huge losses. De Long et al. (1990a) successfully demonstrated the power of noise traders in limiting arbitrage opportunities.
- iii) Implementation Cost: The cost of implementing an arbitrage process in the form of transaction costs such as commissions and bid-ask spread makes mispricing opportunities less attractive to rational traders. Short selling which is considered an important part of executing the arbitrage process further adds the short selling cost to the overall implementation cost.
- iv) Cost of Finding and Learning about Mispricing: Finding mispricing can be expensive and time-consuming learning about them will require highly specialized agents and state-of-the-art technology, most of the time arbitrageurs had to face a hard time detecting these deviations to the extent that they stop bothering about correcting these mispricing in the market.

Thus, it is not easy for arbitrageurs to exploit inefficiencies and explain anomalies in the financial markets. For proper functioning of the arbitrage process, arbitrageurs need capital but they are handicapped by limited funds and difficulty in finding mispricing. Limit to Arbitrage is a part of behavioral finance theory as it tries to explain market anomalies on the basis of investor psychology (Barberis et al. 1998; Hong & Stein 1999; and Barberis & Shleifer 2003).

2.3.4 Categorization of Behavioral Biases.

Different researchers have classified behavioral biases on the basis of various meaningful frameworks according to their own understanding and time. Pompian (2011) classified behavioral biases into two main categories **Cognitive and Emotional biases**. Baker and Puttonen (2017) classified them on the basis of the source of origination of behavioral biases whether they result from internal factors of a person or external factors that are beyond the thinking process of individuals. Again the biases resulting from internal factors include **cognitive** and **emotional** biases and biases resulting from external factors include **social biases**. **Cognitive biases** result from the weakness or constraint in how individuals think. They usually arise when people gather, process, interpret, and try to make information processing simpler. **Emotional biases** occur when individuals tend to act on the basis of feelings rather than facts such biases are more impulsive than intentional and are deeply embedded in a person's inner psyche. **Social biases** develop in an individual when social interactions influence his views and feelings. The media, internet, family, friends, coworker, and culture play an important role in forming social biases within a person. Baker and Puttonen (2017) and Pompian (2013) further subdivided cognitive biases into Belief perseverance biases and Information processing biases. The tendency to avoid conflicts between one's views or opinions and reality is the source of **belief perseverance biases**. Investors generally find it challenging to change their assumptions in the face of new, contradicting evidence and end up feeling mental discomfort in reconciling these differences leading to belief perseverance biases. **Information processing biases** occur when people process information about financial decisions incorrectly in their minds. Baker and Nofsinger (2002), Prosad (2015), Luong and Ha (2011), and Waweru et al., (2008) have divided behavioral biases under two themes Heuristic-driven biases and Frame dependent biases also known as prospect theory biases. **Heuristics or rules of thumb** reduce the complexity of investment decisions by investors. These shortcuts enable the brain to produce estimations prior to fully processing all information, leading to a number of psychological biases. **Prospect theory biases** occur because of certain mental states that may have an impact on how someone makes decisions these include regret aversion, loss aversion, and mental accounting (Waweru et al., 2003; Luong & Ha, 2011). **Frame-dependent biases** arise when the way financial experts structure their options has an impact on investors' decision-making process. This theme

encompasses biases including loss aversion, disposition effect, mental accounting, and narrow framing. Heuristics overlap with belief perseverance biases and information processing biases likewise prospect theory biases and frame-dependent biases also overlap in different research studies.

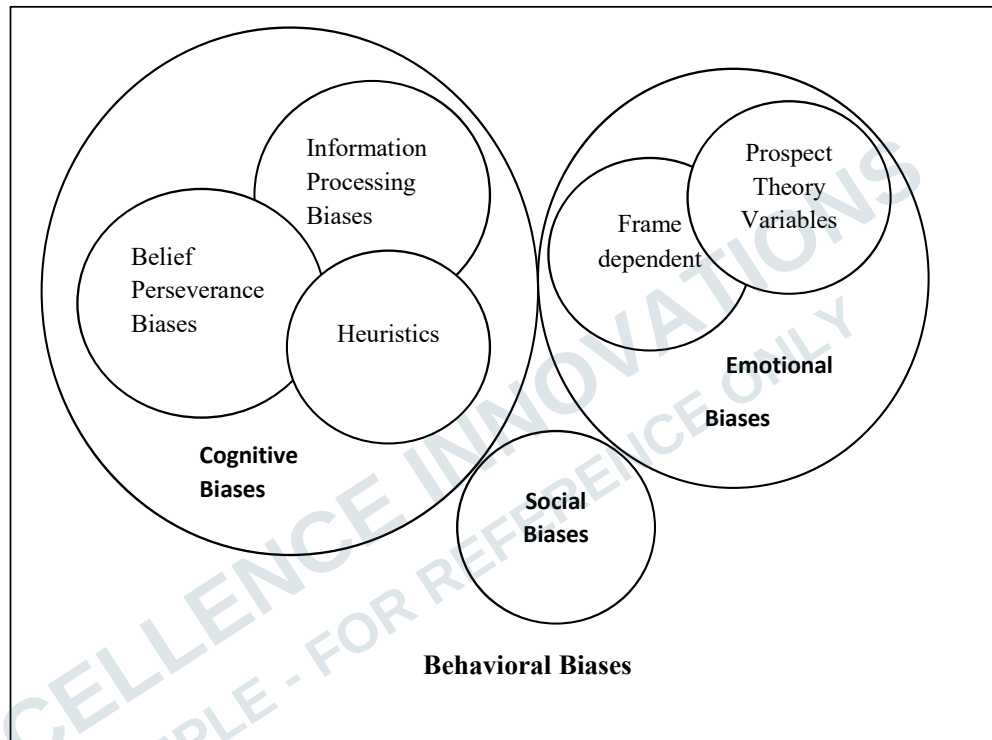


Figure 2.5 classification of behavioral biases

Source: Compiled by Author

2.3.4.1 Cognitive/ Belief Perseverance Biases

- i) **Cognitive Dissonance:** The concept of cognitive dissonance was first given by Festinger (1957) in the book titled “A Theory of Cognitive Dissonance”. It refers to the mental discomfort or anxiety that a person feels when some new information or knowledge conflicts with the preexisting knowledge or information of that person. Thus cognitive dissonance arises with the situation of disagreement between two or more types of thoughts or cognitions. People

generally try to reduce the feeling of dissonance either by adjusting their past beliefs and opinions as per the new information or by simply decreasing the importance of dissonant elements (Graham, 2007).

ii) Conservatism Bias: Conservatism refers to the reluctance of a person to revise his initial beliefs in light of new information. (Edwards, 1968). Conservatism causes investors to react insufficiently to update their existing knowledge as a result it may cause under-reactions in the financial markets. This bias is generally seen as opposite to the representativeness bias and an extension of the anchoring and adjustment bias proposed by Kahneman and Tversky (Soper, 2020).

iii) Ambiguity Aversion Bias: The concept of ambiguity aversion emerged from the seminal work of Ellsberg (1961) in which he presented the Ellsberg Paradox as a piece of evidence that in general people are ambiguity averse. It refers to the phenomenon of people avoiding decision-making under situations of ambiguity i.e. when the probabilities of future outcomes are uncertain. A large body of literature relates this bias to several household portfolio choice puzzles. Dimmock et al., (2015) suggest that ambiguity aversion is the main reason for the nonparticipation or low participation of households in equity portfolios in the U.S. population. This bias can also be held responsible for home bias among investors.

iv) Conservatism Bias: Confirmation bias is the tendency of individuals to interpret or seek information in a way that confirms to their existing beliefs and information. Nickerson (1998) identified confirmation bias as one of the problematic aspects of human reasoning that arises out of individuals' need to reduce cognitive dissonance. People suffering from this bias show unintentional selectivity while gathering and using information from the environment. They heavily overweight information that confirms their beliefs and heavily discounts facts of contradicting views. Park et al., (2010) showed that investors with strong confirmation bias have higher expectations about their investment performance and consequently they trade more excessively and fall victim to the famous overconfidence bias.

- v) **Hindsight Bias:** Hindsight Bias refers to the false belief of individuals that an uncertain event was predictable, after the happening of that event, even though initially it was totally unpredictable. When an individual observes new information after the happening of an uncertain event they don't feel surprised by it as their mind convinces them that they "knew it all along", that is they overestimate the probability of the predictability of that outcome (Arkes, 1988; Roese & Vohs, 2012).
- vi) **Overconfidence Bias:** Overconfidence is the most researched cognitive bias in the theory of behavioral finance. Isidore and Christie (2018) have defined overconfidence as the bias that causes investors to be overconfident about their stock-picking ability, their knowledge, their information processing capability, and their skill set. Severson (1981) and Glaser and Weber (2007) measured overconfidence in terms of "better than average effect". Langer (1975) and Moore and Healy (2008) identified that overconfident individuals think that they have more control over purely uncontrollable events. Self-attribution is also identified as an important aspect of overconfidence. (Hirshleifer, 2001; Daniel, Hirshleifer, and Subrahmanyam 1998; Gervais and Odean, 2001).

2.3.4.2 Cognitive/ Information Processing Biases

- i) **Recency Bias:** The predisposition among people to recall the latest events and information more effectively than the older ones is known as Recency bias. People suffering from recency bias are more likely to take decisions on the basis of the latest information without considering the whole picture which may deter the quality of their decisions and therefore needs to be minimized (Rudiawarni et al., 2020). In the context of investor behavior recency bias make investors believe that the present or recent trend will continue for a long period of time. When combined with hope this bias can result in other cognitive biases such as representativeness and illusion of control (Baker & Puttonen, 2017).
- ii) **Framing Bias:** Framing Bias was one of the biases that surfaced out of the prospect theory proposed by Kahneman and Tversky (1979). Framing bias

refers to the notion that choices made by individuals are not independent of the frames in which they are presented (Ritter, 2003). Frames can be the context of the decision problem or may include some of the elements of the decision problem (Soman, 2004). Tversky and Kahneman (1984) demonstrated that people may reverse their choices depending on the context in which the same problems are presented before them.

- iii) **Representativeness Bias:** Representativeness is the tendency of individuals to classify things or events into discrete groups only based on some noticeable characteristics and includes overreliance on stereotypes (Irshad et al., 2016). Investors prone to this bias take decisions on some representative characteristic of the company this can be recent returns, popularity, or the type of management (Yalcin et al., 2016). Usually, investors suffering from representativeness fail to consider base rate probabilities or sample size, and they also have misconceptions of chance or Gambler's Fallacy.
- iv) **Availability Bias:** Tversky and Kahneman (1974) defined availability bias as a heuristic in which people assess the frequency of an event by the ease with which the instance came into mind. It is a bias in which the decision-makers rely on readily available information and makes investors avoid laborious fact-checking and detailed analysis of information which increases the chance of the decision being flawed.
- v) **Anchoring and Adjustment Bias:** The human tendency to rely too heavily on the "reference points" while making judgments is known as anchoring. Tversky and Kahneman (1974) showed that when people have no idea about the fair value of something they usually forecast it on the basis of some initial value known as 'anchor'. Later on, after observing new information from the environment adjustments in these initial values are often insufficient giving rise to anchoring and adjustment bias.
- vi) **Mental Accounting Bias:** Thaler (1980, 1985) gave the concept of mental accounting. It explores psychological processes such as how people group incomes and expenses in to different categories known as "mental accounts"

ignoring the fungible nature of money. Henderson and Peterson (1992) empirically illustrated the process behind mental accounting with the help of categorization principles. : Cheema and Soman (2006) mental accounts are “self-control devices that consumers employ to prevent excess spending and consumption.”

- vii) **Familiarity Bias:** People’s tendency to be inclined toward investments that are close to their location, familiar to their occupation, and adjacent to their language, culture, and, ethnicity is known as familiarity bias (Seiler et al., 2020). Investors suffering from familiarity bias often mistake a familiar company for a good company. They allocate an inappropriately large portion of their investments to these familiar companies and neglect the benefits of diversification.
- viii) **Home Bias:** Familiarity bias becomes more evident when analysed through a geographical perspective. When it comes to holding domestic or international stocks in their portfolios, investors’ preferences heavily gravitate towards holding domestic stocks over international stocks which gives rise to the home bias (Foad, 2010). Thus it is an extension of familiarity bias in which people overweight domestic stocks and underweight international stocks because of the fear of unfamiliarity.

2.3.4.3 Emotional Biases

- i) **Loss aversion Bias:** Loss aversion causes investors to hold on to the losing stocks in order to avoid the regret of poor decisions. Originally loss aversion was a part of prospect theory developed by Kahneman and Tversky (1979) where they discussed it as a part of the ‘S-shaped’ utility value function. It causes investors to hold on to unprofitable investments, to sell winning stocks too early and does exactly the opposite of the goals of financial decision-making. Tversky and Kahneman (1991) demonstrated that losses and disadvantages have a greater impact on preferences than gains and advantages.
- ii) **Endowment bias:** When people use to attach additional value to the thing they own simply because they belong to them is called the endowment

effect. The endowment effect is one of the most important findings in behavioral economics as it breaks the most fundamental assumption that choices are independent of the endowment. Knetsch (1989) in an experiment proved the existence of endowment effect by giving two different items to two groups of people and allowing them to trade the given item with the other item. Later on, Kahneman, Knetsch, and Thaler (1990) demonstrated that willingness to accept (WTA) greatly exceeds willingness to pay (WTP) and showed the persistence of the endowment effect in a market setting.

- iii) **Status Quo:** Samuelson and Zeckhauser (1988) define status quo bias as the situation of doing nothing or maintaining one's current or previous position. As per Fleming et al. (2009) status quo bias is the subconscious acceptance of the default option of doing nothing by the human brain. Investors suffering from status quo bias hold their current portfolios for too long because of the possible disadvantages of rebalancing their current position. Investors often see alternative investment options either as inferior to the present choice or they don't want to face the uncertainty arising out of changing the risk profiles of the portfolios. Thus, the status quo leads to inappropriate diversification of portfolios.
- iv) **Self-control bias:** Self-control is a behavioral tendency to tradeoff between present consumption and long-term future gains. The temptation to spend more today at the expense of tomorrow is greater in people suffering from a lack of self-control. In the case of self-control, individuals have two sets of coexisting and mutually exclusive options and the willpower or effort made by an individual decides the cost of resisting temptation. Shefrin and Thaler (1988) described self-control as one of the most important features of the behavioral life-cycle hypothesis. Shefrin and Statman (1985) identified a lack of self-control as one of the reasons behind the disposition effect.
- v) **Regret Aversion Bias:** Regret is an emotional feeling that a different past decision could have resulted in a better past and future. Kahneman and Riepe (1998) divided regret into regret of commission (i.e. regret on your past actions) and regret of omission (regret of not doing something) and

concluded that regret of commission is stronger than the regret of omission. Regret is a negative emotion as it brings with it a lot of pain, sadness, and disappointment, therefore people want to avoid this emotional pain as it represents disutility and goes against the basic utility maximization objective of a rational human being (Kahneman & Tversky, (1982); Landman, (1987); Gilovich & Medvec, (1995); Zeelenberg & Pieters, (2004)).

vi) Disposition Effect: The tendency of investors to quickly sell off stocks that have appreciated in value and to keep on holding stocks whose values have decreased is known as the disposition effect (kaustia, 2010). Shefrin and Statman (1985) have given the first formal explanation of the disposition effect by pointing out four ingredients from the behavioral theory that are directly responsible for it i.e. the prospect theory, regret aversion, mental accounting, and self-control. When a stock appreciates in value investor riding on potential profits becomes risk-averse and sells it quickly and when the value of his investment declines he becomes a risk seeker as per the axioms of the prospect theory and keeps on holding losing investments in his portfolio. Many studies have provided substantial evidence in support of the disposition effect (Weber & Camerer, 1998; Frazzini, 2006; Dhar & Zhu, 2006; Grinblatt & Han, 2002; Barberis & Xiong, 2009).

vii) Herding: Herding is a form of social conduct in which the behavior of individuals belonging to a group converges without any central direction. In the context of the financial markets herd behavior arises when individual investors copy the behavior of other investors without adequate information (Bikhchandani & Sharma, 2000). It is the result of the social desire to fit into the group and the unwarranted faith in the judgment of the masses on the basis of the assumption that the majority can't be wrong. (Baker & Puttonen, 2017). Greed and fear are two primary emotions on which herding persists in financial markets. It can make investors buy in a bullish market and sell in a bearish market leading to no abnormal returns in the long term.

CHAPTER 3

REVIEW OF LITERATURE

3.1 Introduction

This chapter seeks to provide an in-depth review of the existing studies on relevant aspects of behavioral finance. It aims to update the reader regarding studies both empirical and theoretical in the area of behavioral biases as well as their impact on natural outcomes of financial decision-making such as investment performance, investment satisfaction, and overall financial satisfaction of individual investors.

To understand behavioral biases and how they affect individual investors, the literature review is broadly divided into seven sections based on the important variables taken into account in the research.

Section 3.2 *Studies on multiple behavioral biases*: This section focuses on research studies that attempt to assess the effect of multiple behavioral biases on individual investors at the same time.

Section 3.3 *Studies on overconfidence bias*: This section specifically focuses on overconfidence bias and its dimensions.

Section 3.4 *Studies on representativeness/ availability/anchoring*: Conceptual papers on these biases and papers exploring the dimensions and scales of these biases are included in this section.

Section 3.5 *Studies on mental accounting/loss aversion/ regret*: This section contains foundational papers as well as articles that investigate the dimensions of these biases.

Section 3.6 *Studies on demographics and behavioral biases*: This section investigates the relationships between demographic and sophistication variables and behavioral biases.

Section 3.7 *Studies on perceived investment performance*: This section contains conceptual studies on perceived investment performance as well as studies relating perceived investment performance to behavioral biases.

Section 3.8 *Studies on investment satisfaction and financial satisfaction*: This section contains articles on investment and financial satisfaction, as well as their links to behavioral biases.

3.2 Studies on Multiple Behavioral Biases

1. **Tversky and Kahneman (1974)** wrote an article in which they described three heuristics namely representativeness, availability, and anchoring. People use these heuristics to assess probabilities and predict values without knowing their detrimental effect on rational decision-making. In this article authors have described the limitation of each heuristic with relatable experiments and real-life examples and lastly, discussed the findings in very technical terms which today is a part of “modern decision theory”.
2. **Kahneman and Riepe (1998)** made important distinctions between cognitive and emotional weaknesses from which investors suffer. The authors have made three important classifications of biases in this paper. ‘Biases of Judgement’ that cover overconfidence, optimism, hindsight, and overreaction. ‘Errors of Preferences’ include the nonlinear weight of probabilities and the tendency of people to value changes, not states, and ‘Regret Aversion’ includes regret of commission and regret of omission. Authors have also given important recommendations to financial advisors so that they can help their clients mitigate the harmful effect of these biases.
3. **Ricciardi and Simon (2000)** compared and contrasted two branches of finance popularly known as standard finance and behavioral finance with the objectives to provide a general overview of behavioral finance and to discuss some of the major themes in behavioral finance. Accordingly, they have discussed four major themes such as overconfidence, prospect theory, regret theory, and financial cognitive dissonance. In the conclusion of the paper, they have suggested strategies to assist individuals to resolve these mental mistakes and errors so that they can develop their criteria to deal with psychological biases.
4. **Baker and Nofsinger (2002)** thoroughly reviewed the field of Behavioral finance. They have used a three-level typology to organize investor psychological biases. First is ‘*How Investors Think*’ this section focuses on various rules of thumb or heuristics that can lead to psychological errors in decision making. The authors have discussed nearly ten heuristics in this section namely representativeness, cognitive dissonance, familiarity bias, mood and

optimism, overconfidence, endowment, status quo, anchoring, the law of small numbers, and mental accounting. The Second is '*How Investors feel*' this section covers biases that are caused by emotional aspects of investors such as the disposition effect, attachment bias, and changing risk preferences. The last section covers the '*Effect of Social Interaction on Investors*' via media, peer groups, and the internet.

5. **Wood and Zaichkowsky (2004)** segmented individual investors based on their share investing attitudes and opinions. Responses were sought from ninety investors on a seven-point Likert scale using snowball and convenience sampling procedures. Four key categories of individual investors were found through a cluster segmentation analysis: risk-intolerant traders, confident traders, young traders who are afraid of losing money, and conservative long-term investors. Each segment used various information sources, bought various stock kinds, and engaged in varying degrees of trading activity.
6. **Chandra (2008)** conducted a study to analyse the impact of behavioral factors and investor psychology on individual investors' decision-making. The research finds out that investors are not as rational in their decision-making as the traditional finance theory suggests. They usually suffer from many psychological and emotional biases
7. **Pompian (2008)** in the article "*Using behavioral investor types to build better relationships with your clients*" coined the term 'Behavioral Alpha Approach' which is a multistep diagnostic process that classifies investors into four behavioral types namely, passive preserver, friendly follower, independent individualists, and active accumulators. The basic purpose of this behavioral alpha approach is to classify investors on their active and passive investor traits. The paper describes each investor type and then discusses various cognitive and emotional biases associated with each investor type. And lastly, suggestions are given to financial advisors on how they can advise their clients according to biases displayed by each investor type which can help them to build a strong relationship with their clients.

8. **Waweru et al. (2008)** explained how investors make decisions in Kenya and other emerging economies. A questionnaire based on an extensive literature review was used to survey the Nairobi stock exchange's institutional investors and fund managers. The SPSS software package was used to analyse the data, and a t-test was used to examine the differences between the factor means. The study supports the notion that behavioral factors such as representativeness, overconfidence, anchoring, gambler's fallacy, availability bias, loss aversion, regret aversion, and mental accounting influenced the decisions of institutional investors trading on the NSE. Furthermore, these investors referred to the trading activity of other institutional investors and frequently displayed institutional-herding behavior in their investment decisions.
9. **Siddiqui and Singh (2009)** conducted a study to find out the influence of investor psychology on financial investment decision making particularly in the Indian context. The study uses a survey method to collect the necessary data. Questionnaires were given to various stock brokers in Delhi-NCR and then the percentage method was used to analyse the data and interpret the results. The major findings of the paper are that the security of the principal amount is the prime concern for the majority of the investors and has received the highest weightage. The majority of them also displayed the disposition effect and admitted that emotions and irrational behavior often influence their financial decisions. Further, they also displayed the tendency of crediting themselves for any kind of profits earned and blaming others for losses suffered.
10. **Agrawal (2012)** tried to find out the interactions and interrelations among various behavioral biases by reviewing the literature in the field of behavioral finance. Biases have always been shown in isolation and thereby ignoring any kind of possible antecedents or causes and outcomes of different behavioral biases. Overconfidence, over-optimism, representativeness, familiarity, and limited attention are the main biases that have been discussed. The two main propositions that have been developed out of this study are overconfident persons are more likely to be over-optimistic which further leads to an illusion of control and there is a complementary relationship between the familiarity bias and the status quo bias leading to an illusion of validity.

11. **Sahi and Arora (2012)** conducted an exploratory inquiry into psychological biases influencing the financial investment behavior of investors. They identified the beliefs and attitudes of individual investors in the context of behavioral biases by conducting their semi-structured interviews. A representative sample of thirty respondents was selected by using snowball sampling and it was necessary to qualify for certain criteria to be a participant in the interview process. The data collected through the interview process was analysed using “*Open Analysis*”. The findings of the study show that people exhibit certain tendencies regarding financial decision-making based on nineteen identified themes and finally, these nineteen themes were clubbed into three broad categories ‘*Affective Influence and Emotions*’, ‘*Information Processing Strategies and Perceptual Organization Principles*’, and ‘*Psychological Motives*’.
12. **Chandra and Kumar (2012)** identified and validated the role of heuristics and biases in Indian individual investors' financial decision-making. Eight behavioral biases were used for the study's purposes, and five additional variables were added on the advice of industry professionals. These thirteen commonly used behavioral factors were presented to respondents in the form of 60 scenario-based questions on a five-point Likert scale and data were collected from 350 individual investors based in Delhi-NCR. According to the results of the study, behavioral biases do have an impact on these investors' decision-making processes. The results show that both heuristic factors and prospect theory have an impact on Indian individual investors, with heuristics like anchoring, availability bias, and regret aversion attitude dominating factors as compared to factors indicated by prospect theory like loss aversion.
13. **Charles and Kasilingam (2016)** studied the impact of six behavioral factors Mood, Emotions, Heuristics, Frames, Gambling, and Personality on the investment decisions of equity investors. Retail investors from the Tamil Nadu state were taken as sample units and a multistage random sampling technique was used to collect data from 780 participants. Discriminant analysis was used to find out the impact of behavioral factors on investment avenues taken as the

categorical dependent variable in the study, and SEM was applied to find out the interrelationship among behavioral factors. The results of the study established six causal relationships in the interdependence model of biases. The relationship between emotions and personality, emotions and heuristics, emotions and gambling, emotions and frames, and personality and heuristics are positive and significant while there is no causal relationship between personality and frames.

14. **Kumar and Goyal (2016)** investigated the relationship between the rational decision-making process and behavioral biases among individual investors in India. To understand rational decision-making the three-stage model of Mintzberg has been used. Three behavioral factors overconfidence, disposition effect, and herding, and demographic variables such as occupation and gender are taken as dependent variables. A six-point Likert scale was used to measure different constructs. A total of 386 valid responses were analysed using SPSS and AMOS 20. Structural equation modelling (SEM), t-test, ANOVA, and Fisher's least significant difference (LSD) test have been used in this study. Results of the study indicate that males are more prone to herding and overconfidence than females and results from other techniques show that investors do follow a rational decision-making process. However behavioral biases also arise at different levels of the decision-making process.

15. **Khan (2017)** looked at how the loss aversion bias and availability heuristic affect the choices made by individual investors and whether or not risk perception affects this relationship. Convenience sampling was used to gather data from 207 investors participating in the Islamabad stock market. Simple regression and correlation were used to analyse the data. This study's findings contradict previous research on behavioral biases in investment decision-making. The availability bias and investment decision-making have a weak negative relationship. Risk perception moderation strengthens the relationship between loss aversion bias and investment decisions while weakening the relationship between availability bias and investment decisions.

16. **Zahera and Bansal (2018)** thoroughly reviewed the field of behavioral finance.

The purpose of the study is to describe various biases that affect individual and institutional investors in the process of decision-making. This piece of literature is most extensive and unique on its own as it covers the research articles right from the year 1979 in which the foundational paper in the area of behavioral finance was published till 2018. The authors have collected all the papers from renowned and reliable sources and have summarized them beautifully in a very compact manner. The article classified biases year-wise, country-wise, and author-wise, and finally identified 17 different types of biases. The methodology used by different researchers to study these biases has been explained in detail. This paper not only focuses on basic principles in behavioral finance but also explains various emerging concepts and theories in the field.

17. **Baker et al. (2018)** conducted a study that examines the relationship between personality traits and exposure to behavioral biases among stock investors in India. To examine the personality traits of individual investors 'The Big Five Personality Model' have been used which has five key dimensions namely neuroticism, extraversion, openness, conscientiousness, and agreeableness. Overconfidence, disposition effect, anchoring, representativeness, mental accounting, herding, and emotional bias have been selected for the study. The study assumes that personality traits are important psychological antecedents related to behavioral biases. Data were collected from 515 retail investors from ten major cities in India and were analysed using factor analysis and structural equation modelling. The findings of the study reveal that there is a significant association between the traits of neuroticism and extraversion with most behavioral biases. However, openness and conscientiousness are only related to mental accounting and herding respectively and agreeableness has no significant relationship with any of the behavioral biases.

18. **Ritika and Kishore (2020)** developed a higher order behavioral bias scale. To develop the scale of thirteen behavioral biases, thirty one items related to various behavioral biases were pooled from the existing literature. For those biases which were not measured using primary data in the existing literature twenty-three new items were added to the behavioral bias scale. For the

validation of the scale, data were collected from the 576 investors of Delhi in two phases. The study uses EFA, CFA, and SEM to analyse the unidimensionality of the factors. The scale that was developed out of the study has many dimensions. It has two second-order constructs and thirteen zero-order constructs. Among the sub-dimensions of cognitive bias, availability came out as the strongest indicator and among the sub-dimensions of emotional bias regret showed a strong presence.

19. **Baker and Puttonen (2017)** in “How behavioral biases can hurt your investing” reviewed different types of behavioral biases that can lead to errors in decision-making and suggested that these biases can be mitigated by changing the personal behavior of investors. They categorized biases into three major categories cognitive, emotional, and social biases. Cognitive biases are further subdivided into information processing and belief-perseverance biases. Emotional biases include a separate category of self-deception biases and herding in the main component of social biases. These biases can be somewhat reduced by being aware of them and creating an investment strategy that takes them into account and is grounded in quantitative techniques and investing principles.

3.3 Studies on Overconfidence Bias

1. **Odean (1999)** in the article “*Do investors trade too much?*” tried to investigate the impact of overconfidence on investors’ trading volume and returns. Odean testified that if the securities that investors buy outperform those that investors sell just enough to cover the brokerage cost and the situation when trading costs are ignored the investors will be assumed to be suffering from overconfidence. The data was collected from 10000 customers of a nationwide discount brokerage house who have an active trading account in the year 1987. Results of the study show that investors suffer a loss through excessive trading due to overconfidence. Even if trading costs are eliminated investors will still lower their returns through excessive trading.

2. **Hirshleifer and Luo (2000)** investigated the reasons why overconfident investors survive in a highly competitive market. The paper offers insights that overconfident investors are better at exploiting mispricing opportunities in the financial markets in comparison to rational traders. The higher the volatility created by noise traders the higher the possibility of surviving overconfident investors.
3. **Glaser and Weber (2007)** in their study tested the hypothesis that overconfident investors trade more than rational investors by correlating overconfidence scores with measures of the trading volume of individual investors. Overconfidence scores were calculated using three variables (1) Miscalibration, calculated using the count of surprises in knowledge and economy-based questions. (2) Overconfidence in volatility estimates is based on the width of confidence intervals for future stock prices and index values. (3) Better than average effect based on self-assessment of investment skills and past performance as compared to other investors' investment skills and past performance. Approximately 3000 investors were asked to answer the questionnaire based on the above three variables and trading volumes were calculated by trades of 215 individuals who answered the questionnaire. Results of the study show that overconfidence as measured by calibration questions is not significantly related to trading volumes and also there is no significant correlation between gross monthly returns and overconfidence measures.
4. **Moore and Healy (2008)** studied overconfidence in three different ways and tried to establish a consensus among different measures of overconfidence. The first way to define overconfidence is "overestimation", the second is "over placement" and the third type of overconfidence is defined in terms of "over precision". A series of experiments were conducted in the experimental laboratory to make the distinction between these three types of overconfidence. Evidence from the experiments made it clear that there is a negative relationship between over-placement and over-estimation. And over-precision of investors is also negatively associated with their over-placement and over-estimation. Thus all three types of overconfidence are not different manifestations of the same construct but they are empirically different.

5. **Oberlechner and Osler (2009)** tested the survival of overconfidence in currency markets by comparing overconfidence among individuals with different levels of trading experience. Overconfidence among dealers is measured based on two dimensions first is 'Miscalibration' which made people overestimate the precision of their information, and the second is called 'Hubris' which made investors overestimate their success. To test the hypothesis a survey of all foreign exchange dealers in North America was conducted. A total of 1080 questionnaires were sent to them out of which 416 were returned in their complete form making the response rate 38.5%. Results indicate that even the most experienced dealers were highly overconfident and overconfidence was not moderated by experience or incentives regardless of whether the experience is measured by years spent trading, age, or professional ranks.
6. **Kautsia and Pertulla (2012)** measured overconfidence among finance professionals in Finland and showed various debiasing attempts to reduce different types of overconfidence. Overconfidence is measured in terms of probability miscalibration, better-than-average beliefs, and unfounded confidence. In this paper authors have attempted to summarize the effect of three studies, in the first study calibration overconfidence is measured using general knowledge questions among students and financial advisors. Results of the study indicate that students and financial professionals are almost equally overconfident. The second study was conducted for financial professionals with debiasing warnings, results of this study indicate a reduction in better than the average type of overconfidence, however, no significant reduction in overconfidence in probability assessments was found. In the third study, a lecture on investors' psychology was shown to subjects and they also showed lower estimates of better than the average type of overconfidence but scores of probability assessments remained unaffected also in this case. These findings suggest that miscalibration and better than the average type of overconfidence are perhaps unrelated.
7. **Hoffmann and Post (2014)** tried to understand the importance of self-attribution bias in consumer financial decision-making and its impact on

investment returns. Self-attribution bias is one of the main components of overconfidence. The study employed a unique methodology wherein the survey data from a Dutch brokerage client are matched with trading records. Clients were asked to indicate the level of agreement or disagreement on a seven-point self-attribution scale and daily changes in the value of investors' portfolios after adjusting transaction costs are treated as proxies for investment returns. After applying linear panel regression authors established that self-attribution scales are positively related to the portfolio returns at the end of the month. However, the results were not significant when that self-attribution scores are compared with the market-level returns.

8. **Trehan and Sinha (2017)** studied the existence and extent of overconfidence bias among Indian investors by surveying about 100 retail investors. The questionnaire consists of thirteen scenario-based questions that judge the level of overconfidence among Indian investors. Self-attribution, Optimism, Better than average effect, Miscalibration, Illusion of control, Trading frequency, and Trading experience are identified as overconfidence variables. Descriptive statistics with mean and standard deviation are used to investigate the existence of overconfidence. Self-attribution is the most prominent factor with the highest mean that contributes to overconfidence
9. **Prosad et al. (2014)** investigated the presence of the disposition effect and overconfidence in the Indian equity market during the period 1st April 2006, to 31st March 2013, and provided some robust empirical evidence. The sample consists of daily total returns and transaction volume for each constituent stock and total returns of the NSE Nifty 50 Index. The study arrives at three key findings. First, the presence of biases, overconfidence, and the disposition effect is detected in the Indian equity market. Second, the impact of these two biases can be distinctly segregated for 20 companies among the companies in the index. Third, the overconfidence bias is found to be predominant of the two biases
10. **Kansal and Singh (2018)** conducted an exploratory analysis of demographic factors and investors' characteristics that causes a change in the extent of

overconfidence level among individuals. Data was collected from 500 retail investors in the city of Delhi, who fulfill certain predefined criteria from both online and offline modes. A close-ended questionnaire is used to capture the impact of four dimensions of overconfidence which are better than average effect, the illusion of control, self-attribution, and planning fallacy. Data collected were analysed through t-test, ANOVA, and standard ordinary least square regression. Results showed that education, age, and gender do not have any significant effect on the level of overconfidence among investors which is contradictory to the previous studies. Rather it is income, investment frequency, time horizon, experience and investment in large-cap stocks are the variables that are responsible for variation in the level of overconfidence among investors.

11. **Ahmad and Shah (2022)** conducted a study to link overconfidence with investment decisions and the investment performance of individual investors operating on the Pakistan stock exchange. The study also explores the mediating role of risk perception and moderating role of financial literacy between overconfidence and the investment performance of investors. The final sample size of the study was 183 investors which were sufficient to fulfill the statistical requirements. A cross-sectional research design was employed and data was collected on a five-point Likert scale. The study confirms that investors behave irrationally and overconfidence has a negative relationship with the investment performance of individual investors. Additionally, the study also found that overconfidence has also a negative relation with the risk perception of individuals which ultimately affects their financial decisions and investment performance.

12. **Grezo (2020)** reviewed and summarized the results of the 34 studies on overconfidence to investigate the relationship between overconfidence and financial decision-making. The study also analysed the moderating effect of measures of overconfidence on trading, investment, and innovativeness. Several exclusion and inclusion criteria were imposed on a total number of 3594 studies collected from different databases to get the most relevant studies and finally, the product-moment correlation coefficient and semi-partial correlation coefficient were employed to analyse 34 studies. It was found that

overconfidence has a significant impact on the financial decision-making of investors and indirect measures of overconfidence strongly moderate the relationship between overconfidence and financial decision-making as compared to direct measures of overconfidence.

3.4 Availability Bias/ Representativeness/ Anchoring

- 1. Furnham and Boo (2010)** reviewed the literature related to the anchoring heuristic which is one of the most robust cognitive heuristics. The article summarizes studies related to anchoring bias in many domains such as general knowledge, probability estimates, legal judgments, purchase decisions, forecasting, negotiations, and self-efficacy. The paper also tries to understand the psychological mechanisms underlying the anchoring process and the types of anchors generally used by people. Studies related to the contributions of mood, attitude, knowledge, the reward for motivation, personality, and cognitive style to anchoring bias have been discussed at length. Lastly, the paper explained the applications of the anchoring bias in everyday life.
- 2. Cen et al. (2013)** examined the effects of anchoring bias on forecast earnings per share (FEPS), earnings surprises, market returns, and stock splits. Six stock analysts from prominent investment banks were interviewed to confirm the possibility that analysts do anchor on the industry norm. To verify the hypotheses, regression analyses and portfolio sorts to address econometric issues were used. According to the study's findings, industry analysts have anchoring bias and are predisposed to favour industry standards. For companies whose forecast EPS is higher than the industry median, stock returns are considerably higher. Additionally, prospective stock returns are considerably lower for firms whose forecasted EPS is below the industry median.
- 3. Irshad et al. (2016)** surveyed investors of the Islamabad stock exchange to find out the impact of representativeness bias on their investment decisions. Regression analysis was used to analyse data from 120 investors and the study concluded that representativeness does affect the investment decisions of investors investing in the Islamabad stock exchange.

4. **Rasheed et al. (2018)** conducted a study in Pakistan to find out the effect of availability bias and representativeness bias on the decision-making of individual investors participating in the Pakistan stock exchange (PSE). Further, they have tried to find out the moderating effect of internal locus of control on the relationship between these two biases and decision-making. The rationale before choosing these two biases is that they affect both experienced and non-experienced investors. Data was collected from a sample of 300 which was large enough to fulfill all the statistical requirements. The survey was conducted in the cities of Islamabad, Lahore, and Sargodha. Finally, SPSS and AMOS were used to analyse the proposed relationships. Results of the study show that the impact of availability and representativeness bias on decision-making is significant. However, locus of control does not moderate the relationship between behavioral factors and decision-making. The results of the study of investors assume that Pakistani investors are significantly affected by these behavioral biases.
5. **Sachan and Chugan (2020)** explored the implications of availability bias and its relationship with the residence of investors. The research explores the idea that rural investors have lesser access to information related to investment as compared to urban investors and therefore they suffer more from availability bias. A survey of around 516 investors was conducted in the state of Gujarat, India to test the above hypothesis, and nonparametric tests such as cross-tabulation and Chi-square were employed to test the hypothesis. Results suggest that availability bias strongly prevails among Gujarati investors and it is stronger in rural regions of Gujarat, as 75.8 % of urban investors and 83.9% of rural investors suffer from this bias and the difference is statistically significant.

3.5 Mental accounting/ Regret Aversion/ Loss aversion

1. **Kahneman and Tversky (1979)** in "*Prospect theory: An analysis of decision under risk*" criticized the expected utility theory as a descriptive theory of decision-making under risk and presented a new theory called "Prospect Theory". Authors have criticized expected utility theory based on three empirical effects (1) Certainty effect (2) Reflection effect (3) Isolation effect

‘Certainty Effect’ refers to the phenomenon when people tend to overweight outcomes that are considered certain and underweight outcomes which are merely probable. ‘Reflection Effect’ implies risk aversion in case of sure gains and risk seeking in case of sure losses and ‘Isolation Effect’ is the process of simplifying alternatives when people often disregard components that the alternative share and focus on the component that distinguishes them. Further, according to this theory, there are two phases of decision-making under risk. The first phase is editing and the second phase is evaluation. The editing phase is like the preliminary analysis of prospects to simplify them which consists of major operations of coding, combination, segregation, and cancellation. During the evaluation phase, some reference point is designated that provides a relative basis for appraising gains and losses value function passing through this reference point is asymmetrical i.e. concave above the reference point (for gains) and convex below the reference point (for losses). This tendency is because of loss aversion. This value function is ‘S-shaped’ and also observed framing bias.

2. **Bell (1982)** explored the role of regret in decision-making and tried to provide explanations for the failure of expected utility theory in terms of decision regret. The entire paper is divided into four sections. The first section of the paper develops a multi-attribute utility function by incorporating the attribute of regret in utility theory. By incorporating regret the utility theory becomes a better predictor and a more convincing guide of decision maker’s behavior. The second section applies the developed utility function to paradoxical situations and finally, the difficulties in the new utility function and extensions are discussed in the last two sections.
3. **Henderson and Peterson (1992)** empirically illustrated the process behind mental accounting. They described how and why mental accounts are formed by linking mental accounting with categorization principles. To explain the process they revisited the Play and Calculator scenario introduced by Tversky and Kahneman (1981). Seven categorization principles have been discussed in the paper. The article extends basic mental accounting ideas by viewing them

in the broader context of information processing by connecting mental accounting and categorization principles.

4. **Gilovich et al. (1995)** answered the question of whether people would regret a negative outcome that stemmed from an action more than an equivalent outcome that stemmed from inaction. An experimental research design was chosen with 120 students of Cornell University participating in a laboratory analogue of the 'Monty Hall' Problem. The data were analysed using One-Way ANOVA and the results of the study indicate that people try to reduce dissonance more for their errors of commission instead of their errors of omission. The results reinforce the significance of the action and inaction distinction in the counterfactual thinking literature.
5. **Shefrin and Thaler (1998)** in "*The behavioral life-cycle hypothesis*" proposed a behaviorally enriched life cycle hypothesis which is a descriptive model for household savings. They suggested that there are three important behavioral features of the life cycle hypothesis (1) Self-control (2) Mental accounting (3) Framing. Key assumptions of the hypothesis are that people treat components of their wealth as non-fungible and prefer to keep it in different mental accounts with different marginal propensity to consume. In the case of self-control there is an ongoing trade-off between the present consumption of income and saving it for a better life in the future. And in the case of mental accounting authors demonstrated that house keeps their wealth mainly in three mental accounts (1) current income (2) current assets and (3) future income or wealth. The results show that households do not prefer to use the future income for financing current consumption unless there are some exceptional circumstances. Therefore mental accounting is what households and investors do all the time.
6. **Gilovich et al. (1998)** developed a set of three studies to deal with disagreements about the popular ideas of regret in their time. In the first study, a set of seven hot and four wishful regrets were developed along with eleven filler emotions and participants were asked about their biggest regret from the past week and their entire life. Further, they were asked to indicate whether hot emotions are more endorsed by action than inaction regret. In the second study,

a third variable namely despair regret caused by the inactions of a person was added. The third and final study validated the existence of all clusters of regret. The findings of the study supported the existence of hot, wishful, and despair regret and they are differently associated with action and inaction regret.

7. **Thaler (1999)** in “*Mental accounting matters*” summarized the current state of knowledge about mental accounting existing today. The goal of the paper is to illustrate how mental accounting matters. Mental accounting refers to the coding, categorization, and evaluation of financial decisions. This term was first coined by Thaler who conducted several experiments to show how people put their money in separate mental accounts and highlighted three main components of mental accounting. The first captures how items are perceived and experienced and how they are subsequently evaluated. Secondly, it involves the task of assigning different activities to different mental accounts and lastly, it is concerned with how frequently different mental accounts are evaluated.
8. **Tsiros and Mittal (2000)** proposed a model of regret that incorporates the antecedents, moderators, and consequences of regret. This model and its assumptions were tested through four different studies in the paper. The first study concluded that regret and satisfaction have different influences on consumers’ repurchase intention. The second study indicated that information on forgone items was not necessary to generate regret. The third and fourth studies examined the cognitive processes underlying the experience of regret in the absence of information on a better-forgone item. The findings of the study show that the repurchase intention of a consumer is directly influenced by regret and the relationship between complaint intentions and regret is mediated by satisfaction it also showed that regret can be experienced even if information about the forgone alternative is not available.
9. **Gilovich et al. (2003)** documented variations in the concept of regret across different cultures of the world. The researchers tested the hypothesis that individuals in collectivist cultures might experience fewer long-term regrets of inaction and more long-term regrets of action than individuals in individualistic cultures. To test this hypothesis separate studies were conducted in three

countries of the world namely China, Japan, and Russia. In all studies, participants were asked in an open-ended form to list their main regrets when they look back on their life with no mention of the distinction between action and inaction regret. Results indicate that participants exhibited the same tendency to regret inactions more than actions in all five studies.

10. Zeelenberg and Pieters (2004) investigated the role of anticipated regret in lottery participation decisions. To do so authors compare two big lotteries in the Netherlands namely, Postcode Lottery and National State Lottery in four different studies. The main difference between the two lotteries underlies the feedback structure. In National State Lottery, lottery numbers are randomly assigned while in the postcode lottery one's postcode is the lottery number. The first study concluded that regret would be the dominant emotion if one's postcode is the winning postcode but one has failed to participate in the lottery. The second study highlighted that the intensity of regret is lower in the case of the state lottery. And the last study confirmed that postcode lottery players anticipate significantly more regret over not playing than state lottery players.

11. Cheema and Soman (2006) explored the malleability of the mental accounting process and how it affects the budgetary role of mental accounts. Two experiments were conducted on students of Midwestern University. The first experiment introduced malleability in the mental accounting process through an expense whose classification is ambiguous. Results showed that individuals exploit this ambiguity by classifying the expense in the account where they have a surplus of funds. The second experiment allowed participants to construct after expenses have been incurred. In this experiment individuals constructed target accounts in such a way that ambiguous expenses can be adjusted in an obvious manner.

12. Johnson et al. (2006) examined the nature of loss aversion and how it differs among individuals, attributes, and measures. The nature of loss aversion has been questioned by authors on many occasions, including: Is loss aversion constant? Is it true? Is it an attribute or a characteristic? Is it a process's result? A survey of 360 persons using in-person interviews was done to address these

problems. According to the study's findings, the decision maker's understanding of the attribute, the relevance of the attribute, and the person's age might all contribute significantly to loss aversion. Some people may be more prone to loss aversion than others, especially those who are older or less educated.

13. Dimmock and Kouwenberg (2010) experimentally investigated the impact of loss aversion on household portfolio decisions. Inter-temporal choice items based on experimental work by Thaler (1981) and Loewenstein are included in the Dutch Household Survey (1988). The survey was carried out online, and the dataset includes data on family wealth, income, and financial assets in addition to a series of questions that are used to derive a measure of loss-aversion. This study offers clear empirical proof of the significance of loss aversion in household decision-making. As a result, the likelihood of directly owning stocks is considerably less likely than the likelihood of owning mutual funds, according to the results. We do not discover a correlation between loss aversion and portfolio allocations to stock after accounting for sample selection.

14. Antonides et al. (2011) developed a self-reported mental budgeting scale and tried to determine how mental budgeting is related to household financial management in the Dutch population. In 2007 a survey was conducted among 4280 individuals of 18 years and above concerning their socio-demographics, financial behavior, knowledge, and attitudes. Instrumental linear regression has been used to analyse the data. Results indicate that level of education, saving goals, time orientation, financial situation, gender, an overview of expenses and current accounts and financial management has a significant and positive impact on mental budgeting while age, religion, and having a partner or a job does not affect mental budgeting of Dutch population.

15. Jain and Prakash (2015) focused on understanding mental accounting while doing investments in gold and gold ETFs and tried to relate this buying behavior of investors to their locus of control. A questionnaire consisting of 24 statements was administered to 200 individuals investing in the commodities market out of which 114 responses were found suitable for further analysis, t-test, ANOVA,

and factor analysis were employed to check the statistical significance of the hypothesis. Results reveal that individual with an internal and external locus of control differs in their mental accounting while taking decisions about investment in gold and gold ETFs. Individuals with different age groups, gender, education, and income also differ in their mental accounting levels for taking investment decisions.

16. Gazel (2015) summarised previous studies on regret aversion in different contexts and tried to examine the impact of this bias on individual investors' decision-making. The article discussed the evolution of cognitive biases, the taxonomy of behavioral biases, regret and prospect theory, and regret aversion bias in consumer purchase decisions and investment decisions. The results of the study concluded that regret aversion bias has a strong theoretical base and must be considered while doing real analysis as it can cause conservatism, herding, and the disposition effect.

17. Mahina et al. (2017) established the effect of loss aversion bias on the investment decisions of investors investing in the Rwanda stock exchange. The study's primary emphasis was on retail investors who registered at RSE between 2010 and 2015. Data from 374 investors were gathered using stratified random sampling followed by simple random sampling. The study used a cross-sectional descriptive survey research design and a linear regression model was used to forecast the probability of various possible results of the dependent variables, which helped forecast the probability that a potential investor would invest in RSE. The findings supported the existence of a substantial positive linear relationship between loss aversion bias and stock market investment in Rwanda.

18. Martin and Davari (2018) tried to examine the extent to which financial risk tolerance is explained by the theory of mental accounting and the behavioral life-cycle hypothesis. Eight hypotheses were framed relating the variables of the behavioral life cycle hypothesis and financial risk tolerance. Data from 243 respondents were collected and analysed using exploratory factor analysis. Results of the survey showed that current assets are positively associated with

financial risk tolerance and higher levels of subjective financial knowledge and future orientation strengthen this relationship.

19. Angle et al. (2019) investigated the impact of mental accounting bias on individual investors' investment perspectives and investment preferences. The population used for this study was limited to active investors in Bangalore, 400 respondents were identified out of which 254 responses were analysed using factor analysis and linear regression models. The study confirms the presence of mental accounting bias among Indian investors and established the fact that investors are most satisfied when they invest in stocks of their preferences and at the time they think is best suitable for investing, even though they do not use any logic behind their decision.

20. Mahapatra and Mishra (2020) explored the influence of mental accounting bias on the financial decisions of Indian households and tried to establish mental accounting as a second-order construct of mental budgeting, current income, current assets, and future income. Data were collected from a total of 512 respondents from the twin cities of Hyderabad and Secunderabad. PLS-SEM using Smart PLS 3.0 have been used to analyse the collected data. The results establish the presence of mental accounting systems among Indian households and reinforce the role of psychological biases in taking investment decisions.

21. Rashwan and Shafqa (2021) conducted a study on Palestinian investors to study the impact of mental accounting on the financial and investment decision-making of investors. The research was primary in nature and survey responses were collected from 136 investors. Regression was employed to analyse the data and the results of the study found that mental accounting contributes to enhancing the risk assessment of financial and investment decisions. And also helped in raising the financial culture among Palestinian portfolio investors.

22. Gachter et al. (2021) provided evidence of the degree of heterogeneity in loss aversion in riskless and risky choices of individual investors they also linked loss aversion bias to the socio-demographic variables of investors. Two separate studies were conducted on 660 customers of a German car manufacturer. The

results of the study proved that people who exhibit loss aversion to riskless choices are most likely to exhibit loss aversion to risky choices. A substantial level of heterogeneity was also observed in individuals' loss aversion and finally, the study also concluded that socio-demographic variables affect both measures of loss aversion in the same manner.

23. Li et al. (2021) created a simple, one-dimensional scale to assess loss aversion.

Previous loss aversion measures were based on complex and time-consuming experiments, so there was a need to address these issues by developing a simple, reliable, and universal scale to assess people's loss aversion. First, eight items were developed for the study based operational definition of loss aversion by Kahneman and Tversky (1979). To validate these items, data were collected using Amazon's Mechanical Turk (MTruk) and analysed using exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The overall results of the test indicate that the seven items of the loss aversion scale had a reasonable degree of reliability and unidimensionality. Finally, the concurrent and predictive validity of the scale was tested using correlation and regression analysis, and the results indicate that the proposed seven items had acceptable measurement validity.

3.6 Demographics and Behavioral Biases

- 1. Bajtelsmit and Bernasek (1996)** surveyed the existing literature regarding gender differences in investments and tried to provide explanations for these differences. This review classifies studies on various parameters such as studies using large datasets, studies relating to consumer finances, health and retirement surveys, and other studies. All these studies provided strong evidence for the fact that women differ from men in allocating their portfolios and they have a more conservative attitude toward risk than their male counterparts which leaves them with lower levels of savings and wealth for their retirement period.
- 2. Barber and Odean (2001)** in the paper "*Boys will be boys: Gender, overconfidence, and common stock investment.*" investigated whether men are more overconfident than women in financial markets. Overconfidence leads to

overtrading which in turn hurts the performance of men. Authors have used account data of 35000 households from a large brokerage firm from February 1991 to January 1997 and their test provides strong support for this behavioral finance model. The results show that men trade 45% more than women and this trading reduces men's return by 2.65% points a year as compared to 1.72% points for women. Furthermore, these differences are more prominent in the case of single men and single women as opposed to married men and married women. Single men average traded 67% more than single women.

3. **Bhandari and Deaves (2006)** conducted an exploratory demographic analysis of overconfidence bias. The survey was conducted on 2000 Canadian pension plan members to ascertain how demographic variables such as age, education, income, and wealth determine overconfidence. Two sources of overconfidence have been identified for the study i.e. certainty and knowledge. The results revealed that certainty levels in males are higher in comparison to females. Concerning education, those who have formal education think that they have more knowledge than self-educated investors and consequently overall results of the study suggest that highly educated males who are close to their retirement are more susceptible to overconfidence bias.
4. **Prasad and Mohta (2012)** in their study integrated two of the most important biases overconfidence and loss aversion with gender. The study was conducted by administering a well-structured questionnaire and collecting empirical evidence from a final set of 128 investors consisting of both males and females. Results of the study showed that there is a significant difference in the overconfidence and loss aversion displayed by males and females. Women investors are more loss averse in their decisions than their male counterparts and men are more overconfident than females.
5. **Subash (2012)** explored the presence the certain identified behavioral biases and their impact on the decision-making process of retail portfolio investors in Kerala. Data were collected from 97 respondents out of which two sub-samples of 46 were created based on experience i.e. young investors and experienced investors. Results from data based on discriminant analysis and weighted

scoring method revealed that “*Investor type*” act as a significant discriminator and both investor types think alike in the process of decision-making. However, results from chi-square tests were contrary to the above and indicate that there is no significant difference between the two groups and both are equally impacted by the behavioral biases.

6. **Matsumoto et al. (2013)** conducted an experimental study among business students at the University of Brazil to understand the effect of overconfidence and herding bias. Initially, students were asked to answer questions individually and in the second stage these students were divided into groups and then were asked to answer questions jointly. The objective of the methodology was to evaluate the difference between the individual and group behavior of these students. Individual responses of students reveal that women suffer more from overconfidence and men are more rational although these results are not statistically significant. Group results indicate that women are more susceptible to herding with a decline in measures of overconfidence as compared to men.
7. **Arora and Kumari (2015)** investigated the impact of demographic factors such as age and gender on the risk-taking ability of investors through behavioral biases such as regret and loss aversion. This study integrates several important aspects of demographic variables, behavioral biases, and risk-taking through their interaction. A total of 450 investors participated in the study, who were segregated based on gender and age. Age and gender are exogenous variables while loss aversion and regret aversion are taken as endogenous variables. The conceptual framework for the study was formulated and tested using AMOS 20. In total 9 hypotheses were formulated and tested using path analysis using the maximum likelihood method for estimating different variables. Results of the study confirm that psychological biases such as loss aversion and regret aversion act as mediating factors which influence the linkage between age and gender in the risk-taking ability of the individual. Individuals within the age group 41-55 are found to be more loss averse as compared to the age group 20-40 and females show more loss aversion as compared to males and consequently are less risk tolerant.

8. **Baker et al. (2018)** examined how financial literacy and demographic variables are related to behavioral biases in India. The study uses the survey method to collect data from 516 retail investors in India. The questionnaire involves issues related to financial literacy, demographic variables (gender, age, education, occupation, marital status, income level, and investment experience), and specific behavioral biases (overconfidence and self-attribution, the disposition effect, anchoring bias, representativeness, mental accounting, emotional biases, and herding). One-way analysis of variance, factor analysis, and multiple regression techniques have been used to analyse the data. The findings of the study suggest that investors are more exposed to three biases which are mental accounting, overconfidence, and self-attribution, and less prone to familiarity, availability, and hindsight bias. The evidence also suggests that financial literacy and demographic characteristics are related to specific behavioral biases. The results reveal that financial literacy has a negative association with the disposition effect and herding bias and a positive effect on mental accounting but is unrelated to overconfidence bias. In context with demographic variables age, occupation, and investment experience are the most important variables that relate to behavioral biases.

9. **Isidore and Christie (2019)** surveyed investors in the city of Chennai (Tamil Nadu) to test the relationship between annual income earned by the investors and eight behavioral biases such as mental accounting, anchoring, gambler's fallacy, availability, loss aversion, regret aversion, representativeness, and overconfidence. All the respondents were members of the Tamil Nadu Investors Association and clients of the popular financial service company "*Integrated*". Correlation and Analysis of Variance (ANOVA) on both normalized and non-normalized versions of the data were performed to test the above relationships. The findings of the study showed that in all the significant biases except the overconfidence bias investors who earned higher annual income were less prone to biases and investors with lower income are more prone to these biases.

3.7 Perceived Investment Performance

1. **Park et al. (2010)** conducted an experiment to analyse the impact of confirmation and overconfidence bias and their subsequent influence on the investment performance of the members of stock virtual communities in South Korea. To achieve the objectives of the study data were collected from the members of a popular South Korean virtual community Naver.com. Regression analysis was performed on the data collected from 502 community members. The study's findings show that when investors analyse information from message boards, they exhibit confirmation bias, and stronger confirmation bias leads to increased overconfidence. Therefore, these online communities may not inherently improve people's financial well-being and are not helpful for making investment decisions. Instead, they contribute to behavioral biases.
2. **Le Luong and Thi Thu Ha (2011)** explored the behavioral factors influencing individual investors' decision at the Ho Chi Minh Stock Exchange and their relations with investment performance were also examined. Based on the literature they classified behavioral factors into four major groups namely heuristic theory, prospect theory, market-related factors, and herding. Representativeness, Anchoring, Overconfidence, Gambler's fallacy, and Availability were classified under heuristics. Loss aversion, regret aversion, and mental accounting under prospect theory. Market information and price changes were considered market-related factors. Exploratory factor analysis was conducted to verify whether these behavioral factors belong to their respective behavioral groups or not. Descriptive statistics were used to analyse the impact levels of these biases on the investment decisions of individual investors. Covariance-based structural equation modelling is used to study the impact of behavioral factors on the perceived investment performance of individual investors. Results of EFA indicate that these behavioral factors do belong to their respective behavioral groups. Descriptive statistics reveal that most of the behavioral biases have a moderate impact on investment decisions except for market-related factors and the results of covariance-based SEM reveal that at HOSE herding and heuristics have a positive influence on

investment performance while market and prospect factors have no and negative impact respectively on Investment performance.

3. **Kengatharan and Kengatharan (2014)** explored the impact of behavioral factors on individual investors' decisions and investment performance at the Colombo stock exchange. A cross-sectional design was employed and a six-point Likert scale questionnaire was utilized to collect data from investors using stratified random sampling. The questionnaire was divided into three parts (1) personal information (2) behavioral factors such as heuristics, prospect theory variables, market-related factors, and herding variables (3) investment performance variables. The collected data were analysed using SPSS. The results show that almost all variables of the four behavioral factors have a moderate impact on investment decisions except anchoring which has a high influence on investment decisions and the 'Choice of stock' variable from herding has a very low influence on investment decisions. As far as the impact of behavioral factors on investment performance is concerned overconfidence has a negative significant impact whereas anchoring has a positive significant influence on investment performance. Choice of stock, which is variable from herding also has a negative significant impact on investment performance. Apart from these three factors, all other variables do not influence investment performance.

4. **Khan et al. (2017)** examined the relationship between past portfolio returns, optimism, and financial decisions. A field survey was conducted on retail and institutional investors in the Malaysian stock exchange where institutional investors dominate the market to achieve the objectives of the study. In total 1054 questionnaires were distributed out of those 454 usable responses were collected using non-probability sampling techniques. Ordinary least square regressions were estimated to test the proposed hypothesis. The main conclusion drawn from the study is that perception of past portfolio returns has a positive influence on retail and institutional investors' portfolio returns and trading intentions.

5. **Javed et al. (2017)** explored the influence of four behavioral biases on the perceived investment performance of the collectivist culture of Pakistan. A quantitative and cross-sectional research design has been used in the study. The data was collected from 220 respondents on the basis of judgemental sampling. The results of the regression analysis found that herding, overconfidence, availability, and representativeness all have a positive and significant impact on the perceived investment performance of individual investors in Pakistan.
6. **Shah et al. (2017)** attempted to clarify the mechanism by which heuristics influences individual investor investment decisions and market-perceived efficiency in the context of Pakistan. Individual investors at the PSX as well as brokers who make investments on behalf of investors made up the population for this research. The data on 143 investors were gathered using a convenient and purposeful sampling method, and correlation and regression analysis were used to verify the hypotheses. According to the findings, heuristic biases like overconfidence, representativeness, availability, and anchoring have a pronouncedly detrimental effect on the investment choices made by individual investors who regularly trade on the PSX as well as on the perception of market efficiency.
7. **Akhtar et al. (2018)** analysed the moderating impact of social influence on the relationship between the personality traits of individual investors and perceived investment performance. The Big Five Personality Model is chosen to highlight the basic characteristics of an individual. Stratified random sampling and then quota sampling methods were employed to collect data from three mid-sized districts of Jharkhand. Hierarchical regression analysis and structural equation modelling using AMOS version 21 were employed to analyse the collected data. The study indicated that social influence positively moderates the relationship between extraversion and investment performance and negatively moderates the relationship between agreeability and investment performance. While the moderating impact of social influence on the relationship between other personality dimensions (Openness, Neuroticism, and conscientiousness) and perceived investment performance was found to be insignificant

8. **Pandey and Jessica (2018)** looked into the connection between behavioral biases, investment satisfaction, and reinvestment intention while taking evolutionary psychology into consideration. Data were collected from 560 respondents who have invested in real estate to earn profits, using structured and close-ended questionnaires using a multi-stage stratified sampling method. The questionnaire was initially validated using PLS-SEM and AMOS 20 was used to analyse the mediation model using the structural equation model (SEM). The results of the research support the idea that behavioral biases have an impact on real estate investment choices. Additionally, it is discovered that investment satisfaction has a substantial and complementary partial mediating impact. The relationship between behavioral biases and reinvestment intention is positively mediated by investment satisfaction, demonstrating that biases are innate tendencies that arise in reaction to learning limitations and can be explained by evolutionary psychology.
9. **Akhtar et al. (2018)** in their study, examined the relationship between investors' personality traits and the financial results of their choices. An individual's personality characteristics are assessed using the big five personality model and financial results in terms of perceived investment success. Through a stratified and quota sampling method, cross-sectional data were gathered from individual investors. To determine how strongly the categories are related to one another, data were analysed using correlation, regression, hierarchical regression, and structural equation modelling (SEM). The research's conclusions indicated that people who identify as conscientious, agreeable, or neurotic are more likely to be pleased with the performance of their investments. These results suggest that personality traits can be used to manage personal finances effectively and improve perceived investment success.
10. **Akhtar and Das (2019)** examined the relationship between personality traits and perceived investment performance in the presence of psychological biases, specifically financial risk tolerance (FRT) and overconfidence. 983 individual investors in India were surveyed using a cross-sectional, quantitative study methodology. Their personality traits, investment success, and psychological

characteristics were all evaluated in separate sections of the questionnaire. To verify the connection proposed by the hypothesis, the collected data was then examined using AMOS and SPSS. The study's findings show that individual investors' personality traits are linked to their financial risk tolerance (FRT), financial overconfidence, and perceived investment performance. FRT and financial overconfidence are also associated with lower perceived investment performance. Additionally, the mediation analysis revealed that the two psychological characteristics completely mediated the association between personality characteristics and investment performance.

11. **Malik et al. (2021)** carried out a study in Pakistan to investigate the impact of heuristics on the investment decision-making process and individual investor performance. The study also determines the level of impact of stock market anomalies (fundamental and technical anomalies) in mediating the relationship between heuristic factors and investment performance. Primary data was collected from 250 respondents who invested in the Karachi, Lahore, and Islamabad stock exchanges for the purpose of the study. To investigate the cause-and-effect relationships between variables, SPSS was used to perform factor analysis, reliability analysis, t-test, ANOVA, and multivariate analysis. The study's findings imply that the fundamental and technical anomalies are significantly and positively related to investment performance. The illusion of control and conservatism cause market fundamental and technical anomalies, which have an impact on investment performance. The market does not experience technical or fundamental anomalies as a result of anchoring bias, availability bias, or gambler's fallacy, and individual investors' investment performance remains unaffected.

3.8 Investment satisfaction and Financial Satisfaction

1. **Joo and Grable (2004)** presented a framework exploring factors determining financial satisfaction. They identified various demographic, socioeconomic, and attitudinal factors that have a direct and indirect impact on financial satisfaction. These factors include financial behavior, financial stress levels, income, financial knowledge, financial satisfaction, risk tolerance, and education. The

data used to test the robustness of the framework were collected from a mail survey of white-collar clerical workers from a community in west Texas. 500 questionnaires were mailed to respondents using random sampling out of which 220 responses were received. Path analysis, using SPSS for windows, was used to analyse the data, and bivariate correlation was used to check the multicollinearity situations. Overall results of the path analysis revealed that financial behavior is the most influential determinant of financial satisfaction followed by a person's financial stress levels and financial knowledge.

2. **Toscano et al. (2006)** conceptualized financial satisfaction as a particular aspect of an individual's overall subjective well-being. The paper also highlights the importance of income and its attributes in the determination of financial satisfaction. The research also provides empirical evidence to separate the effects of income and its characteristics on financial satisfaction after taking into account individual heterogeneity. To meet the research's goals, data from the *Survey on Living Conditions and Poverty* for Andalucía (Spain) was used, which also provided information on each person's stated level of financial satisfaction as well as their income and income valuation measures. The results of the study suggest that the inclusion of income and its characteristics in an individual's utility function enriches the complex concept of financial satisfaction.
3. **Wang et al. (2006)** studied the psychological mechanisms underlying risky investment behavior in Chinese stock markets. The goal of the research was to identify the characteristics of various information types that influence risk perception and, in turn, how they influence reinvestment intention and investment satisfaction. The research also made an effort to investigate how institutional factors affected participants' perceptions of risk in the context of China's collectivist society. Utilizing stratified random sampling, a 42-item questionnaire was created and given to 1547 individual investors. Amos 4.0 was used to perform structural equation modelling (SEM) in order to build and validate the proposed conceptual framework for the psychological mechanisms of investment behavior. The study found that Chinese investors

perceived subjective risks and excessive speculation as less risky than objective risks.

4. **Sahi (2013)** examined the effect of socioeconomic and demographic variables on Indian financial consumers' financial satisfaction. A mix of judgment and snowballing sampling methods, which are non-probability based sampling techniques, were used to determine the sample's composition. In the NCR of Delhi, India, about 450 individual investors were contacted, and 374 responses were taken into account for final data analysis. To determine which socioeconomic and demographic factors were connected to a person's level of financial satisfaction, one-way ANOVA, t-test, and correlation were used. The findings demonstrated that all other variables, besides gender, education, and household type, were found to be substantially associated with financial satisfaction.
5. **Sahi and Kalra (2013)** in their research have tried to explore the impact of the financial risk-taking attitude on the financial satisfaction of individual investors. The financial risk-taking attitude has been measured on two dimensions speculative risk scores and risk control scores. The study proposes that both these dimensions are independently active in individual investors and affect the levels of financial satisfaction. Based on the sample of 377 investors drawn from the population of Indian individual investors, the results of the study show that though individual risk control and speculative risk constructs are not significantly associated with financial satisfaction, however, the clusters of the dimensions of financial risk-taking were found to be significantly associated with financial satisfaction and for high-risk control attitude, an increase in speculative risk tendency increases financial satisfaction.
6. **Yap et al., (2016)** examined the effect of financial literacy and attitude on financial management behavior and financial satisfaction of Indonesian households. The nonprobability sampling technique was used to collect data from 200 respondents. The data collected was analysed using multiple regressions. Results from the data analysis show that the most important variable determining financial satisfaction is financial management behavior

and the authors concluded that financial satisfaction comes into life through good financial behavior.

7. **Asif (2016)** examined the existence of behavioral biases among the small investors at the Lahore Stock Exchange. The research also examined the impact of behavioral biases on investment performance and the relative investment satisfaction of individual investors. The study considers overconfidence, overtrading, herding, anchoring, and disposition effect as independent variables and investment satisfaction as the main dependent variable. Data were collected from 180 respondents using the snowball sampling technique and analysed using regression analysis. The results revealed that the disposition effect is negatively related to investment satisfaction while other variables do not have a significant impact on the investment satisfaction of individual investors of Lahore.
8. **Sahi (2017)** examined the impact of psychological biases on the financial satisfaction of individual investors. This study is very unique and novel on its own as such kind of attempt has not been made by any of the researchers in the existing literature. Financial satisfaction is the measure of satisfaction with one's financial situation. The authors used eight items of financial dimensions on a five-point Likert scale to measure financial satisfaction and then the relationship between financial satisfaction and different behavioral biases have been checked. The sequential mixed method has been used and both quantitative and qualitative techniques were applied. Non –Probability sampling technique was used for the study and data is collected from a sample of 377 investors and then finally analysed after satisfying various statistical conditions by using regression and multiple regressions. The results showed that overconfidence bias, reliance on the expert bias, and having a positive and significant association with financial satisfaction and association of few other biases have been checked under control conditions. The study provides further insights into investor behavior and has provided ample opportunities for further research in this area.

9. Parmitasari et al. (2018) analysed the impact of investment ethics and investment behavior on the financial satisfaction of capital market investors in South Sulawesi, Indonesia. The study uses explanatory research which describes the relationship through hypothesis testing. Primary data for the research was collected from 16 securities companies from South Sulawesi Indonesia and a total of 227 responses were analysed using SEM with the PLS method. Based on the data analysis of the respondent the study concluded that investment ethics have a positive and direct contribution to financial satisfaction and investment behavior. And positive investment behavior also leads to an increase in the levels of financial satisfaction of investors which is consistent with the theory of subjective well-being.

10. Saurabh and Nandan (2018) examined the relationship between financial knowledge, socialization, and financial satisfaction with financial risk attitude and financial behavior as mediators in the city of Allahabad, Uttar Pradesh, India. The nonprobability sampling techniques were used to collect data from 286 respondents. Exploratory factor analysis and multiple regression analysis were used to analyse the data and the results of the study revealed that financial risk attitude and financial behavior both mediate the relationship between financial socialization and financial satisfaction as well as between financial knowledge and financial satisfaction

11. Saurabh and Nandan (2019) evaluated the direct and indirect effects of financial education and socialization on the financial satisfaction of individual investors using financial risk attitude as a mediator in the Indian city of Allahabad. The information was collected from 286 respondents using a self-reported survey based on snowball and judgment sampling techniques. To verify proposed associations, the mediated regression analysis was used. Financial knowledge and financial satisfaction were found to have strong favourable relationships, with financial risk attitude acting as the mediator. Similar findings were made regarding the link between financial socialization and financial satisfaction, with financial risk attitude serving as the mediator.

Financial knowledge and financial satisfaction, as well as financial socialization and financial satisfaction, are found to be mediated by financial risk attitude.

3.9 Research Gaps

The following research gaps are identified after an extensive review of the literature:-

1. In Western countries, there is a wealth of literature on behavioral finance, but behavioral finance studies in India are still in their infancy. Findings from western or individualistic societies may not be applicable in the Indian context because India has a diverse social and economic profile. As a result, there is a need to understand investment behavior in the context of collectivist societies such as India.
2. As the area of behavioral finance is relatively new most of the empirical research studies in India are confined to exploring the relationships between demographic, socioeconomic variables, and behavioral biases of individual investors completely ignoring the important role of investor sophistication or trading behavior in determining behavioral biases of individual investors in India.
3. Most of the behavioral finance studies in India are limited to investigating the presence of behavioral biases among Indian investors and little emphasis is placed on examining the effects of behavioral biases on financial outcomes, so there is a need to ascertain how these behavioral factors affect the inevitable results of financial choices.
4. The review shows that the majority of the primary data research studies in India have been conducted on heuristics, especially on the outcomes overconfidence, and limited research has been carried out on emotional biases such as loss aversion, regret aversion, and mental accounting and their impact on Indian individual investors.
5. The review shows that in most of the behavioral biases, empirical findings are indecisive. This is because some studies have found a negative impact of behavioral biases on the perceived investment performance of individual

investors while some studies have found a positive impact of behavioral biases on the perceived investment performance of individual investors.

6. The extensive review of the literature reveals that previous studies have examined the direct impact of behavioral biases on the financial satisfaction of individual investors paying less attention to the underlying mechanisms through which these relationships and effects flow. There has been no evidence of a study that uses the mediating role of perceived investment performance and investment satisfaction in the relationship between behavioral biases and financial satisfaction.
7. The behavioral finance literature provides mixed evidence regarding the impact of behavioral biases on investment decisions; some argue that behavioral biases have a negative impact, while others argue that behavioral biases have a positive impact on investment decisions. As a result, it remains unclear how heuristics and biases affect a person's financial well-being and investment performance. Consequently, it highlights the urgent need for research into how behavioral biases affect investors' levels of financial satisfaction, investment satisfaction, and performance.
8. Prior studies published in the literature assessed behavioral biases directly through manifest variables without accounting for the antecedents that caused those manifest variables. So there is a need to investigate the antecedents of each bias and developed scales to measure each bias in light of its antecedents.

CHAPTER 4

RESEARCH METHODOLOGY

4.1 Introduction

The present chapter deals with the development of a research design for the study. Research design is the framework within which the research is to be conducted. An effective research design ensures the smooth functioning of various research functions. The current chapter outlines specific objectives, develops a conceptual framework, and formulates hypotheses to have a better understanding of the purpose of the study. The target population is defined, sampling techniques and methods are explained, and the sample size is determined using the G*power software. Additionally, the chapter also explains the questionnaire design and measurements along with attempting to demonstrate how the analysis was conducted using multivariate data analysis techniques such as independent samples t-test, one-way analysis of variance (ANOVA), and Welch- F test, in SPSS statistics version 21 and variance-based partial least squares structural equation modelling (PLS-SEM), partial least squares multigroup analysis (PLS-MGA) using SmartPLS 4, version 4.0.8.5 of the software.

4.2 Purpose of the Study

Indian financial market is an integrated well-functioning network of the capital market, money markets, government securities market, forex, and other derivative markets. The trading volumes in these markets have witnessed significant growth over the past few years. Due to the availability of innovative financial products and numerous investment opportunities, the participation of retail investors in the Indian financial markets is rising day by day. There has been an addition of a whopping 142 lakh demat accounts at NSDL and CSDL in the financial year 2021 itself (Sultana & Ramarathinam, 2021). The competition and complexity have increased more than ever. These retail investors are constantly required to make several decisions simultaneously like how much to save, where to invest; what and when to buy and sell, and how long to hold, when faced with too many decisions the results can be paralyzing. In such a situation investors make use of financial “rules of thumb” to help them make a better financial choice. These financial shortcuts or heuristics help investors to lessen the psychological pressure in financial decision-making and to be quick about their judgments but they

act as a double-edged sword, greater reliance on these shortcuts and instincts makes investors prone to certain psychological and behavioral biases that can be detrimental to their overall financial wellbeing. Therefore to understand the individual investor better, it is important to be aware of the irrationality and psychological biases present in their investment behavior. Existing literature suggests that varied demographic characteristics of the investor population further accentuate the complexities that arise because of deep-seated behavioral biases in the minds of investors. (Baker et.al, 2018; Prosad et.al, 2015). However, investor sophistication measures are thought to improve the investment performance of individual investors by assisting them in avoiding costly investment errors (Seru et al., 2010; Grinblatt et al., 2011). The study uses diagnostic research to establish the association of demographic variables and sophistication measures with behavioral biases of individual investors in India. Further, the study uses descriptive research to understand the role of behavioral biases in determining the overall financial well-being of Indian individual investors.

4.3 Objectives of the study

According to the existing literature available on financial decision-making and behavioral finance, individual investors exhibit numerous behavioral biases. Additionally, it draws focus to the areas of behavioral finance in India that have received little attention and where more research is required. The following research objectives have been formed based on the gaps identified in the existing literature.

- 1) To examine how socio-demographic and investor sophistication variables are related to behavioral biases.
- 2) To examine the impact of select behavioral biases on the perceived investment performance of individual investors.
- 3) To examine the impact of select behavioral biases on the investment satisfaction of individual investors.
- 4) To examine the impact of select behavioral biases on the financial satisfaction of individual investors.
- 5) To assess the mediating role of the perceived investment performance and investment satisfaction in the relationship between behavioral biases and financial satisfaction.

- 6) To examine the moderating effects of key demographic variables and investor sophistication measures on the structural model relationships.

4.4 Conceptual Framework for the Study

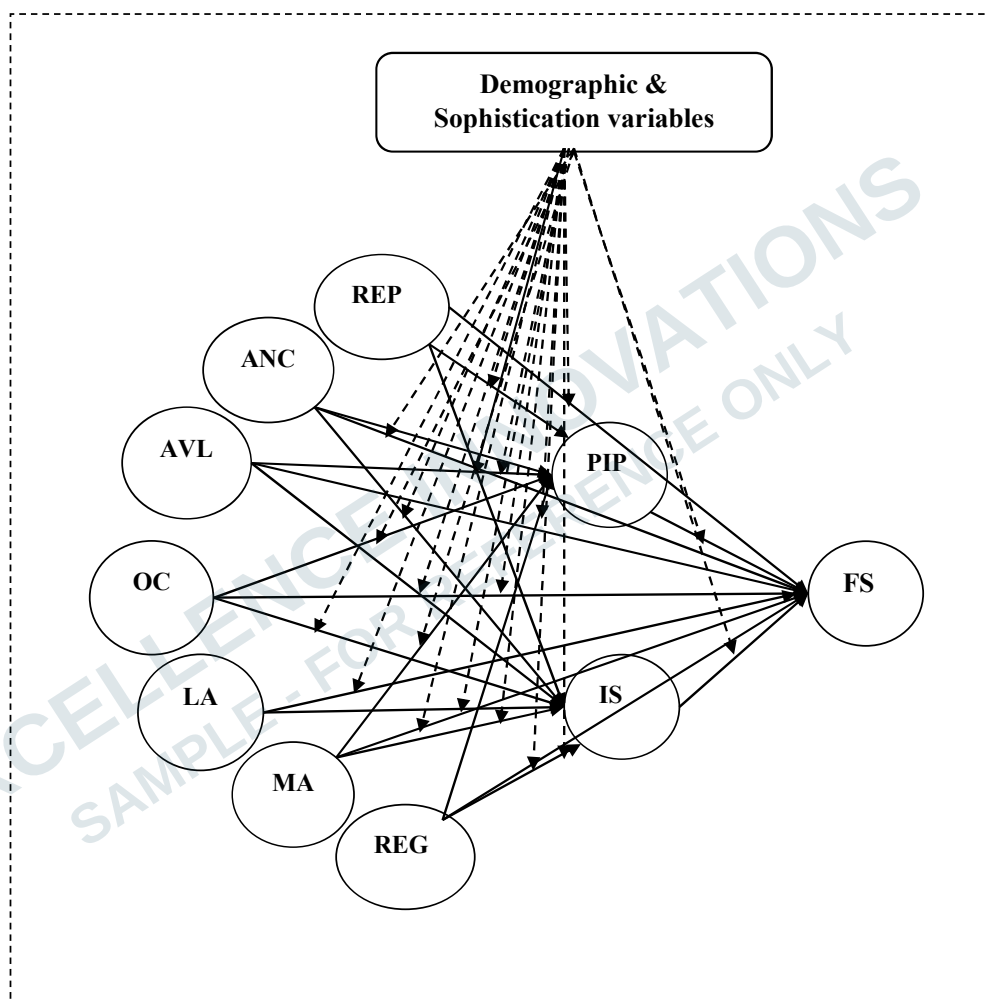


Figure 4.1 Conceptual model for the study

Source: Developed by the researcher

Notes: Rep = Representativeness, ANC= Anchoring, AVL = Availability, OC= Overconfidence, LA = Loss aversion, MA = Mental accounting, REG = Regret aversion, IS = Investment Satisfaction, PIP= Perceived investment performance, FS = Financial Satisfaction

The conceptual model is deduced based on a substantive literature review. The proposed model investigates the direct and indirect impact of behavioral biases on the financial satisfaction of individual investors it also incorporates perceived investment performance and investment satisfaction as mediating variables that have been mostly overlooked by past studies. The inferred model also investigates the role of demographic variables and investor sophistication measures in moderating the relationships between independent and dependent variables. Therefore, the prime objective of the study is to validate the holistic model depicting the impact of behavioral biases on the financial well-being of individual investors.

4.5 Hypotheses of the Study

H1: There is an association between demographic variables and behavioral biases of individual investors

H1.1 There is an association between gender and behavioral biases

H1.2 There is an association between age and behavioral biases

H1.3 There is an association between education and behavioral biases

H1.4 There is an association between marital status and behavioral biases

H1.5 There is an association between occupation and behavioral biases

H1.6 There is an association between Income and behavioral biases

H2: There is an association between investor sophistication measures and behavioral biases of individual investors.

H2.1 There is an association between investment amount and behavioral biases

H2.2 There is an association between investment experience and behavioral biases

H2.3 There is an association between investment frequency and behavioral biases

H3: Behavioral biases have a significant impact on the perceived investment performance (PIP) of individual investors.

H3.1: Overconfidence has a significant impact on PIP

H3.2: Availability has a significant impact on PIP

H3.3: Anchoring has a significant impact on PIP

H3.4: Representativeness has a significant impact on PIP

H3.5: Mental accounting has a significant impact on PIP

H3.6: Loss aversion has a significant impact on PIP

H3.7: Regret has a significant impact on PIP

H4: Behavioral biases have a significant impact on the investment satisfaction (IS) of individual investors.

H4.1: Overconfidence has a significant impact on IS

H4.2: Availability has a significant impact on IS

H4.3: Anchoring has a significant impact on IS

H4.4: Representativeness has a significant impact on IS

H4.5: Mental accounting has a significant impact on IS

H4.6: Loss aversion has a significant impact on IS

H4.7: Regret has a significant impact on IS

H5: Behavioral biases have a significant impact on the financial satisfaction (FS) of individual investors.

H5.1: Overconfidence has a significant impact on FS

H5.2: Availability has a significant impact on FS

H5.3: Anchoring has a significant impact on FS

H5.4: Representativeness has a significant impact on FS

H5.5: Mental accounting has a significant impact on FS

H5.6: Loss aversion has a significant impact on FS

H5.7: Regret has a significant impact on FS

H6: Perceived investment performance has a significant impact on the financial satisfaction of individual investors.

H7: Investment satisfaction has a significant impact on the financial satisfaction of individual investors.

H8: Perceived investment performance mediates the relationship between behavioral biases and financial satisfaction.

H8.1: PIP mediates the relationship between OC and FS

H8.2: PIP mediates the relationship between AVL and FS

H8.3: PIP mediates the relationship between ANC and FS

H8.4: PIP mediates the relationship between REP and FS

H8.5: PIP mediates the relationship between MA and FS

H8.6: PIP mediates the relationship between LA and FS

H8.7: PIP mediates the relationship between REG and FS

H9: Investment satisfaction mediates the relationship between behavioral biases and the financial satisfaction of individual investors

H9.1: IS mediates the relationship between OC and FS

H9.2: IS mediates the relationship between AVL and FS

H9.3: IS mediates the relationship between ANC and FS

H9.4: IS mediates the relationship between REP and FS

H9.5: IS mediates the relationship between MA and FS

H9.6: IS mediates the relationship between LA and FS

H9.7: IS mediates the relationship between REG and FS

4.6 Research Design

A research design specifies the entire research process and makes it possible to systematically measure, collect and analyse data with the aim to achieve the objectives of the study. A descriptive research design is employed in this study which is a more refined form of conclusive research design and assumes that the researcher has prior knowledge about the research problem through an extensive literature review and is based on the formulation of research hypotheses. The descriptive research design has been further narrowed down to a cross-sectional research design because data would be collected only once from the sample respondents throughout the period of the study.

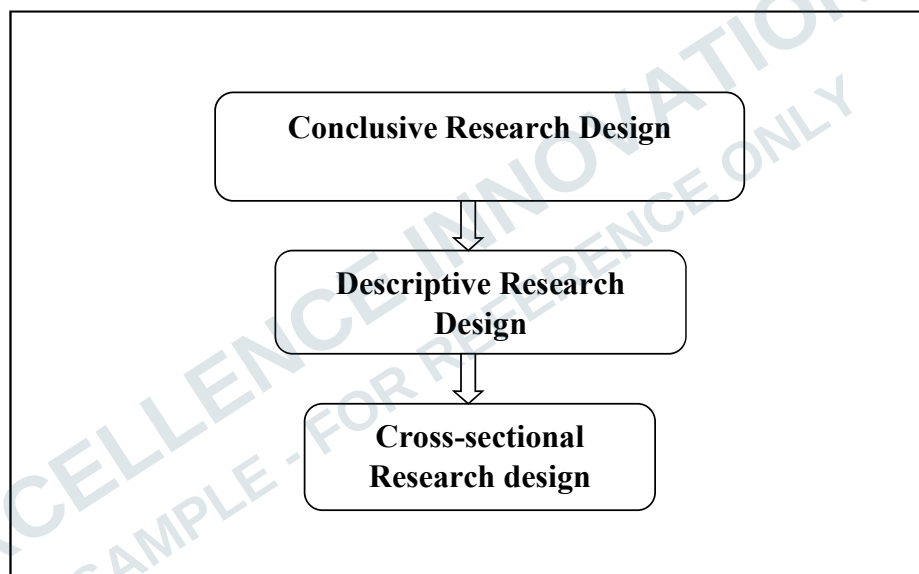


Figure 4.2 Research design of the study

Source: Adapted from Malhotra and Dash (2017)

4.7 Sampling Design

Sampling Design is one of the most important components of research design. The sampling design process consists of five steps i.e. defining the target population, determining the sample frame, selecting the sampling technique, determining the sample size, and executing the sampling process. (Malhotra & Dash, 2017)

4.7.1 Target population

The target population for the study consists of investors who are directly investing in the Indian stock markets and are residents of the Delhi NCR region. Thus, the target population is defined in terms of investors who fulfill these two conditions simultaneously. First, they should directly be investing in the Indian stock markets. The Indian stock market is predominantly represented by two stock exchanges i.e. the National stock exchange (NSE) and the Bombay stock exchange (BSE). Any person who is above 18 years of age having a demat account can invest any amount in any company listed on these stock exchanges depending on his/her financial situation. The value of stocks traded on these exchanges can range from as low as 1 rupee to as high as 70,000 rupees. Thus all investors who are above 18 years of age come under the purview of the target population irrespective of their income and investment amount.

The second condition is, the person must be a resident of the National Capital Region (NCR), India. The NCR constitutes the NCT of Delhi and several districts of the surrounding states of Haryana, Uttar Pradesh, and Rajasthan. Prominent cities in the NCR region are Delhi, Noida, Gurugram, Faridabad, and Ghaziabad.

NCR is chosen for the purpose of the study as it is India's largest and the world's second-largest urban agglomeration inhabiting more than 54 million people of India's population with diverse socio-economic and cultural backgrounds. NCR is also the fastest-growing economic region of India and as per the economic survey report for the FY 2021-22 the per capita income of Delhi is three times higher when compared with the per capita income of India hence, in a way NCR represents the whole of India and investors residing here are financially eligible to become the respondents in the present survey.

4.7.2 Sample Unit: Data will be gathered from individual investors fulfilling the requirement of being a component of the target population for the purpose of this study.

4.7.3 Sample Frame: There is no official list from where data about investors investing in the Indian stock market and residing in the Delhi NCR region can be directly obtained. Therefore, no sampling frame exists for the target population.

4.7.4 Sampling technique: Primary data for the present research has been gathered using a survey-based technique. Since no sampling frame of the investors was available,

data was collected subjectively from a relevant portion of the population (Prosad et al, 2015). As the researcher could not give every investor the same opportunity of being selected, probability sampling techniques in terms of stratified, systematic, cluster, and random sampling have not been utilized in the present research. Instead, the study follows the approach employed by previous researchers such as Davar and Gill (2007); S. Sahi, (2017); and Prosad et al (2015), and the selection of sample units was based on a combination of two non-probability sampling techniques i.e. judgment sampling and snowball sampling methods. Judgment sampling is a form of convenience sampling in which the researcher selects the sampling units based on his/her judgment, keeping in mind the objectives of the research. In the case of snowball sampling, the initial set of respondents was asked to identify the other respondents out of their acquaintances belonging to the same target population, and then subsequent respondents were also asked to do the same. Also, the present research requires obtaining certain specific financial information from the respondent and every investor's willingness to share such sensitive information is not the same, therefore, only those respondents who gave their consent to voluntarily participate in the study were contacted. Considering these challenges and, time and cost constraints in the data collection process, judgment, and snowball sampling techniques were found most suitable to achieve the objectives of the study.

4.7.5 Sampling Procedure

A list of potential stock investors was compiled from contacts and friends; these individuals were then directly contacted via phone calls, WhatsApp, email, Facebook, and LinkedIn to confirm that they are actively investing in stock markets and are willing to take the survey. After getting their permission, forms via Google links were sent to them, and they were asked to complete the survey and provide the information of other investors they knew from their social networks or families. In this way, 150 responses were collected. In addition to this, a small number of stock brokers and stock training institutions were personally contacted and visited in various parts of Delhi-NCR. They were briefed about the survey and asked to share the Google form links with their clients in the case of stock brokers, and in the case of stock training institutions, permission was sought from the director of the institution to collect survey data from trainees using Google Forms. A total of 324 responses were gathered; however, 17 of them were

discarded because they contained improper information, as a result, 307 responses were used for further data analysis after validation checks.

4.7.6 Sample Size Determination

Sample size determination for a particular study depends on a variety of factors such as the nature of the study, the number of variables under consideration, statistical software, and methods that the researcher intends to use for the data analysis. An ideal sample size should be selected in such a manner that it allows making valid inferences about the population from the sample. Since the objective of the present research is prediction rather than confirmation of the structural relationships the variance-based PLS-SEM (using SmartPLS 4) is the appropriate method to test the structural model (Hair et al., 2011). The minimum sample size required to ensure the robustness of the statistical method is calculated using two different approaches suggested in the recent literature. First is the rough guideline, better known as the “10 times rule” which recommends that the minimum sample size required for PLS-SEM analysis should be 10 times the largest number of structural paths directed at a particular construct in a structural model (Hair et al., 2011; 2017). In the conceptual model nine arrows are pointing towards the main endogenous variable i.e. financial satisfaction and propose that a sample size of 90 (9×10) is sufficient to analyse the model. The second is with the help of G* power software version 3.1.9.7 (Faul et al., 2007; 2009) as shown in figure 4.3. The settings of the software were as follows: effect size (f^2) = 0.05 (small), significance level (α) = 0.05, and the power of the test ($1-\beta$) = 0.95. The power of a statistical test is the ability to reject the null hypothesis when it is false. Cohen (1992) proposed a value of 0.80 or higher as a convention when performing power analysis and the number of predictors in the model for the main endogenous variable is 9. Given all these conditions the minimum sample size required to test the model is 262, whereas the study used a sample of 307 which satisfies the appropriate sample size requirements.

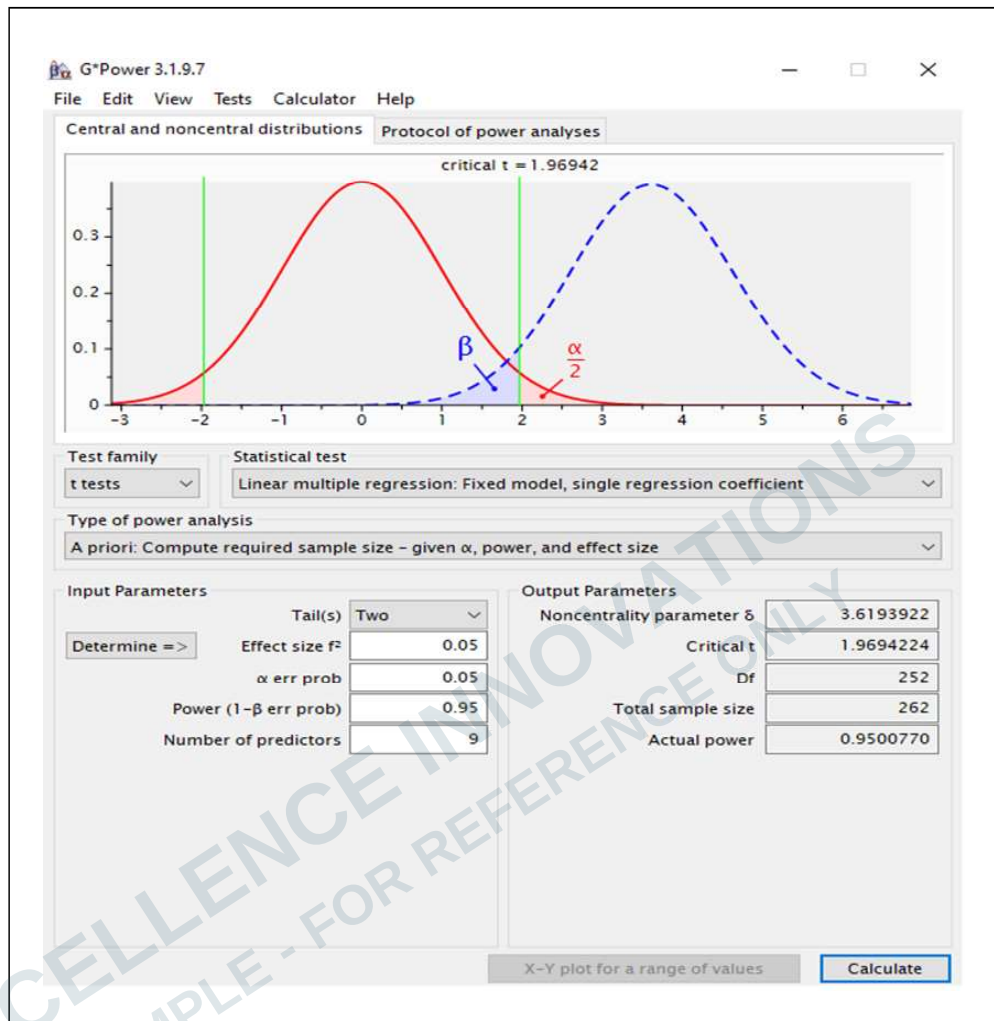


Figure 4.3 Sample size determination

Source: G*Power Analysis (Faul et al., 2007; 2009)

4.8 Questionnaire Design and Measurements

4.8.1 Structure of the questionnaire

Data were collected through a structured and close-ended questionnaire to test the hypothesized relationships among the latent variables. Since the focus of the study is on behavioral biases and the perceived performance and satisfaction of individual investors investing in financial markets an extensive literature review was conducted to get the pool of items measuring different constructs in the conceptual model (table 4.1). These adopted items from established scales were then scrutinized by professionals and

domain experts to eliminate any possible errors in understanding and completing the survey by individual investors. The administered questionnaire consists of a total of 55 questions (Appendix 2) and is divided into three broad sections. To increase the response rate, an assurance, that information provided by respondents would be kept confidential along with the estimated time to complete the survey was given to respondents at the beginning of the questionnaire.

The first section of the questionnaire is based on 33 questions measuring seven behavioral biases of individual investors and their dimensions. The constructs measured in this section namely overconfidence, availability, anchoring, representativeness, mental accounting, loss aversion, and regret are treated as exogenous variables in the conceptual model, and responses were sought on a seven-point Likert type scale with 1 indicating “strongly disagree” and 7 indicating “strongly agree”.

Section 2 is based on 11 psychographic items pertaining to perceived investment performance, investment satisfaction, and financial satisfaction of individual investors measured on a seven-point Likert-type scale ranging from 1 (Highly Dissatisfied) to 7 (Highly Satisfied).

Section 3, the last section of the questionnaire consists of 11 questions, 6 items relating to the demographic and socio-economic background of the investors and 5 items related to investors’ sophistication measures and their stock portfolio details.

4.8.2 Measures of key constructs under study

Overconfidence: An eight-item scale is created to assess overconfidence and is designed to capture the four main aspects of overconfidence bias. These include the better than average effect, self-attribution, the planning fallacy, and the illusion of control. Two items to measure better than average effect are adapted from Wood and Zaichkowsky (2004). Rest of the three dimension are captured by six items taken from Kansal and Singh (2018).

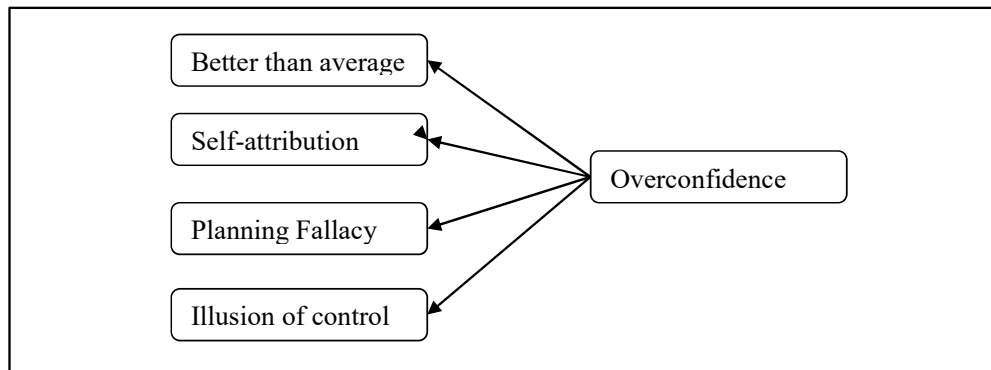


Figure 4.4 Antecedents of Overconfidence

Availability: A four-item scale is developed to measure two aspects of availability bias in the present study i.e. *Retrievability* and *Exposure effect*. To measure retrievability, three questions are asked of investors out of which the first two are taken from Kudryavtsev et al. (2013). The third item to measure retrievability is taken from Phuoc Luong and Thi Thu Ha (2011). To measure the exposure effect one question is asked from investors again taken from Phuoc Luong and Thi Thu Ha (2011).

Representativeness: Present study measures three aspects of representativeness bias base rate neglect, sample size neglect also known as dependency on recent returns, and gambler's fallacy. A four-item scale was developed out of prior studies to measure these three aspects. Base rate neglect was measured by a single question taken from Waweru et al. (2008). To measure dependency on recent returns two questions have been asked from investors that are taken from Rasheed et al. (2018). To measure Gambler's fallacy one question is asked that is taken from Waweru et al. (2008) and Pandey and Jessica (2018).

Anchoring: In the current research, a four-item scale is created including one reverse-coded item to assess three different types of anchors that investors commonly use when making investment decisions. These are moving averages along with 52-week high or low prices measured by one item taken from Baker et al. (2019), recent prices measured by an item taken from Jain et al. (2020) and two items related to initial purchase price were adopted from Ritika and Kishor (2020).

Mental accounting: Based on two major categories of mental functions that the human brain performs, categorization and mental budgeting, two dimensions of mental accounting have been investigated in the current study. The current study uses a four-item scale that was adapted from Sahi (2017) and has two questions in each category of mental accounting.

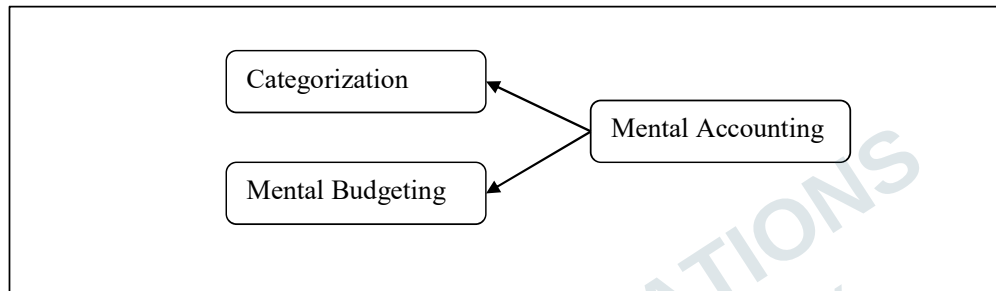


Figure 4.5 Antecedents of Mental accounting

Regret aversion: In the current research, the two distinct aspects of regret i.e. anticipated regret and experienced regret, have been taken into account in order to measure this emotion. A four-item scale with two questions in each regret category was used; it was adapted from Schwartz et al. (2002).

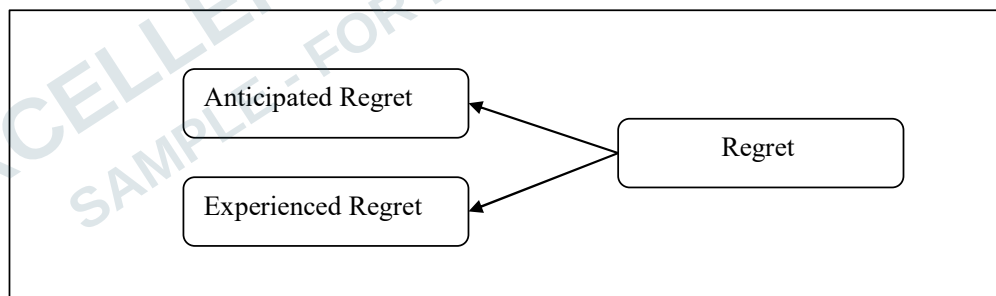


Figure 4.6 Antecedents of Regret

Loss aversion: Five of a seven-item standardized scale developed by Li et al. (2021) was used in the current research to measure the impact of loss aversion bias while keeping in mind the operational definition of loss aversion.

Financial satisfaction: Currently, there is no consensus among researchers regarding the best way to measure financial satisfaction, some studies have measured it with a single-item scale, while others measured it with a multiple-item scale.

To measure financial satisfaction in the present study an eight-item scale is adapted from Sahi (2017). The eight dimensions of financial satisfaction assess how satisfied a person feels about their current income, savings, ability to cover unexpected expenses, ability to meet future requirements, inflation, capacity to repay credit and loans, and tax-saving potential.

Investment Satisfaction: Investment satisfaction is measured directly through one statement asking respondents to provide their satisfaction level with regard to their investment decisions on a seven-point Likert scale adopted from Asif (2016) “*I feel satisfied with my investment decisions in the last year (including selling, buying, choosing and deciding on stock volumes)*”.

Perceived investment performance: In order to measure investors' perceived investment performance, this research employs attitude measurements. It specifically compares the actual rate of return to the investor's own expectations and the market rate of return two items to measure this aspect of investment performance are taken from Phuoc Luong and Thi Thu Ha (2011). One aspect to include the inflation component in the performance measure is adapted from Sato et al. (2011) and Akhtar et al. (2017).

Table 4.1 Scales for measuring the constructs

Main Construct	Dimensions	References	No. of items in the scale
Overconfidence Bias	Better than average effect	Glaser and Weber (2007); Wood and Zaichkowsky (2004)	2
	Self-attribution	Kansal and Singh (2018)	2
	Planning Fallacy	Kansal and Singh (2018)	2
	Positive Illusion	Kansal and Singh (2018)	2
		Total	8

Availability Bias		Kudryavtsev et al. (2013); Phuoc Luong and Thu Ha (2011)	4
Anchoring Bias		Baker et al. (2019); Jain et al (2020)	4
Representativeness Bias		Waweru et al. (2008); Rasheed et al. (2018)	4
Mental accounting	Categorization	Sahi, (2017)	4
	Mental Budgeting		
Loss aversion		Li et al. (2021)	5
Regret	Anticipated regret	Schwartz et al. (2002)	4
	Experienced regret		
Perceived Investment performance		Le Luong and Thi Thu Ha (2011); and Sato et al. (2011).	3
Investment Satisfaction		Wang et al. (2006)	1
Financial Satisfaction		Joo and Grable (2004); Sahi (2017)	7

4.9 Pretesting of the Questionnaire

With the aim of refining the questionnaire, a pilot survey study was undertaken with a sample of ninety Delhi-based investors who invest in the Indian stock market. Sample elements for the pilot survey were approached on the basis of convenience and judgmental sampling. The reliability and validity of the constructs were checked to ensure the suitability of the questionnaire. Cronbach's alpha values were calculated independently for each construct to ensure the questionnaire's initial reliability. Table 5.1 depicts the values of Cronbach's alpha calculated for variables using IBM SPSS in the pilot phase.

Table 4.2 Reliability Analysis for Pilot Testing

S.no.	Variable	Initial Items	Final Items	Cronbach's Alpha
1	Overconfidence	8	8	0.779
2	Representativeness	4	3	0.719
3	Availability	4	4	0.608
4	Mental Accounting	4	4	0.849
5	Regret aversion	5	5	0.724
6	Loss Aversion	5	5	0.845
7	Anchoring	4	3	0.819
8	Perceived Investment Performance	4	4	0.880
9	Financial Satisfaction	7	7	0.839

The Alpha value for each variable shown in Table 5.1 came out to be in the range of 0.600 to 0.966 exceeding the widely accepted minimum value of 0.6 (Malhotra & Dash, 2017) after deleting one item in the representativeness construct and one item belonging to anchoring construct. Hence, it was concluded that there were no reliability concerns with the questionnaire. The final version of the questionnaire measured a total of 7 independent and 3 dependent variables using a total of 43 items.

4.10 Statistical Tools for Data Analysis

To analyse the data in the present study various statistical techniques were used. The employment of these techniques primarily depends on the research objectives framed by the researcher. The first objective of the present research is to examine the differences among behavioral biases in terms of the socio-demographic and investor sophistication characteristics of the respondents. Descriptive statistics (mean and standard deviation), independent samples t-test, one-way analysis of variance (ANOVA), Welch- F test, and Tamhane's and Tukey HSD post hoc analysis were used to achieve this objective of the research study. The rest of the objectives of the present research were achieved by employing Variance-Based Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4, version 4.0.8.5 of the software.

PLS-SEM is an advance and comprehensive data analysis technique that can assess the measurement model and structural model simultaneously. In the context of the PLS-SEM measurement model is evaluated based on the following criteria: indicator's outer loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), Fornell and Lacker criteria, HTMT ratio, and cross-loadings of the indicators and the standard assessment criteria for the structural model include Coefficient of determination (R^2), Adjusted R^2 , Predictive relevance (Q^2), Standardized root mean square residual (SRMR), and Statistical significance of path coefficients.

4.10.1 The rationale for using PLS-SEM

Structural equation modelling (SEM) for multivariate analysis can be applied using two approaches, CB-SEM (covariance-based SEM) and PLS-SEM (variance-based SEM). It's been noted in recent literature from social science that there has been an increase in the usage of PLS-SEM as it offers greater flexibility in terms of data requirement and creating and analyzing complex models. Present research employs PLS-SEM because of the following reasons:

The conceptual framework for the study is complex although it has been developed on a solid literature base, still it is unique as it aims at testing many relationships among the latent variables that have not been tested before in the existing literature. Therefore the objective of the present research is the prediction and exploration of the relationships among the latent constructs and not the generalization of the existing models hence, variance-based PLS-SEM is the appropriate method in this case. Further, the conceptual framework of this study includes three higher-order constructs that allow researchers to capture the more abstract dimensions of a particular construct, six first-order constructs, and one single-item construct and PLS-SEM is a technique that can easily incorporate all these types of constructs in a single model. Finally, conducting research with large sample sizes is often hard, especially when the population elements are widely scattered and difficult to access (like the investor population in the present case). In such situations, PLS-SEM provides optimal solutions with small sample sizes and less restrictive assumptions in comparison to CB-SEM, without compromising the quality of the research.

4.10.2 Statistical tools used for the measurement model

The first step in the evaluation of the measurement model using PLS-SEM involves assessing the reliability and validity of the construct measures. Since all the latent variables in the conceptual model are reflective in nature, they are assessed using the following criteria:

- 1) Indicator reliability
- 2) Internal consistency reliability
- 3) The average variance extracted (AVE)
- 4) Discriminant Validity

4.10.2.1 Indicator reliability

The first step in assessing the reflective measurement model involves the examination of the indicator loadings of the construct items. Loadings above 0.70 are recommended (Hair et al., 2013). However, items having indicator loadings between 0.40 and 0.70 can be retained in the model if they are not contributing to the improvement of content validity and composite reliability of the constructs.

4.10.2.2 Internal consistency reliability

Internal consistency reliability of the scale items has been evaluated by using two criteria Cronbach's Alpha (α) and composite reliability (ρ_c).

Cronbach's Alpha describes the extent to which all the items in a scale measure the same concept, hence it is related to the interconnectedness of the scale items (Tavakol and Dennick, 2011). Cronbach's alpha is a traditional approach to estimating internal consistency reliability. It assumes that all the indicators have equal outer loadings on the construct and tends to underestimate the internal consistency reliability. Due to these limitations of Cronbach's alpha, we calculate **composite reliability** which is a liberal and non-conventional method of estimating internal consistency reliability. It assumes that each indicator has a different outer loading on the latent variable. The values of both measures of reliability range from 0 to 1. Reliability values between 0.6 and 0.7 are considered acceptable, while values between 0.7 and 0.9 are considered good, but the reliability values above 0.09 are totally undesirable as they indicate that the scale items are redundant and reduce the construct reliability (Diamantopoulos et al., 2012; Drolet and Morrison, 2001).

4.10.2.3 Average variance extracted (AVE)

The estimation of AVE is the third step in assessing the reflective measurement models. AVEs are utilized to establish the convergent validity of each measurement construct. It is defined as the grand mean of the squared loadings of the indicators associated with the construct. AVE value of 0.5 or above indicates that the construct explains more than half of the variance of its indicators and an AVE of less than 0.50 indicates that the error residing in the items is more than the variance explained by the construct (Hair et al., 2014)

4.10.2.4 Discriminant validity

There are three different methods that are generally used by the researcher to assess the discriminant validity of the model. First is, the **cross-loadings of the indicators** second is the **Fornell –Larcker criterion** and third is the **Heterotrait-Monotrait (HTMT) criterion**.

- i) According to the **Fornell and Larcker** criterion, the square root of the AVE of each construct should be higher than the construct's highest correlation with any other construct in the model. (Hair et al., 2016)
- ii) According to **Cross loadings of the indicator's** approach discriminant validity is established when an indicator's cross-loading on a construct is higher than all of its cross-loadings with other constructs.
- iii) **HTMT Criterion:** Fornell and Larcker criterion and cross-loadings are traditionally used techniques to evaluate the discriminant validity, but these criteria work in situations of heterogeneous loading patterns and high sample sizes, due to these critical issues in these traditional techniques Henseler et al., (2015) presented a new technique in the form of HTMT ratio, it demonstrates superior performance in assessing discriminant validity as it has high sensitivity rates (Henseler et al., 2015) in comparison to above mentioned traditional methods. Discriminant validity as per this criterion is established if HTMT values are below the threshold value of 0.85.

4.10.3 Collinearity assessment test

The coefficients that are derived in the structural model for the relationships among the constructs are based on a series of regression equations and the collinearity among the constructs is a major factor that can make the regression results biased and imprecise. Therefore collinearity must be examined before assessing the structural model. Variance Inflation Factor (VIF) is calculated to diagnose the collinearity issues among the predictor variables. $VIF > 5$ indicates the presence of multi-collinearity among the predictor variables (Hair et al, 2016) but according to Mason and Perreault, (1991); Becker et al. (2015) collinearity can also create problems if VIF values are between 3 and 5. Therefore, VIF values close to or lower than 3 are preferable.

4.10.4 Statistical tools for structural model assessment

When the measurement model is satisfactory and there are no collinearity issues among the predictive constructs, the next step is the evaluation of the structural model on the basis of the following criteria:

- i) Coefficient of determination (R^2)
- ii) Predictive relevance (Q^2)
- iii) Model fit using SRMR
- iv) Statistical significance of path coefficients

4.10.4.1 Coefficient of determination (R^2)

The coefficient of determination (R^2) is a measure of the variance in the endogenous construct that is explained by all the exogenous constructs that are connected with it. Therefore it measures the explanatory power of the model (Shmueli and Koppius, 2011). It is also known as the model's in-sample predictive power (Rigdon, 2012). R^2 values range from 0 to 1. Since the coefficient is the squared correlation of actual and estimated value, higher R^2 values indicate a higher predictive ability of the structural model.

4.10.4.2 Predictive relevance (Q^2)

Q^2 , also known as Stone-Geisser's Q^2 value (Geisser, 1974; Stone, 1974) is a measure of the predictive accuracy of the structural model. . It is obtained by using the

blindfolding procedure. Blindfolding is a sample reuse technique that omits some data points from the endogenous variables at a certain omission distance and then tries to estimate these data points with the help of the remaining data points. Prediction errors are then calculated as the difference between omitted and estimated values and finally, Q^2 values are calculated with the help of these prediction errors (Rigdon, 2014b; Sarstedt et al., 2014). When the difference between the predicted and observed value is small Q^2 value is high, leading to the higher predictive accuracy of the model.

4.10.4.3 Model fit using SRMR

Unlike CB-SEM, PLS-SEM's reliance on the concept of model fit is much less. A comprehensive assessment of model fit measures for PLS-SEM has not been conducted so far (Hair et al., 2019). Currently, standardized root mean square residual (SRMR) is dominantly used as an approximate model fit criterion for PLS-SEM (Henseler, 2017). An SRMR value of less than 0.08 indicates an acceptable fit for the model in the context of PLS-SEM (Hu and Bentler, 1999)

4.10.4.4 Statistical Significance of path coefficients

Determination of the statistical significance of path coefficients is the final step in assessing the structural model in PLS-SEM. Since PLS-SEM is a non-parametric method, the statistical significance of these path coefficients is assessed with the help of t-values and standard error of estimates obtained through the bootstrapping procedure (Chin, 1998). Bootstrapping is a non-parametric technique that resamples a single dataset into multiple simulated datasets. When the t-value $[t = \frac{P_{13}}{Se}]$ obtained with the help of bootstrapping standard error is greater than the critical values at a certain level of significance (5% in the present study), the path coefficient is determined as significant and vice-versa.

4.10.5 Partial least squares multigroup analysis (PLS-MGA) technique

Multigroup analysis or PLS-MGA is used to compare the path coefficients in the PLS path models across two or more groups. While conducting a multigroup analysis it is assumed that the population parameter is different for two or more subpopulations. Generally, it consists of two steps in the first step group wise parameter is calculated for each subpopulation in the analysis, and in the second step significance of the difference between each subpopulation's parameter is evaluated. An unpaired sample

t-test is typically used to analyse the difference between the parameters of two subpopulations (Henseler, 2015).

According to Henseler et al., (2016) Measurement Invariance of the Composites (MICOM) must be established before performing PLS-MGA. This approach consists of three steps:

Step 1: Assessing configural invariance: This step ensures that the same number of constructs and the same number of indicators are present in different models for all the groups, even data treatment and algorithm settings should also be the same.

Step 2: Assessing compositional invariance: It is established when the composite scores are the same across the groups. A permutation test is conducted to check the presence of compositional invariance in the data sets. For each permutation run, composite scores using weights for group 1 are compared with composite scores using weights for group 2 and if the correlation between these groups is high we say that compositional invariance is present. PLS-MGA is meaningless without establishing configural and compositional invariance in the data sets.

Step 3: Assessing equality of mean and variances: Equality of mean and variances are also tested through the permutation process. If mean and variances are equal we say there is **full invariance** otherwise we can still proceed for **PLS-MGA** with **partial invariance** in the data sets.

CHAPTER 5

DATA ANALYSIS AND INTERPRETATION

This chapter begins with the tabulation and summary of data collected from individual investors who invest in Indian financial markets. First, a detailed investigation of the respondents' socio-demographic profile was conducted using SPSS software to understand the differences in behavioral biases displayed by different categories of investors. Following that, the structural equation modelling technique was used with SmartPLS 4 version 4.0.8.5 of the software to analyse the impact of behavioral biases on various endogenous variables. Prior to using structural equation modelling, the multivariate analysis assumptions were checked to ensure that we understood the type of data we were dealing with. Subsequently, the data were analysed and interpreted using the appropriate statistical techniques and procedure for applying PLS-SEM as described in the previous chapter.

5.1 Assumptions of Multivariate Analysis and Data Cleaning

5.1.1 Missing values

The present study utilizes Google forms to collect data from the respondents, all the questions asked in the Google form survey were made mandatory in the process of data collection in order to avoid any missing values. This ensures only complete surveys are included during this process and any unfinished responses are automatically checked. So there was no missing data that can create problems in the analysis.

5.1.2 Invalid responses and outlier diagnostics

A total of 324 responses were received for data analysis; however, 17 of them were invalid and thus discarded because they had a standard deviation of zero or near zero for all answers combined, and 307 responses were used for further data analysis. Then, using the Boxplot function in SPSS, some insignificant outliers were found. However, because the data did not have any significant Skewness and Kurtosis issues, it was decided not to remove the outliers in order to maintain the actual reliability and validity of the data.

5.1.3 Normality Test

Although PLS-SEM does not require data to be normal, it is still important to know the type of data we have in hand because all the analysis would be meaningless if the data is inappropriate. Normality influences the ability of the model to make valid inferences from the data (Streukens & Leroi-Werelds, 2016). Extremely non-normal data can create a problem in the assessment of parameters' significance it can also inflate standard errors and decrease the probability of some relations being assessed as significant.

To test the normality of the distributions in this data set, we calculated two distribution measures: Skewness and Kurtosis. Skewness is a measure of how symmetrical a variable's distribution is around the mean. If the distribution looks the same to the left and right of the center point, it is symmetric. A normal distribution has no skewness. Similarly, kurtosis is a measure of the distribution's peakedness or flatness. A pointy distribution is indicated by a high kurtosis value, whereas a flat distribution is indicated by a low kurtosis value. A normal distribution's kurtosis is also zero.

A general guideline to test the normality of the distribution is that the values of both skewness and kurtosis should be between +1 and -1. Distribution exceeding these limits would be considered non-normal. (Hair et al., 2014)

Measures of skewness and kurtosis obtained from IBM SPSS Statistics software have been summarized in table 5.1 which shows that skewness and kurtosis values of all the indicators of latent variables in the research model are within the acceptable range of -1 and +1.

Table 5.1 Assessment of Normality

Variables	Min	Max	Skew	Kurtosis
Overconfidence				
OC_BTA1	1	7	-.680	-.002
OC_BTA2	1	7	-.164	-.460
OC_SA1	1	7	-.887	.448
OC_SA2	1	7	-.940	.304
OC_PF1	1	7	-.261	-.490
OC_PF2	1	7	-.623	-.207

OC_UO1	1	7	-.746	.075
OC_UO2	1	7	-.885	.893
Representativeness				
RP_BRN	1	7	-.588	.279
RP_SSN1	1	7	-.839	.947
RP_SSN2	1	7	-.391	-.010
Availability				
AVL_R1	1	7	-.073	-.950
AVL_R2	1	7	-.180	-.931
AVL_R3	1	7	-.264	-.804
AVL_ER	1	7	-.905	-.456
Mental Accounting				
MA_C1	1	7	-.668	-.441
MA_C2	1	7	-.638	-.682
MA_B1	1	7	-.974	.443
MA_B2	1	7	-.744	-.290
Regret				
R_AR1	1	7	-.654	.343
R_AR2	1	7	-.571	-.345
R_ER	1	7	-.394	-.483
R_SB	1	7	-.860	.380
R_RC	1	7	.236	-.901
Loss Aversion				
LA1	1	7	-.627	-.410
LA2	1	7	-.946	.473
LA3	1	7	-.875	.692
LA4	1	7	-.662	.296
LA5	1	7	-.625	-.199
Anchoring				
ANC1	1	7	-.675	.559
ANC2	1	7	-.561	.209
ANC3	1	7	-.620	.075

ANC_RC	1	7	.513	-.504
Perceived Investment Performance				
PIP1	1	7	-.360	-.194
PIP2	1	7	-.300	-.235
PIP3	1	7	-.405	-.500
Investment Satisfaction				
IS1	1	7	-.507	-.299
Financial Satisfaction				
FS1	1	7	-.604	.248
FS2	1	7	-.694	.107
FS3	1	7	-.417	-.549
FS4	1	7	-.664	.461
FS5	1	7	-.553	.121
FS6	1	7	-.956	.906
FS7	1	7	-.397	-.401

5.2 Demographic Profile of the Respondents

Understanding the demographic and socio-economic profile of the respondents provides a glimpse of the heterogeneity present in the target population. This heterogeneity is also known as observed heterogeneity present in the sample characteristics. Prior research studies in the domain of behavioral finance have shown that various demographic factors have an influence on the levels of behavioral biases, investment performance, and financial satisfaction of retail investors participating in the Indian stock market. Every individual is different from others on the basis of factors such as gender, age, education, marital status, occupation, and income. Therefore it is important to study the variations in behavioral biases due to these demographic and socio-economic characteristics. Table 5.2 summarizes the demographic profile of 307 individual investors residing in the National Capital Region (NCR) of India.

The sample consists of 220 (76.6%) males and 87 (28.37%) females. It shows that the majority of the investors participating in financial markets are males. However, the situation is changing rapidly with the growing financial independence of women in

India. In terms of age, 43% of respondents come from the age group of 18-30 years, evidencing the fact that youngsters are increasingly investing in direct equities more than ever, 38.4 % of the respondents come from the age group of 31-40 years, these two groups jointly account for the largest portion of the sample and the remaining 18.56% investors are above 40 years of age. Education levels of the respondents reveal that the majority of the respondents i.e. 56.35% are highly educated and hold a postgraduate degree to their credit. The number of participants who could not even complete their graduation degree is quite low in the sample i.e. only 5.86%. This shows that education is playing a major role in the participation of investors in the Indian financial markets. Regarding the marital status of the respondents, 56.68 % of them are married and the remaining are unmarried. With respect to occupation, respondents are divided into four categories, young investors who are investing in the financial market while pursuing their higher education side by side are classified into the students/scholars group, this group comprised 17.92 % of the total respondents. The next category of investors is those who are employed in government or semi-government organizations, they account for 22.15% of total investors while the majority of the respondents in the sample are coming from the private sector i.e. 43.97% and investors who are engaged in professional practice or running their own business are categorized into the self-employed group, they account for only 15.96% of total respondents. On the basis of annual income, respondents are classified into a total of five categories. 12.38% of the respondents belong to the lower income group they are earning less than 2.5 lakh per annum. The majority of the respondent i.e. 27.69% are earning between 2.5 to 5 lakh per annum and 20.52% of respondents belong to the higher income group as they are earning more than ten lakh per annum.

Table 5.2 Demographic profile of the respondents

	Frequency	%	Cumulative percent
<i>Gender</i>			
Male	220	71.66	71.66
Female	87	28.34	100.00
Total	307	100	
<i>Age</i>			
18-30	132	43.00	43
31-40	118	38.44	81.44
41-50	46	14.98	96.42
Above50	11	3.58	100.00
Total	307		
<i>Education</i>			
Undergraduate	18	5.86	5.86
Graduate	116	37.79	43.65
Postgraduate	173	56.35	100.00
Total	307	100	
<i>Marital status</i>			
Single	133	43.32	43.32
Married	174	56.68	100.00
Total	307	100.00	
<i>Occupation</i>			
Students/Scholars	55	17.92	17.92
Govt/Semi-govt	68	22.15	40.07
Private service	135	43.97	84.04
Self-Employed	49	15.96	100.00
Total	307	100.00	
<i>Income</i>			
Less than 2.5 lakhs	38	12.38	12.38
2.5-5 lakhs	85	27.69	40.07
5-7.5 lakhs	67	21.82	61.89
7.5-10 lakhs	54	17.59	79.48
More than 10 lakhs	63	20.52	100.00
Total	307	100.00	

Source – Author's Calculations

5.3 Portfolio Details and Sophistication measures

Individual investor sophistication is generally defined as investors' ability to avoid making investment mistakes (Stalnacke, 2018). Investor sophistication is an important determinant of an individual's financial decisions. Sophistication measures together play a significant role in mitigating the behavioral biases of individual investors (Prosad et al., 2014) and they are found to be positively related to individual investors' portfolio performance (Grinblatt et al., 2012). Five investment-related measures such as the number of stocks owned, investment amount, investment experience, investment frequency, and type of investments have been asked as sophistication proxies in the present study. Table 5.3 summarizes details about investors' portfolio and their sophistication measures.

With respect to the number of stocks, the respondents in the sample are categorized into five groups. 8.47 % of the respondents are beginners and hold shares in only one company. Around 31% of respondents have made their investment in 2 to 5 companies and only 15.31% of respondents hold well-diversified stock portfolios and have more than 20 stocks in their stock portfolio. Regarding investment amount, 17.59% of investors are very small investors as they have invested less than 10000 rupees in the stock market. 26.06% of investors have invested 10,000 to 50,000 rupees in their stock portfolio. The majority of the investors have invested between 1 lakh to 5 lakh rupees in their stock portfolios and only 11.07% of investors have investments exceeding 5 lakh rupees. As per the investment experience of respondents, 28.34% of investors have experience of fewer than two years and they may be considered beginners in the financial markets. The majority of the investors have investment experience of two to five years. 24.43% of investors have investment experience between five to ten years and only 12.38% of respondents have investment experience of more than 10 years. The trading frequency of respondents determines how actively or passively they are investing funds in the capital market. Out of a total of 307 respondents, 60 (19.54%) respondents are intraday traders. The majority of the respondents i.e. 64.17%, trade at least once in 0 to 3 months and 3 to 12 months, they can be considered active investors as their investment horizon is less than one year. 16.14% of investors are investing passively as their trading frequency is more than a year. With respect to the type of investment options, the majority of the investors i.e. 79.16%, are comfortable investing in only stocks and mutual funds, 5.54 % of investors are investing in derivatives and

commodities and only 2.61% of investors are comfortable investing in high-grade corporate bonds.

Table 5.3 Investor sophistication measures

	Frequency	%	Cumulative percent
<i>Number of stocks in portfolio</i>			
One	26	8.47	8.47
2 to 5	96	31.27	39.74
5 to 10	82	26.71	66.45
10 to 20	56	18.24	84.69
More than 20	47	15.31	100.00
Total	307	100.00	
<i>Investment amount</i>			
Less than 10 thousand	54	17.59	17.59
10- 50 thousand	80	26.06	43.65
50 thousand - 1 lakh	52	16.94	60.59
1 lakh - 5 lakh	87	28.34	88.93
More than 5 lakh	34	11.07	100.00
Total	307	100.00	
<i>Investment Experience</i>			
since last two years	87	28.34	28.34
Two to Five years	107	34.85	63.19
Five to ten years	75	24.43	87.62
more than ten years	38	12.38	100.00
Total	307	100.00	
<i>Investment Frequency</i>			
Intraday	60	19.54	19.54
0-3 months	119	38.76	58.30
3-12 months	78	25.41	83.71
12-36 months	21	6.84	90.55
more than 36 months	29	9.45	100.00
Total	307	100.00	
<i>Investment Type</i>			
Only stocks	99	32.25	32.25
Stocks and Mutual Funds	144	46.91	79.16
Derivatives and Commodities market	39	12.70	91.86
High-grade corporate bonds	17	5.54	97.40
Others	8	2.61	100.00
Total	307	100.00	

5.4 Descriptive Analysis of Behavioral Biases and other Key Variables

To analyse the impact levels of behavioral biases, perceived investment performance, investment satisfaction, and financial satisfaction among individual investors, summated mean scores and standard deviation of each variable have been calculated and then they are ranked in order of their prominence. Table 5.4 summarises the descriptive statistics for each variable. Impact levels are classified into three groups. Because all variables were assessed using a seven-item Likert scale. A mean score of 4 indicates a neutral impact, mean values greater than 4 indicate that individual investors have behavioral biases in their investment decisions, and a mean score less than 4 indicates that behavioral biases have less of an impact on individual investors' investment decisions.

Table 5.4 Descriptive statistics of behavioral biases and other key variables

Variables	Mean	St.dev	Rank
Overconfidence	5.3	0.789	II
Representativeness	5.38	0.923	I
Availability	4.39	1.250	VII
Anchoring	4.86	0.926	IV
Mental Accounting	4.82	1.293	V
Loss aversion	5.17	1.063	III
Regret	4.66	0.931	VI
Perceived investment performance	5.28	5.288	
Investment satisfaction	5.02	1.443	
Financial satisfaction	4.9	1.058	

Results from table 5.4 suggest that the mean values of all the biases are greater than four which indicates that these behavioral biases influence the investment behavior of individual investors of Delhi NCR. Representativeness, Overconfidence, and Loss aversion have come out to be the most prominent behavioral biases with mean scores of 5.35, 5.3, and 5.28 respectively followed by Anchoring, Mental accounting, and regret with mean values of 4.86, 4.82, and 4.66 respectively and finally, the availability bias has the least impact on individual investors of Delhi NCR. Measures of investment

and financial satisfaction reveal that generally individual investors are satisfied with their investment performance and financial situation.

5.5 Demographic Variables and Behavioral Biases.

To analyse the difference in the means of behavioral biases across several demographic variables descriptive statistics, independent samples t-test, and one-way analysis of variance (ANOVA) have been used. Levene's test of homogeneity of variance is also conducted to check whether different investor groups created on the basis of demographics are homogenous or not, if the assumption of homogeneity of variance is broken in any case then Welch's F was utilized as an alternate measure to ANOVA. Further, to analyse which groups have significant mean differences, post-hoc multiple comparisons using Tukey also known as Tukey's HSD and Tamhane's T2 were conducted and reported separately in the appendix.

5.5.1 Gender and Behavioral Biases

To determine the variation among behavioral biases across gender descriptive statistics and independent samples t-tests have been used. The following hypotheses are tested in this connection:

H.1.1 There is an association between gender and behavioral biases of investors

This hypothesis can be divided into seven sub-hypotheses.

H1.1a: There is an association between gender and overconfidence

H1.1b: There is an association between gender and representativeness

H1.1c: There is an association between gender and availability

H1.1d: There is an association between gender and anchoring

H1.1e: There is an association between gender and mental accounting

H1.1f: There is an association between gender and loss aversion

H1.1g: There is an association between gender and regret

Table 5.5.1 represents the final results of the association between the selected variables.

Results of the descriptive statistics and independent samples t-test

Mean values from table 5.5.1 suggest that overconfidence in male investors (mean = 5.40) is significantly higher than the overconfidence levels in female investors (mean = 5.07), $t(305) = 3.35$, $P < 0.05$. This means that male investors are more overconfident than female investors, hence, H1.1a is supported. Mean values of representativeness, availability and anchoring bias are slightly higher in males as compared to female investors but this difference is not significant as p-values are greater than 0.05. Therefore, H1.1b, H1.1c, and H1.1d are not supported by the results obtained through data analysis. Mental accounting bias in female investors (mean = 5.03) is significantly higher than mental accounting in male investors (mean = 4.74), $t(305) = -1.775$, $p < 0.05$. This suggests that females allocate their money to different mental accounts more often than male investors. Hence, H1.1e is also supported. Also, the loss aversion levels in males (mean = 5.07) are significantly less than the loss aversion levels in females (mean = 5.43), $t(305) = -2.747$, $p < 0.05$. This means that female investors are more loss averse as compared to male investors, supporting H1.1f. As far as regret in males and females is concerned female investors (mean = 4.77) tend to suffer more from regret than male investors (mean = 4.63), but this difference is not significant ($p > 0.05$) hence, H1.1g is not supported.

Table 5.5.1: Gender and Behavioral Biases of respondents

	Group statistics			Levene's test		t-test	
	Gender	Mean	stdev	F	Sig.	t	Sig.
<i>Overconfidence</i>	Male	5.40	0.777	0.21	0.647	3.35	0.001**
	Female	5.07	0.775				
<i>Representativeness</i>	Male	5.43	0.959	0.605	0.437	1.26	0.24
	Female	5.29	0.821				
<i>Availability</i>	Male	4.41	1.302	5.787	0.017**	0.423	0.672
	Female	4.35	1.113				
<i>Anchoring</i>	Male	4.87	0.933	0.031	0.86	0.22	0.827
	Female	4.84	0.913				
<i>Mental accounting</i>	Male	4.74	1.383	8.128	0.005**	-1.775	0.043**
	Female	5.03	1.006				

<i>Loss aversion</i>	Male	5.07	1.118				
	Female	5.43	0.857	5.417	0.021**	-2.747	0.006**
<i>Regret</i>	Male	4.63	0.986				
	Female	4.77	0.768	7.924	0.005**	-1.159	0.198

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.5.2 Age and Behavioral Biases

One-way analysis of variance (ANOVA) and Welch's F test has been used to analyse the variation in behavioral biases with respect to age. In this connection, the following hypotheses were formulated and tested:

H1.2 There is an association between age and behavioral biases of investors.

This hypothesis can be divided into seven sub hypotheses

H1.2a: There is an association between age and overconfidence

H1.2b: There is an association between age and representativeness

H1.2c: There is an association between age and availability

H1.2d: There is an association between age and anchoring

H1.2e: There is an association between age and mental accounting

H1.2f: There is an association between age and loss aversion

H1.2g: There is an association between age and regret

Table 5.5.2 represents the final results of the association between the selected variables.

Results of descriptive statistics, ANOVA, and Welch's F

Table 5.5.2 shows that the mean of overconfidence is lowest in the 18-30 year age group, moderate in the 31-40 year age group, and highest in investors who are above 40 years of age. Overconfidence bias is significantly and positively related to the age of investors ($F(2,304) = 3.181, P < 0.05$) thus, H1.2a is supported. This means that as the age of the investors is increasing their overconfidence levels are also increasing. On conducting Tamhane's T2 post hoc analysis it was found that investors in the age group of 18-30 years have significantly lower levels of overconfidence (mean = 5.22) as

compared to investors in the above 40 age group (mean = 5.51) (Mean difference = -0.28907, $p < 0.05$). (Appendix 1.1). The mean value of representativeness bias is lowest in the 31-40 year age group (mean = 5.25), moderate in 18-30 years of age (mean = 5.45), and highest in investors who are above 40 years of age (mean = 5.55). The age of the investors has a significant impact on the representativeness bias exhibited by individual investors ($F(2,304) = 3.073$, $P < 0.05$) hence, H1.2a was supported. However, the results of Tamhane's post hoc comparisons revealed that these differences between the age groups are not significant (Appendix 1.1). The mean values of mental accounting bias are almost similar in the age groups of 18-30 years and 31-40 years, but it is significantly higher for investors in the above 40 age group ($F(2, 304) = 3.793$, $P < 0.05$). Results of the Tukey HSD post hoc comparisons revealed that levels of mental accounting in the 18-30 years age group (mean = 4.73) are significantly lower than investors who are above 40 years of age (mean = 5.25), (mean difference = -0.51077, $P < 0.05$). Similarly, the mean of MA in 31-40 years (mean = 4.72) is significantly lower than the mean of mental accounting in the above 40 age group (mean = 5.25), (mean difference = -0.52528, $P < 0.05$). Thus, H1.2e is also supported. However, the p-values of H1.2c, H1.2d, H1.2f, and H1.2g are greater than 0.05, therefore, these hypotheses are not supported by the results obtained through data analysis.

Table 5.5.2: Age and Behavioral Biases or respondents

Group statistics				Levene's test		ANOVA	
		Mean	Std. Dev	F	sig.	F/Welch	sig
Overconfidence	18-30	5.22	0.85	3.181	0.043**	3.999	0.02**
	31-40	5.31	0.81				
	Above 40	5.51	0.56				
Representativeness	18-30	5.45	1.00	3.158	0.044**	3.073	0.049**
	31-40	5.25	0.91				
	Above 40	5.55	0.73				
Availability	18-30	4.36	1.39	3.194	0.042**	0.095	0.909
	31-40	4.42	1.16				
	Above 40	4.43	1.10				
Anchoring	18-30	4.85	0.98	0.526	0.592	0.056	0.946
	31-40	4.89	0.89				
	Above 40	4.85	0.88				
Mental accounting	18-30	4.73	1.35	1.407	0.246	3.793	0.024**
	31-40	4.72	1.28				
	Above 40	5.25	1.10				
Loss aversion	18-30	5.20	1.14	1.717	0.181	0.177	0.838
	31-40	5.17	1.04				
	Above 40	5.10	0.93				
Regret	18-30	4.65	1.02	2.044	0.131	0.111	0.895
	31-40	4.67	0.89				
	Above 40	4.72	0.81				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.5.3 Education and Behavioral Biases

The following hypotheses are tested through one-way analysis of variance (ANOVA) and Welch's F to determine the association between education and behavioral biases of investors.

H1.3 There is an association between education and behavioral biases

This hypothesis is divided into seven sub hypotheses

H1.3a There is an association between education and overconfidence

H1.3b There is an association between education and representativeness

H1.3c There is an association between education and availability

H1.3d There is an association between education and anchoring

H1.3e There is an association between education and mental accounting

H1.3f There is an association between education and loss aversion

H1.3g There is an association between education and regret

Table 5.5.3 summarises the final results of the association between the selected variables.

Results of Descriptive analysis, ANOVA, and Welch's F

Results from table 5.5.3 shows that education has a significant impact on the overconfidence levels of individual investors ($F(2,304) = 7.004$, $P < 0.01$). Hence, H1.3a is supported. Further, the results of Tukey post hoc multiple comparisons (Appendix 1.2) revealed that the overconfidence level in undergraduate investors (mean = 4.92) is significantly lower than the overconfidence level in graduate investors (mean = 5.50), (mean difference = -0.58226, $p < 0.01$). Similarly, the mean of undergraduate investors (mean = 4.92) is significantly lower than the mean of postgraduate investors (mean = 5.22), (mean difference = -0.30082, $p < 0.01$). Also, the overconfidence levels of postgraduate investors (mean = 5.22) are significantly lower than the overconfidence levels of graduate investors (mean = 5.50), (mean difference = 0.28144, $p < 0.01$). Regarding anchoring graduate investors are more susceptible to anchoring bias as compared to undergraduate and postgraduate investors ($F(2,304) = 4.487$, $p < 0.05$). Tukey post hoc results show that anchoring bias in undergraduate investors (mean = 4.38) is significantly lower in comparison to graduate investors (mean = 5.02), (mean

difference = -0.64224, $P < 0.05$), similarly anchoring bias in postgraduate investors (mean = 4.81) is also lower than anchoring bias in graduate investors (mean = 5.02), (mean difference = 0.20655, $p < 0.05$). Thus, H1.3d is supported. Levels of representativeness, availability, and mental accounting are also higher in graduate investors as compared to undergraduate and postgraduate investors, however, these differences are not significant hence, and H1.3b, H1.3c, and H1.3e are not supported. Levels of loss aversion and regret are higher in undergraduate investors as compared to postgraduate investors, this may be because most undergraduate investors are young and their loss-bearing capacity is less than the aged investors and they regret more for their losses as compared to other categories, however, these differences are not significant hence, H1.3f and H1.3g are also not supported.

Table 5.5.3: Education and Behavioral Biases of Investors

Group Statistics				Levene's test		ANOVA	
		Mean	Std. Dev	F	Sig.	F	sig.
Overconfidence	Undergraduate	4.92	1.02				
	Graduate	5.50	0.70	2.701	0.069	7.004	0.001*
	Postgraduate	5.22	0.79				
Representativeness	Undergraduate	5.15	1.01				
	Graduate	5.48	0.90	0.975	0.378	1.299	0.274
	Postgraduate	5.35	0.92				
Availability	Undergraduate	4.40	1.52				
	Graduate	4.45	1.34	2.869	0.058	0.203	0.817
	Postgraduate	4.36	1.16				
Anchoring	Undergraduate	4.38	1.36				
	Graduate	5.02	0.90	1.953	0.144	4.487	0.012**
	Postgraduate	4.81	0.87				
Mental accounting	Undergraduate	4.40	1.22				
	Graduate	4.89	1.29	0.349	0.706	1.098	0.335
	Postgraduate	4.83	1.30				

<i>Loss aversion</i>	Undergraduate	5.29	0.92				
	Graduate	5.26	1.15	0.916	0.401	0.968	0.381
	Postgraduate	5.10	1.02				
<i>Regret</i>	Undergraduate	4.64	0.92				
	Graduate	4.75	1.00	0.77	0.464	0.741	0.478
	Postgraduate	4.62	0.88				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.5.4 Marital status and Behavioral Biases

To determine the variation among behavioral biases across the marital status of respondents descriptive statistics and independent samples t-tests have been used. The following hypotheses are tested in this connection:

H1.4 There is an association between marital status or respondents and behavioral biases

This hypothesis is divided into seven sub hypotheses

H1.4a There is an association between marital status and overconfidence

H1.4b There is an association between marital status and representativeness

H1.4c There is an association between marital status and availability

H1.4d There is an association between marital status and anchoring

H1.4e There is an association between marital status and mental accounting

H1.4f There is an association between marital status and loss aversion

H1.4g There is an association between marital status and regret

Table 5.5.4 summarises the final results of the association between the selected variables

Results of the descriptive statistics and independent samples t-test

Table 5.5.4 suggest that marital status is not related to any of the behavioral biases of investors therefore, none of the above hypotheses are supported by the results obtained through data analysis. However, some inferences can still be drawn based on the mean values reported in table 5.5.4. Mean values of overconfidence, availability, anchoring,

mental accounting, and regret are higher for married investors as compared to unmarried investors but these differences are not significant as p-values for all the variables are greater than 0.05. In addition, contrary to the aforementioned findings, unmarried investors' mean values of representativeness and loss aversion are higher than those of married investors, but these differences likewise are not statistically significant because their p-values are larger than 0.05.

Table 5.5.4: Marital status and Behavioral Biases or Respondents

	Group Statistics			Levene's test		t-test	
	Marital status	Mean	Std. Dev	F	Sig.	t	Sig.
<i>Overconfidence</i>	single	5.27	0.83	0.858	0.355	-0.615	0.539
	Married	5.33	0.76				
<i>Representativeness</i>	single	5.43	1.07	8.838	0.003**	0.658	0.511
	Married	5.36	0.79				
<i>Availability</i>	single	4.33	1.33	1.745	0.188	-0.842	0.401
	Married	4.45	1.18				
<i>Anchoring</i>	single	4.86	0.99	1.465	0.227	-0.131	0.896
	Married	4.87	0.87				
<i>Mental accounting</i>	single	4.74	1.38	1.159	0.283	-1.034	0.302
	Married	4.89	1.22				
<i>Loss aversion</i>	single	5.20	1.16	2.447	0.119	0.366	0.714
	Married	5.15	0.99				
<i>Regret</i>	single	4.65	1.02	3.616	0.058	-0.282	0.779
	Married	4.68	0.86				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.5.5 Occupation and Behavioral Biases

One-way analysis of variance (ANOVA) and Welch's F test have been used to analyse the variation in behavioral biases with respect to the occupation of investors. In this connection, the following hypotheses were formulated and tested:

H1.5 There is an association between the occupation of respondents and behavioral biases

This hypothesis is divided into seven sub hypotheses

H1.5a There is an association between occupation and overconfidence

H1.5b There is an association between occupation and representativeness

H1.5c There is an association between occupation and availability

H1.5d There is an association between occupation and anchoring

H1.5e There is an association between occupation and mental accounting

H1.5f There is an association between occupation and loss aversion

H1.5g There is an association between occupation and regret

Table 5.5.5 summarises the final results of the association between the selected variables

Results of Descriptive analysis, ANOVA, and Welch's F

The results from table 5.5.5 show that occupation has a significant impact on the overconfidence levels of individual investors ($F(2,304) = 3.794, p < 0.05$), hence, H1.5a is supported. Further, the results from Tamhane's T2 post hoc analysis (Appendix 1.3) revealed that the overconfidence levels in student investors (mean = 5.05) are significantly lower than the overconfidence levels of investors who are employed in the private sector (mean = 5.39), (mean difference = -0.34333, $p < 0.05$). Similarly, overconfidence levels in student investors (mean = 5.05) are also significantly lower than the overconfidence levels in self-employed investors (mean = 5.49), (mean difference = -0.44689, $p < 0.05$) (Appendix 1.3). Additionally, the overconfidence levels in self-employed investors and those employed in the private sector are also higher than the overconfidence levels in investors employed in the government sector. The levels of representativeness, availability, anchoring, and regret are highest in investors employed in the private sector in comparison to investors employed in other occupations but these differences are not significant hence H1.5b, H1.5c, H1.5d, and H1.5g are not supported. Mental accounting and Loss aversion are also lowest in self-employed investors in comparison to other investors but again these differences are not significant leading to the rejection of H1.5e and H1.5f.

Table 5.5.5 Occupation and Behavioral Biases of respondents

Group Statistics		Levene's test		ANOVA			
		Mean	Std. Dev	F	Sig.	F/We lch	Sig.
Overconfidence	Student	5.05	0.81	0.468	0.705	3.794	0.011**
	Govt/Semi-govt	5.22	0.80				
	Private Service	5.39	0.72				
	Self-employed	5.49	0.87				
Representativeness	Student	5.30	1.04	2.07	0.104	0.364	0.779
	Govt/Semi-govt	5.43	0.93				
	Private Service	5.43	0.81				
	Self-employed	5.33	1.07				
Availability	Student	4.25	1.14	2.275	0.08	0.612	0.608
	Govt/Semi-govt	4.44	1.19				
	Private Service	4.48	1.23				
	Self-employed	4.27	1.48				
Anchoring	Student	4.95	1.01	1.269	0.285	0.265	0.851
	Govt/Semi-govt	4.81	0.97				
	Private Service	4.87	0.81				
	Self-employed	4.83	1.08				
Mental accounting	Students	4.67	1.30	2.945	0.033**	0.773	0.511
	Govt/Semi-govt	4.92	1.24				
	Private Service	4.91	1.17				
	Self-employed	4.64	1.65				
Loss aversion	Student	5.34	0.89	1.338	0.262	0.709	0.547
	Govt/Semi-govt	5.09	1.01				
	Private Service	5.17	1.10				
	Self-employed	5.08	1.19				
Regret	Student	4.56	0.94	0.716	0.543	0.589	0.623
	Govt/Semi-govt	4.68	0.85				
	Private Service	4.74	0.94				
	Self-employed	4.59	1.00				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.5.6 Income and Behavioral Biases

The ANOVA was conducted for each bias to test the following hypotheses:

H1.6 There is an association between the income and behavioral biases of respondents

This hypothesis is divided into seven sub hypotheses

H1.6a There is an association between income and overconfidence

H1.6b There is an association between income and representativeness

H1.6c There is an association between income and availability

H1.6d There is an association between income and anchoring

H1.6e There is an association between income and mental accounting

H1.6f There is an association between income and loss aversion

H1.6g There is an association between income and regret

Table 5.5.6 summarises the final results of the association between the selected variables

Results of Descriptive analysis, ANOVA, and Welch's F

The results presented in Table 5.5.6 we can infer that respondents belonging to various income categories differed in terms of overconfidence, mental accounting, and loss aversion. Income has a significant impact on the overconfidence levels of individuals ($(F(2,304) = 2.429, p < 0.05)$), hence, H1.6a is supported. The respondents in the annual income category of above 10 lakhs have the highest mean of 5.32, and the respondents in the annual income category of Rs 2.5 to 5 lakhs have the lowest mean of 4.93. With respect to mental accounting, respondents in the annual income category of Rs 0 to 2.5 lakh have the lowest mean, and respondents in the annual income category of Rs 7.5 to 10 lakhs have the highest mean ($(F(2,304) = 2.806, p < 0.05)$), hence, H1.6e is also supported. Further, based on the Tukey post hoc test (Appendix 1.4), the mean of the mental accounting bias in the annual income category of Rs 0 to 2.5 lakhs is significantly lower than the mean of mental accounting in the annual income category of Rs 7.5 to 10 lakhs (mean difference = -0.68500, $p < 0.05$). As far as the loss aversion bias of investors is concerned, it has the highest mean of 5.54 in the annual income category of Rs 0 to 2.5 lakhs, and the lowest mean of 4.89 in the annual income category

of Rs 2.5 to 5 lakhs. Tukey post hoc test further reveals that the mean of loss aversion bias in the annual income category of Rs 0 to 2.5 lakhs is significantly lower than the mean of loss aversion in the annual income category of Rs 2.5 to 5 lakh (mean difference = 0.64703, $p < 0.05$). Additionally, it also revealed that the mean of loss aversion in the annual income category of Rs 0 to 2.5 lakhs is significantly lower than the mean of loss aversion in the annual income category of Rs 7.5 to 10 lakhs (mean difference = 0.61200, $p < 0.05$), supporting H1.6f. Other biases such as representativeness, availability, anchoring, and regret also vary with the annual income of the respondents but the differences are not significant to support H1.6b, H1.6c, H1.6d, and H1.6g.

5.5.6 Income and Behavioral Biases of Individual Investors

		Group statistics		Levene's test		ANOVA	
		Mean	Std. Dev	F	sig.	F/Welch	sig.
<i>Overconfidence</i>	0 - 2.5 Lakhs	5.14	0.934	1.215	0.304	2.429	0.048**
	2.5 - 5 lakhs	4.93	0.842				
	5 - 7.5 lakhs	5.05	0.762				
	7.5- 10 lakhs	5.30	0.680				
	> 10 lakhs	5.32	0.794				
<i>Representativeness</i>	0 - 2.5 Lakhs	5.28	0.923	0.434	0.784	0.354	0.841
	2.5 - 5 lakhs	5.26	0.866				
	5 - 7.5 lakhs	5.12	0.833				
	7.5- 10 lakhs	5.17	0.731				
	> 10 lakhs	5.24	0.856				
<i>Availability</i>	0 - 2.5 Lakhs	4.55	1.41	1.021	0.396	0.657	0.622
	2.5 - 5 lakhs	4.23	1.20				
	5 - 7.5 lakhs	4.32	1.26				
	7.5- 10 lakhs	4.44	1.30				
	> 10 lakhs	4.43	1.19				
<i>Anchoring</i>	0 - 2.5 Lakhs	4.95	1.03	1.752	0.139	0.868	0.483
	2.5 - 5 lakhs	4.79	0.94				
	5 - 7.5 lakhs	4.98	0.90				
	7.5- 10 lakhs	4.72	1.07				
	> 10 lakhs	4.91	0.71				

<i>Mental accounting</i>	0 - 2.5 Lakhs	4.74	1.38	1.193	0.314	2.806	0.026**
	2.5 - 5 lakhs	4.77	1.25				
	5 - 7.5 lakhs	4.76	1.42				
	7.5- 10 lakhs	5.40	1.05				
	> 10 lakhs	4.80	1.32				
<i>Loss aversion</i>	0 - 2.5 Lakhs	5.54	0.94	2.162	0.083	4.375	0.002**
	2.5 - 5 lakhs	4.89	1.20				
	5 - 7.5 lakhs	5.27	1.00				
	7.5- 10 lakhs	4.93	1.12				
	> 10 lakhs	5.11	0.87				
<i>Regret</i>	0 - 2.5 Lakhs	4.63	0.97	1.019	0.398	0.883	0.474
	2.5 - 5 lakhs	4.58	0.96				
	5 - 7.5 lakhs	4.60	1.02				
	7.5- 10 lakhs	4.73	0.76				
	> 10 lakhs	4.84	0.90				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.6 Investor Sophistication and Behavioral Biases

5.6.1 Investment Experience and Behavioral Biases

To analyse the impact of investment experience on the behavioral biases of individual investors ANOVA and Welch's F test were performed the and following hypotheses were formulated and tested in this connection:

H2.1 There is an association between investment experience and behavioral biases of investors

This hypothesis can be divided into seven sub hypotheses

H2.1a: There is an association between investment experience and overconfidence

H2.1b: There is an association between investment experience and representativeness

H2.1c: There is an association between investment experience and availability

H2.1d: There is an association between investment experience and anchoring

H2.1e: There is an association between investment experience and mental accounting

H2.1f: There is an association between investment experience and loss aversion

H2.1g: There is an association between investment experience and regret

Table 5.6.1 represents the final results of the association between the selected variables.

The results from table 5.6.1 suggest that the investment experience of investors is significantly and positively associated with the overconfidence levels of investors ((F (2,304) = 2.668, P < 0.05), Hence, H2.1a is supported. Further, the results from Tamhane's post hoc analysis (Appendix 1.5) revealed that the overconfidence of investors with less than 2 years of experience (mean = 5.047) is significantly lower than the overconfidence of investors having more than 10 years of experience (mean = 5.487), (mean difference = -.43943, P < 0.05) (Appendix 1.5). However, investment experience is not found to be related to representativeness, availability, anchoring, mental accounting, loss aversion, and regret, therefore, hypotheses H2.1b, H2.1c, H2.1d, H2.1e, H2.1f, H2.1g are not supported from the data results.

Table 5.6.1 Investment Experience and Behavioral Biases

		Levene's test			ANOVA		
	Invest. exp	Mean	Stdev	F	Sig.	F/welch	Sig.
<i>Overcon fidence</i>	up to 2 years	5.047	0.930				
	2-5 years	5.125	0.800	3.557	0.015	2.668	0.048**
	5-10 years	5.123	0.798				
	>10 years	5.487	0.591				
	Total	5.147	0.824				
<i>Represn tativenes</i>	up to 2 years	5.221	0.831				
	2-5 years	5.241	0.847	0.678	0.566	0.127	0.944
	5-10 years	5.177	0.931				
	>10 years	5.270	0.745				
	Total	5.223	0.849				
<i>Availabi lity</i>	up to 2 years	4.569	1.190				
	2-5 years	4.320	1.221	0.441	0.724	1.018	0.385
	5-10 years	4.263	1.316				
	>10 years	4.474	1.326				
	Total	4.396	1.250				
<i>Anchori ng</i>	up to 2 years	4.868	1.126				
	2-5 years	5.115	0.962	1.932	0.124	1.304	0.273
	5-10 years	5.080	0.930				
	>10 years	5.184	1.096				
	Total	5.045	1.022				

<i>Mental account</i>	up to 2 years	4.968	1.222				
	2-5 years	4.752	1.261	0.438	0.726	0.622	0.601
	5-10 years	4.877	1.373				
	>10 years	5.013	1.338				
	Total	4.876	1.286				
<i>Loss aversion</i>	up to 2 years	5.384	0.957				
	2-5 years	5.021	1.216	2.666	0.048	2.478	0.061
	5-10 years	5.056	0.959				
	>10 years	5.326	0.953				
	Total	5.170	1.063				
<i>Regret</i>	up to 2 years	4.956	0.873				
	2-5 years	4.783	0.995	0.249	0.862	1.009	0.389
	5-10 years	4.779	1.050				
	>10 years	5.016	0.957				
	Total	4.860	0.971				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.6.2 Trading Frequency and Behavioral Biases

To analyse the impact of trading frequency on the behavioral biases of individual investors ANOVA was performed the and following hypotheses were formulated and tested in this connection:

H2.1 There is an association between trading frequency and behavioral biases of investors

This hypothesis can be divided into seven sub hypotheses

H2.1a: There is an association between trading frequency and overconfidence

H2.1b: There is an association between trading frequency and representativeness

H2.1c: There is an association between trading frequency and availability

H2.1d: There is an association between trading frequency and anchoring

H2.1e: There is an association between trading frequency and mental accounting

H2.1f: There is an association between trading frequency and loss aversion

H2.1g: There is an association between trading frequency and regret

Table 5.6.2 represents the final results of the association between the selected variables.

Results of descriptive statistics, ANOVA, and Welch's F

Results from table 5.6.4 suggest that the trading frequency of investors is positively and significantly associated with the availability bias of investors ((F (2,304) = 5.015, P < 0.05), thus H2.1c is supported. As trading frequency decreases availability bias in investors decreases. On conducting Tukey post hoc analysis it was found that investors engaged in intraday trading have significantly higher levels of availability bias than the rest of the investor categories. Similarly, mental accounting bias is also found to be positively related to the trading frequency of investors. The mean of mental accounting in intraday traders (mean = 4.817) is significantly lower than the mean of mental accounting traders investing for 12-36 months (mean = 5.762), (mean difference = -.94524, p < 0.05) (Appendix 1.6). Hence, H2.1e is also supported. Levels of overconfidence, representativeness, loss aversion, and regret also vary to some extent with the trading frequency of investors, however, these differences are not significant, therefore, H2.1a, H2.1b, H2.1d, H2.1f, H2.1g are not supported.

Table 5.6.2 Trading Frequency and Behavioral Biases

	Trading freq.	Group stats.		Levene's test		ANOVA	
		mean	Stdev	F	Sig.	F/welch	Sig.
<i>Overconfidence</i>	Intraday	5.217	0.938				
	0 - 3 months	5.091	0.799				
	3 - 12 months	5.178	0.782	1.945	0.103	0.284	0.889
	12-36 months	5.185	0.654				
	>36 months	5.125	0.926				
	Total	5.147	0.824				
<i>Representativeness</i>	Intraday	5.371	0.863				
	0 - 3 months	5.147	0.859				
	3 - 12 months	5.164	0.885	1.387	0.238	1.263	0.285
	12-36 months	5.476	0.891				
	>36 months	5.207	0.587				
	Total	5.223	0.849				
<i>Availability</i>	Intraday	4.988	1.382				
	0 - 3 months	4.254	1.209				
	3 - 12 months	4.385	1.058	1.229	0.299	5.015	0.00**
	12-36 months	4.012	1.395				

	>36 months	4.060	1.162				
	Total	4.396	1.250				
<i>Anchoring</i>	Intraday	5.117	1.229				
	0 - 3 months	4.971	1.033				
	3 - 12 months	5.042	0.879	1.568	0.183	0.817	0.515
	12-36 months	4.905	1.005				
	>36 months	5.310	0.878				
	Total	5.045	1.022				
<i>Mental accounting</i>	Intraday	4.817	1.234				
	0 - 3 months	4.714	1.389				
	3 - 12 months	4.901	1.131	2.665	0.03*	3.116	0.01**
	12-36 months	5.762	0.812				
	>36 months	4.957	1.421				
	Total	4.876	1.286				
<i>Loss aversion</i>	Intraday	5.173	1.196				
	0 - 3 months	5.266	1.016				
	3 - 12 months	5.056	1.043	0.461	0.765	0.84	0.5
	12-36 months	5.324	1.009				
	>36 months	4.966	1.061				
	Total	5.170	1.063				
<i>Regret</i>	Intraday	4.943	1.077				
	0 - 3 months	4.849	0.996				
	3 - 12 months	4.703	0.843	1.141	0.337	1.16	0.329
	12-36 months	5.152	0.881				
	>36 months	4.945	1.010				
	Total	4.860	0.971				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.6.3 Investment Amount and Behavioral Biases

One-way analysis of variance (ANOVA) has been used to analyse the variation among the behavioral biases with respect to age and the following hypotheses are tested in this connection:

H2.3 There is an association between investment amount and behavioral biases of individual investors

This hypothesis can be divided into seven sub hypotheses

H2.3a: There is an association between investment amount and overconfidence

H2.3b: There is an association between investment amount and representativeness

H2.3c: There is an association between investment amount and availability

H2.3d: There is an association between investment amount and anchoring

H2.3e: There is an association between investment amount and mental accounting

H2.3f: There is an association between investment amount and loss aversion

H2.3g: There is an association between investment amount and regret

The final results of the association between the selected variables represented in table 5.6.3 suggest that investment amount is not related to any of the behavioral biases of investors therefore, none of the above hypotheses are supported by the results obtained through data analysis. However, some inferences can still be drawn based on the mean values reported in table 5.6.3. Mean values of overconfidence, representativeness, and anchoring are higher for individuals with high investment amounts in their portfolios as compared to investors with low investment amounts but these differences are not significant as p-values for all the variables are greater than 0.05, therefore H2.3a, H2.3b, and H2.3d are not supported. Additionally, mental accounting, loss aversion, and regret are more or less the same in all categories of investors irrespective of their investment amounts, therefore, H2.3c, H2.3e, H2.3f, and H2.3g are also not supported by the results obtained through empirical analysis.

Table 5.6.3 Investment Amount and Behavioral Biases

				Levene's test		ANOVA	
	Invest. amount	Mean	Stdev	F	Sig.	F/ welch	Sig.
Overconfid ence	Less than 10K	5.185	0.782				
	10K-50K	5.230	0.852				
	50K-1 lakh	5.438	0.709	0.877	0.478	1.975	0.098
	1 lakh- 5 lakh	5.466	0.717				
	More than 5 lakh	5.581	0.893				
	Total	5.306	0.789				
Representa tiveness	Less than 10K	5.093	1.077				
	10K-50K	5.458	0.937				
	50K-1 lakh	5.327	0.913	0.743	0.563	2.107	0.08
	1 lakh- 5 lakh	5.483	0.800				

	More than 5 lakh	5.559	0.871				
	Total	5.390	0.923				
<i>Availability</i>	Less than 10K	4.486	1.250				
	10K-50K	4.613	1.301				
	50K-1 lakh	4.361	1.109	0.77	0.545	1.317	0.263
	1 lakh- 5 lakh	4.267	1.205				
	More than 5 lakh	4.125	1.411				
	Total	4.396	1.250				
<i>Anchoring</i>	Less than 10K	4.611	0.996				
	10K-50K	4.881	0.906				
	50K-1 lakh	4.889	1.046	1.238	0.295	1.803	0.128
	1 lakh- 5 lakh	4.879	0.823				
	More than 5 lakh	5.140	0.864				
	Total	4.863	0.926				
<i>Mental accounting</i>	Less than 10K	4.889	1.138				
	10K-50K	4.872	1.358				
	50K-1 lakh	4.707	1.166	0.832	0.505	0.217	0.929
	1 lakh- 5 lakh	4.782	1.364				
	More than 5 lakh	4.897	1.418				
	Total	4.824	1.293				
<i>Loss aversion</i>	Less than 10K	5.226	1.082				
	10K-50K	5.198	1.169				
	50K-1 lakh	5.177	0.995	0.882	0.475	0.212	0.932
	1 lakh- 5 lakh	5.163	0.952				
	More than 5 lakh	5.024	1.183				
	Total	5.170	1.063				
<i>Regret</i>	Less than 10K	4.519	0.875				
	10K-50K	4.750	0.924				
	50K-1 lakh	4.543	0.908	0.669	0.614	0.962	0.429
	1 lakh- 5 lakh	4.713	0.921				
	More than 5 lakh	4.802	1.081				
	Total	4.669	0.931				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.6.4 Number of Stocks in the Portfolio and Behavioral biases

One-way analysis of variance (ANOVA) has been used to analyse the variation among the behavioral biases with respect to the number of stocks in an investor's stock portfolio and the following hypotheses are tested in this connection:

H2.4 There is an association between the number of stocks and the behavioral biases of individual investors

This hypothesis can be divided into seven sub hypotheses

H2.4a: There is an association between the number of stocks and overconfidence

H2.4b: There is an association between the number of stocks and representativeness

H2.4c: There is an association between the number of stocks and the availability

H2.4d: There is an association between the number of stocks and anchoring

H2.4e: There is an association between the number of stocks and mental accounting

H2.4f: There is an association between the number of stocks and loss aversion

H2.4g: There is an association between the number of stocks and regret

The final results of the association between the selected variables represented in table 5.6.4 suggest that the number of stocks is significantly related to the regret aversion biases of an investor. The more the number of stock held by a person in his portfolio, the more regret averse he is ((F (2,304) = 2.685, $P < 0.05$), hence H2.4g is supported. Further, the results of Tukey post hoc analysis revealed that levels of regret in an investor holding one stock (mean = 4.57) is significantly lower than the level of regret in a person holding more than 20 stocks (mean = 5.027), (mean difference = .57124, $p < 0.05$) (Appendix 1.7).

Additionally, all other behavioral biases such as overconfidence, representativeness, availability, anchoring, mental accounting, and loss aversion, are not found to be related to the stock holdings of an individual, therefore, H2.4a, H2.4b, H2.4c, H2.4e, and H2.4f are not supported by the results obtained through empirical analysis.

Table 5.6.4 Number of Stocks in the Portfolio and Behavioral biases

		Group statistics		Levene's test		ANOVA	
		Mean	Std dev	F	Sig.	F/Welch	Sig.
<i>Overconfidence</i>	One	5.159	0.774	0.507	0.73	1.375	0.243
	1-5	5.315	0.853				
	5-10	5.241	0.818				
	10-20	5.266	0.687				
	More than 20	5.532	0.707				
	Total	5.306	0.789				
<i>Representativeness</i>	One	5.282	0.893	0.456	0.768	0.868	0.484
	1-5	5.281	1.025				
	5-10	5.398	0.805				
	10-20	5.512	0.936				
	More than 20	5.511	0.898				
	Total	5.390	0.923				
<i>Availability</i>	One	4.510	1.397	1.639	0.164	0.984	0.417
	1-5	4.490	1.245				
	5-10	4.430	1.176				
	10-20	4.103	1.123				
	More than 20	4.431	1.430				
	Total	4.396	1.250				
<i>Anchoring</i>	One	4.635	1.082	2.366	0.053	0.733	0.57
	1-5	4.805	0.998				
	5-10	4.899	0.906				
	10-20	4.955	0.694				
	More than 20	4.936	0.965				
	Total	4.863	0.926				
<i>Mental Accounting</i>	One	4.817	1.260	1.18	0.32	0.163	0.957
	1-5	4.815	1.457				
	5-10	4.753	1.203				
	10-20	4.848	1.270				
	More than 20	4.942	1.168				
	Total	4.824	1.293				
<i>Loss aversion</i>	One	4.946	1.248	0.646	0.63	1.792	0.13
	1-5	5.348	1.104				
	5-10	4.973	0.897				
	10-20	5.171	1.113				
	More than 20	5.272	1.036				
	Total	5.170	1.063				

	One	4.577	0.877				
	1-5	4.693	0.939				
<i>Regret</i>	5-10	4.613	0.916	0.416	0.797	2.685	0.032**
	10-20	4.855	0.917				
	More than 20	5.027	0.918				
	Total	4.669	0.931				

* Significant at 1%, ** significant at 5%

Source: Author's calculations

5.7 Assessment of the Measurement Model

The measurement model, also known as the outer model in the context of PLS-SEM describes the relationship between latent variables and their corresponding indicators. The study uses a total of ten latent variables out of which three variables (overconfidence, mental accounting, and regret) are hierarchical latent variables in the reflective-reflective type model. These hierarchical component models (HCM) are established by defining them as combinations of their sub-dimensions, which is a top-down approach to establishing HCMs. While evaluating the inner model we are concerned only with the higher-order constructs and additional information about higher-order constructs can be obtained by studying their sub-dimensions or lower-order constructs. Six latent variables (representativeness, availability, anchoring, loss aversion, perceived investment performance, and financial satisfaction) in the measurement model are established as first-order constructs measured by multiple items, and one construct (Investment satisfaction) is operationalized by a single item, drawn on the basis of prior research studies. All the constructs have reflective measurement models as indicated by the arrows pointing from the constructs to the indicators in figure 5.1

To establish the reflective-reflective higher-order constructs of behavioral biases disjoint two-stage approach is employed as specified by Sarstedt et al. (2019). The disjoint two-stage approach is a two-step procedure, in the first step path model is constructed only using the lower-order components of the higher-order constructs (i.e. without the presence of higher-order constructs), and latent variable scores are obtained for lower-order constructs. These latent variable scores are then used in the second stage to measure the higher-order construct. These higher-order models are evaluated using the same criteria (i.e. internal consistency reliability, convergent validity, and

discriminant validity) as for any other PLS-SEM model (Chin, 2010b) with the only difference that we have two measurement models, in this case, the first measurement model for lower order components and second measurement model for higher-order components

5.7.1 Evaluation of the reflective measurement model at lower order

5.7.1.1 Outer loadings relevance test/ Indicator reliability

The first step in assessing the measurement model is examining the outer loadings of all reflective constructs in the model. Outer loading measures the correlation between the construct and its indicators. Loading above 0.708 are desirable as they would show that the construct is responsible for more than 50 percent of the variability in the indicator. Outer loadings in the range of 0.40 and 0.70 should be removed from the scale only if it does not affect the scale's content validity or improve its composite reliability and AVE above the threshold level (Hair et al., 2019). Indicators with outer loadings below 0.40 should unarguably be removed from the existing scale. Outer loadings and indicator reliability values of all reflective constructs in the present study are reported in table xx. Most of the indicators in table 5.7.1 have outer loadings greater than the recommended value of 0.708. However, indicators *AVL_1*, *LA3*, *FS6*, and *FS7* have outer loadings less than 0.708 but they are still in the acceptable range of 0.40 to 0.708 and are retained in the model because their removal will lower the content validity of the scales. Further the scales used in the study are only developed in recent years therefore, it's normal to get a few indicator loadings below 0.708. Indicator *RC_ANC4* has the lowest outer loading (0.455) and indicator reliability 0.207 therefore this item has been removed from the scale that measures anchoring bias.

Table 5.7.1 Outer loadings and Indicator reliability

Latent Variables	Indicators	Outer loadings	Indicator reliability
Better Than Average (BTA)	OCBTA1	0.8	0.640
	OCBTA2	0.912	0.832
Self-Attribution (SA)	OCSA1	0.908	0.824
	OCSA2	0.868	0.753

Planning Fallacy (PF)	OCPF1	0.876	0.767
	OCPF2	0.82	0.672
Unrealistic Optimism (UO)	OCUO1	0.902	0.814
	OCUO2	0.798	0.637
Availability (AVL)	AVL_1	0.62	0.384
	AVL_2	0.754	0.569
	AVL_3	0.783	0.613
	AVL_4	0.712	0.507
Anchoring (ANC)	ANC1	0.732	0.536
	ANC2	0.865	0.748
	ANC3	0.806	0.650
	RC_ANC4	0.455	0.207
Representativeness (REP)	REP_1	0.828	0.686
	REP_2	0.825	0.681
	REP_3	0.719	0.517
Budgeting (Budg)	MA_B1	0.899	0.808
	MA_B2	0.902	0.814
Categorization (Catg)	MA_C1	0.921	0.848
	MA_C2	0.922	0.850
Anticipated Regret (AR)	R_AR1	0.937	0.878
	R_AR2	0.745	0.555
Experienced Regret (ER)	R_ER1	0.815	0.664
	R_ER2	0.92	0.846
Loss Aversion (LR)	LA1	0.753	0.567
	LA2	0.753	0.567
	LA3	0.654	0.428
	LA4	0.765	0.585
	LA5	0.713	0.508
Perceived Investment Performance (PIP)	PIP1	0.789	0.623
	PIP2	0.799	0.638
	PIP3	0.831	0.691
Investment Satisfaction (IS)	IS	Single-Item	Single-Item

Financial Satisfaction (FS)	FS1	0.767	0.588
	FS2	0.763	0.582
	FS3	0.805	0.648
	FS4	0.797	0.635
	FS5	0.764	0.584
	FS6	0.675	0.456
	FS7	0.671	0.450

5.7.1.2 Internal consistency Reliability

Both measures of Internal consistency reliability i.e. Cronbach's Alpha (α) and composite reliability (ρ_c) have been used in the present study to evaluate the measurement model. Cronbach's alpha is considered as the lower bound and the composite reliability is taken as the upper bound for internal consistency reliability (Hair et al., 2019). As Cronbach's alpha is a conservative approach it produces lower values than composite reliability and being a liberal method, composite reliability naturally produces higher values. The true value of internal consistency reliability lies between these two measures of reliability (Hair et., 2019).

Cronbach's alpha (α) and Composite reliability (ρ_c) are interpreted in the same way. Values between 0.6 and 0.7 are acceptable and values between 0.7 and 0.9 are considered satisfactory (Nunally and Bernstein, 1994). Composite reliability of below 0.6 indicates a lack of internal consistency.

The results for both Cronbach's alpha (α) and Composite reliability (ρ_c) are presented in table 5.7.2. Cronbach's alpha ranged from 0.613 to 0.877 whereas the values of composite reliability ranged from 0.815 to 0.918. Both indicators of reliability have reliability statistics within the acceptable range, hence construct reliability is established.

Table 5.7.2 Construct reliability analysis (Cronbach Alpha and Composite Reliability)

Lower Order Constructs	Cronbach's alpha	Composite reliability (rho_c)
Better Than Average(BTA)	0.652	0.847
Self-attribution (SA)	0.734	0.882
Planning Fallacy (PF)	0.613	0.837
Unrealistic Optimism (UO)	0.629	0.84
Representativeness (Rep)	0.708	0.834
Availability (AVL)	0.697	0.81
Anchoring (ANC)	0.730	0.844
Budgeting (Budg)	0.768	0.896
Categorization (Catg)	0.822	0.918
Anticipated Regret (AR)	0.634	0.833
Experienced Regret (ER)	0.686	0.86
Loss Aversion (LA)	0.791	0.849
Financial Satisfaction (FS)	0.87	0.9
Perceived investment performance (PIP)	0.732	0.848

5.7.1.3 Convergent Validity

Convergent validity is a measure of construct validity that measures the extent to which the scale correlated positively with other measures of the same construct (Malhotra & Dash, 2017) Average Variance Extracted (AVE) is the common measure to establish the convergent validity of the construct. An acceptable AVE is 0.50 or higher indicates that the construct explains at least 50 percent of the variance of its indicators. AVE is not calculated for single-item construct, since the indicator's outer loading is fixed at 1. The AVE values of all the constructs are above the recommended value of 0.5 (Fornell & Larcker, 1981) which indicates that the research measurement model has sufficient convergent validity.

Table 5.7.3 Convergent validity assessment (AVE)

Lower Order constructs	Average variance extracted (AVE)
Better Than Average(BTA)	0.736
Self-attribution (SA)	0.789
Planning Fallacy (PF)	0.72
Unrealistic Optimism (UO)	0.725
Representativeness (Rep)	0.628
Availability (AVL)	0.519
Anchoring (ANC)	0.645
Budgeting (Budg)	0.811
Categorization (Catg)	0.849
Anticipated Regret(AR)	0.716
Experienced Regret (ER)	0.755
Loss Aversion (LA)	0.531
Financial Satisfaction (FS)	0.563
Perceived investment performance (PIP)	0.65

5.7.1.4 Discriminant Validity

Discriminant Validity is a type of construct validity that assess the extent to which a measure does not correlate with other constructs from which it is supposed to differ (Malhotra & Dash, 2017). Thus the presence of discriminant validity ensures that a construct is unique and measures a phenomenon that is different from the phenomenon measured by other constructs in the conceptual model. (Hair et al., 2010). The present research utilizes three different approaches to assess the discriminant validity of the measurement model. **Fornell and Larcker** criterion, Cross loadings of the indicators and HTMT criteria.

- i) **Fornell and Larcker criterion:** Square roots of the AVEs of all the reflective constructs are shown on the diagonal of table 5.7.4 and the correlations between the constructs with other latent variables in the lower left triangle. The square root of AVEs of all lower-order reflective constructs located on the diagonal is greater than the correlations of these constructs with other

latent variables in the measurement model, therefore, the Fornell and Lacker criterion is establishing the discriminant validity in the measurement model.

- ii) **Cross-Loadings:** Alternate valuation for discriminant validity can be done by assessing the cross-loadings of the indicators. Table 5.7.5 shows the loading and cross-loading for every indicator. It is clearly visible in table 5.7.5 that all the measurement items have the highest value of loadings with their corresponding construct, while all the cross-loadings with other constructs are considerably lower. Thus, the overall cross-loadings as well as the Fornell and Lacker criteria provide evidence for the construct's discriminant validity.
- iii) **HTMT Criterion:** As a replacement for Fornell and Larcker criteria for assessing discriminant validity Henseler et al. (2015) proposed an advanced technique in the form of the heterotrait-monotrait (HTMT) ratio. Higher HTMT values are undesirable as they suggest a lack of discriminant validity among the constructs. Generally, the HTMT value should be below 0.9 but when the constructs are conceptually different a more conservative approach is followed and the suggested threshold value is 0.85 (Henseler et al., 2015). The results of the HTMT criteria presented in table 5.7.6 show that the HTMT values of all constructs are below the threshold value of 0.85, establishing the discriminant validity of the lower-order measurement model.

Table 5.7.4 Discriminant validity- Fornell and Lacker criterion.

	ANC	AR	AVL	BTA	Budg	Catg	ER	FS	IS	LA	PF	PIP	Rep	SA	UO
ANC	0.803														
AR	0.272	0.846													
AVL	0.262	0.161	0.72												
BTA	0.182	0.134	0.111	0.858											
Budg	0.132	0.287	0.166	0.181	0.901										
Catg	0.250	0.289	0.203	0.17	0.598	0.921									
ER	0.295	0.461	0.344	0.132	0.177	0.265	0.869								
FS	0.241	0.179	0.178	0.223	0.326	0.302	0.224	0.75							
IS	0.346	0.204	0.279	0.203	0.204	0.264	0.192	0.322	1						
LA	0.365	0.289	0.378	0.071	0.206	0.193	0.365	0.179	0.126	0.729					
PF	0.253	0.096	0.238	0.414	0.218	0.224	0.224	0.208	0.258	0.188	0.849				
PIP	0.376	0.267	0.347	0.218	0.277	0.294	0.373	0.287	0.504	0.306	0.422	0.806			
Rep	0.425	0.315	0.154	0.281	0.248	0.266	0.182	0.178	0.245	0.305	0.27	0.285	0.792		
SA	0.273	0.09	0.08	0.475	0.2	0.212	-0.032	0.119	0.216	0.089	0.417	0.222	0.269	0.888	
UO	0.209	0.172	0.082	0.308	0.227	0.21	0.121	0.086	0.306	0.08	0.508	0.303	0.281	0.44	0.852

Table 5.7.5 Cross loadings of the indicators

	ANC	AVL	Rep	AR	ER	FS	BTA	SA	PF	UO	IS	LA	Budg	Catg	PIP
ANC1	0.737	0.116	0.445	0.223	0.148	0.24	0.112	0.176	0.197	0.161	0.225	0.324	0.161	0.223	0.258
ANC2	0.874	0.263	0.329	0.271	0.335	0.205	0.21	0.264	0.226	0.151	0.39	0.284	0.073	0.214	0.345
ANC3	0.792	0.234	0.265	0.139	0.183	0.133	0.088	0.203	0.181	0.209	0.165	0.285	0.105	0.166	0.293
AVL_1	0.283	0.62	0.271	0.162	0.262	0.11	0.171	0.169	0.241	0.199	0.282	0.249	0.198	0.137	0.285
AVL_2	0.075	0.755	0.023	0.11	0.211	0.06	0.064	0.035	0.143	-0.009	0.155	0.258	0.091	0.118	0.217
AVL_3	0.106	0.783	0.022	0.069	0.205	0.154	0.054	0.062	0.141	0.012	0.172	0.255	0.132	0.219	0.191
AVL_4	0.22	0.712	0.042	0.092	0.279	0.182	-0.012	-0.081	0.116	-0.033	0.142	0.311	0.017	0.108	0.264
REP_1	0.355	0.216	0.828	0.26	0.181	0.156	0.246	0.204	0.301	0.205	0.184	0.315	0.214	0.245	0.301
REP_2	0.365	0.008	0.825	0.239	0.086	0.103	0.177	0.212	0.16	0.248	0.246	0.185	0.2	0.209	0.184
REP_3	0.281	0.132	0.719	0.254	0.168	0.172	0.254	0.235	0.159	0.224	0.147	0.213	0.172	0.167	0.172
R_AR1	0.311	0.186	0.36	0.937	0.45	0.199	0.152	0.108	0.154	0.176	0.219	0.335	0.309	0.355	0.273
R_AR2	0.095	0.054	0.109	0.745	0.31	0.073	0.048	0.022	-0.05	0.098	0.098	0.094	0.137	0.056	0.156
R_ER1	0.276	0.322	0.176	0.483	0.815	0.146	0.073	-0.033	0.121	0.069	0.152	0.388	0.099	0.181	0.244
R_ER2	0.247	0.289	0.149	0.352	0.92	0.23	0.145	-0.026	0.247	0.131	0.179	0.273	0.194	0.267	0.383
FS1	0.199	0.245	0.109	0.201	0.254	0.767	0.126	0.061	0.131	0.069	0.259	0.214	0.326	0.301	0.268
FS2	0.159	0.07	0.083	0.138	0.161	0.763	0.19	0.101	0.154	0.052	0.19	0.06	0.216	0.269	0.131
FS3	0.146	0.158	0.109	0.086	0.231	0.805	0.162	0.01	0.227	0.012	0.188	0.137	0.21	0.226	0.289
FS4	0.251	0.089	0.253	0.228	0.152	0.797	0.233	0.145	0.191	0.059	0.305	0.188	0.287	0.192	0.264
FS5	0.202	0.078	0.106	0.132	0.116	0.764	0.168	0.136	0.133	0.132	0.284	0.081	0.277	0.245	0.138
FS6	0.193	0.076	0.188	0.059	-0.015	0.675	0.155	0.153	0.105	0.085	0.252	0.097	0.214	0.173	0.16

FS7	0.078	0.208	0.037	0.047	0.272	0.671	0.133	0.006	0.141	0.042	0.178	0.115	0.138	0.185	0.214
OCBTA1	0.097	0.058	0.239	0.125	0.102	0.203	0.8	0.376	0.35	0.261	0.121	0.115	0.145	0.132	0.164
OCBTA2	0.2	0.123	0.246	0.11	0.123	0.187	0.912	0.435	0.365	0.271	0.213	0.026	0.165	0.158	0.206
OCSA1	0.209	0.072	0.23	0.088	-0.023	0.137	0.468	0.908	0.383	0.398	0.214	0.023	0.201	0.2	0.205
OCSA2	0.283	0.07	0.25	0.071	-0.036	0.069	0.368	0.868	0.356	0.384	0.167	0.147	0.15	0.175	0.188
OCPF1	0.182	0.217	0.174	0.011	0.204	0.22	0.336	0.351	0.876	0.429	0.193	0.128	0.225	0.209	0.413
OCPF2	0.255	0.186	0.296	0.166	0.174	0.125	0.372	0.358	0.82	0.436	0.25	0.198	0.139	0.169	0.295
OCUO1	0.208	0.106	0.237	0.111	0.129	0.072	0.268	0.363	0.436	0.902	0.294	0.072	0.199	0.193	0.3
OCUO2	0.14	0.02	0.246	0.198	0.069	0.077	0.26	0.398	0.436	0.798	0.22	0.063	0.19	0.163	0.206
IS	0.346	0.279	0.245	0.204	0.192	0.322	0.203	0.216	0.258	0.306	1	0.126	0.204	0.264	0.504
LA1	0.243	0.335	0.263	0.163	0.234	0.182	0.112	0.08	0.258	0.088	0.124	0.753	0.218	0.213	0.262
LA2	0.199	0.236	0.16	0.264	0.363	0.14	-0.024	-0.024	0.036	-0.032	0.071	0.753	0.059	0.105	0.173
LA3	0.125	0.198	0.172	0.308	0.257	0.04	-0.066	-0.003	0.011	0.048	-0.032	0.654	0.132	0.114	0.142
LA4	0.244	0.201	0.23	0.201	0.285	0.116	0.023	0.063	0.07	0.02	0.06	0.765	0.158	0.161	0.217
LA5	0.41	0.339	0.244	0.198	0.231	0.126	0.113	0.138	0.187	0.12	0.151	0.713	0.148	0.091	0.258
MA_B1	0.148	0.128	0.26	0.266	0.199	0.254	0.213	0.232	0.238	0.247	0.196	0.223	0.899	0.564	0.238
MA_B2	0.089	0.17	0.188	0.251	0.12	0.332	0.114	0.128	0.156	0.162	0.171	0.15	0.902	0.513	0.261
MA_C1	0.272	0.194	0.256	0.293	0.241	0.259	0.138	0.184	0.223	0.203	0.231	0.186	0.52	0.921	0.28
MA_C2	0.189	0.18	0.234	0.241	0.247	0.297	0.175	0.207	0.191	0.183	0.255	0.169	0.581	0.922	0.261
PIP1	0.325	0.261	0.203	0.232	0.292	0.191	0.138	0.151	0.274	0.285	0.48	0.197	0.206	0.223	0.789
PIP2	0.279	0.312	0.247	0.216	0.323	0.207	0.176	0.163	0.314	0.167	0.338	0.261	0.19	0.272	0.8
PIP3	0.308	0.268	0.237	0.202	0.29	0.287	0.208	0.216	0.42	0.279	0.406	0.276	0.267	0.219	0.83

Table 5.7.6 Discriminant validity-HTMT criterion.

	ANC	AR	AVL	BTA	Budg	Catg	ER	FS	IS	LA	PF	PIP	Rep	SA
ANC	0.335													
AR	0.368	0.195												
AVL	0.232	0.187	0.195											
BTA	0.187	0.374	0.228	0.255										
Budg	0.322	0.333	0.266	0.23	0.753									
Catg	0.398	0.698	0.485	0.185	0.231	0.342								
ER	0.291	0.203	0.238	0.3	0.388	0.358	0.284							
FS	0.378	0.233	0.311	0.24	0.232	0.291	0.229	0.338						
IS	0.444	0.379	0.469	0.136	0.249	0.23	0.527	0.187	0.133					
LA	0.380	0.217	0.336	0.66	0.313	0.314	0.325	0.276	0.333	0.235				
PF	0.507	0.371	0.464	0.307	0.366	0.38	0.509	0.344	0.591	0.373	0.613			
PIP	0.590	0.414	0.269	0.421	0.334	0.342	0.267	0.231	0.288	0.38	0.404	0.382		
Rep	0.269	0.125	0.172	0.676	0.263	0.272	0.048	0.166	0.25	0.148	0.621	0.298	0.38	
SA	0.309	0.269	0.203	0.485	0.328	0.289	0.168	0.122	0.379	0.119	0.824	0.434	0.428	0.655

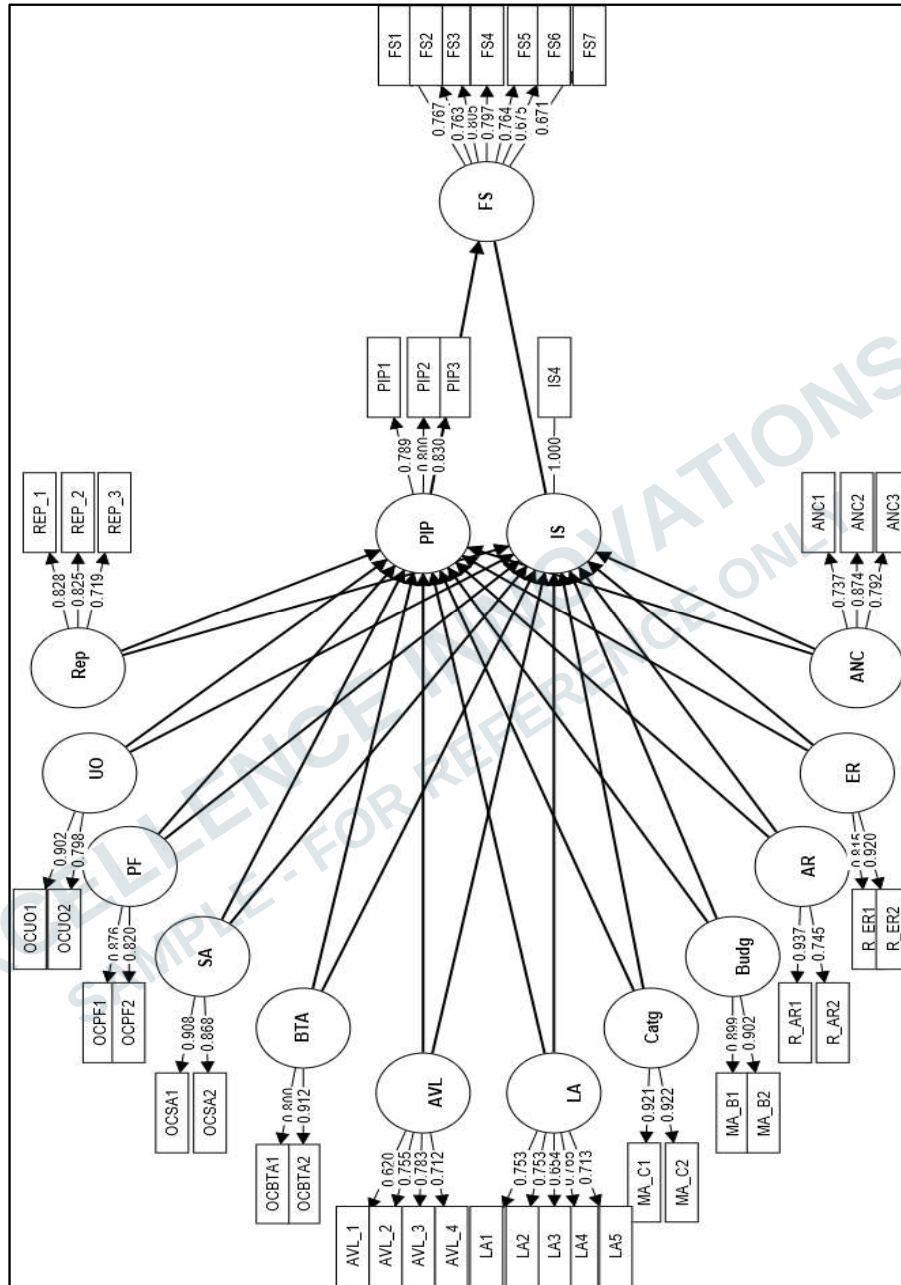


Figure 5.1 Lower order measurement model

Source: SmartPLS 4Output

5.7.2 Evaluation of the reflective measurement model at higher order.

Overconfidence, Mental accounting, and regret are established as second-order constructs of their dimensions for the purpose of this study. These higher-order constructs are also validated as part of assessing the measurement model. The reliability and validity of the higher-order constructs are evaluated as for any other PLS-SEM model. Also, the discriminant validity of these higher-order constructs is tested along with other lower-order constructs following the recommendations of Sarstedt et al, (2019). The reliability values of all higher-order constructs are within the acceptable range of 0.6 to .9 (table 5.7.7) and the AVE values of all higher-order constructs are above 0.5, establishing the internal consistency reliability and convergent validity of the measurement model at higher order (table 5.7.8). The results of Fornell and Larcker (1981) show that the square of AVEs of all constructs at higher-order are higher than the correlation of these constructs with all other constructs in the model (table 5.7.9) and also the HTMT values are below the threshold of 0.85 (Henseler et al., 2015), thus establishing the discriminant validity of the higher order model (table 5.7.10).

Table 5.7.7 Higher Order Internal Consistency Reliability

	Cronbach's alpha	Composite reliability (rho_c)
Mental accounting (MA)	0.751	0.889
Overconfidence (OC)	0.749	0.839
Regret (REG)	0.631	0.843

Table 5.7.8 Higher Order Convergent Validity

	Average variance extracted (AVE)
Mental accounting (MA)	0.801
Overconfidence (OC)	0.567
Regret (REG)	0.729

Table 5.7.9 Fornell and Larcker- Higher Order Discriminant Validity

	ANC	AVL	FS	IS	LA	MA	OC	PIP	REG	REP
ANC	0.733									
AVL	0.182	0.703								
FS	0.353	0.115	0.784							
IS	0.268	0.291	0.348	single-item						
LA	0.306	0.39	0.186	0.138	0.718					
MA	0.135	0.217	0.312	0.284	0.214	0.895				
OC	0.231	0.17	0.286	0.308	0.139	0.318	0.748			
PIP	0.313	0.273	0.343	0.468	0.227	0.232	0.347	0.876		
REG	0.262	0.316	0.241	0.23	0.378	0.277	0.197	0.292	0.853	
REP	0.342	0.174	0.208	0.242	0.305	0.214	0.366	0.205	0.281	0.794

Source: Smart PLS Output

Table 5.7.10 HTMT- Higher Order Discriminant Validity

	ANC	AVL	FS	IS	LA	MA	OC	PIP	REG	REP
ANC										
AVL	0.252									
FS	0.384	0.172								
IS	0.271	0.311	0.361							
LA	0.335	0.469	0.2	0.133						
MA	0.187	0.287	0.371	0.328	0.258					
OC	0.297	0.229	0.342	0.358	0.159	0.424				
PIP	0.345	0.301	0.392	0.51	0.236	0.289	0.42			
REG	0.322	0.423	0.331	0.291	0.563	0.409	0.29	0.383		
REP	0.405	0.269	0.256	0.288	0.38	0.292	0.508	0.265	0.436	

Source: Smart PLS Output

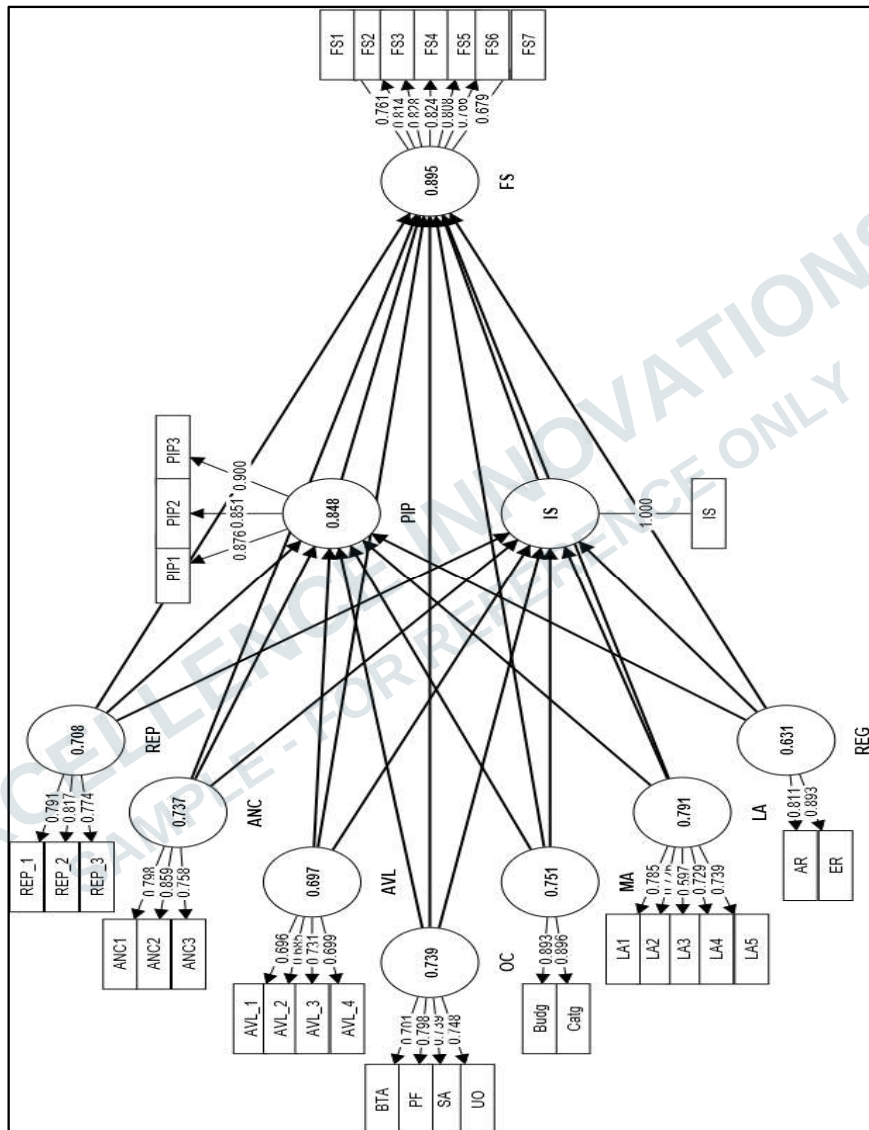


Figure 5.2 Higher order measurement model

Source: SmartPLS output

5.8 Collinearity Assessment

After establishing the reliability and validity of the measurement model (outer model) but before the evaluation of the structural model (Inner model) it is important to assess the collinearity issues among the predictor latent variables. Since PLS-SEM is based on OLS regression, collinearity among the predictive constructs will lead to biased estimates of path coefficients, therefore we check for the collinearity issues between each set of predictor variables in the structural model. In order to diagnose multi-collinearity issues, we have calculated VIF (Variance Inflation Factor) for each set of predictor variables as well as for each indicator. The corresponding VIF values for the multi-collinearity assessment of indicators (outer model) are presented in table 5.8.1 and the VIF values of each of the constructs in their respective predictor variable set (inner model) are summarized in Table 5.8.2. Specifically, two sets of predictor variables are assessed for collinearity in the structural model. Set-1 *OC, AVL, ANC, REP, MA, LA, and REG*; Set-2 *OC, AVL, ANC, REP, MA, LA, REG, IS, and PIP*. All VIF values presented in tables 5.8.1 and 5.8.1 are not only below the threshold of 5 (Hair et al, 2016) but are also less than 3 ($VIF < 3$), a more stringent criterion for collinearity assessment given by Mason and Perreault (1991); Becker et al. (2015). Therefore, collinearity among the predictor constructs is not an issue in the structural model.

Table 5.8.1 Multicollinearity Assessment (VIF) for Indicators

Indicators	VIF
ANC1	1.454
ANC2	1.452
ANC3	1.472
AVL_1	1.051
AVL_2	2.789
AVL_3	2.892
AVL_4	1.327
BTA	1.414

Budg	1.567
Catg	1.567
AR	1.27
ER	1.27
FS1	1.869
FS2	2.223
FS3	2.501
FS4	2.312
FS5	2.108
FS6	1.821
FS7	1.612
IS	1
LA1	1.385
LA2	1.992
LA3	1.877
LA4	1.979
LA5	1.274
PF	1.449
PIP1	2.143
PIP2	1.875
PIP3	2.241
REP_1	1.35
REP_2	1.503
REP_3	1.35
SA	1.508
UO	1.423

Table 5.8.2 Collinearity Assessment among Predictor Constructs

First Set	VIF	Second Set	VIF
ANC	1.232	ANC	1.298
AVL	1.25	AVL	1.309

LA	1.391	IS	1.435
MA	1.2	LA	1.407
OC	1.264	MA	1.23
REG	1.309	OC	1.349
REP	1.339	PIP	1.467
		REG	1.332
		REP	1.349

5.9 Evaluation of the Structural Model.

After assessing the collinearity statistics, the next step is to assess the structural model results (inner model). The structural model represents the hypothesized relationships among the constructs. The research study makes an effort to examine the influence of select behavioral biases on the perceived investment performance (PIP) and Investment satisfaction (IS) of individual investors and finally the impact of perceived investment performance and investment satisfaction on the financial satisfaction (FS) of Indian retail investors. The structural model presented in fig xx consists of seven exogenous constructs including three higher-order constructs of reflective-reflective type (Overconfidence, Availability, Anchoring, Representativeness, Mental accounting, Loss aversion, and Regret). Two first-order constructs namely perceived investment performance (PIP) and investment satisfaction (IS) are mediating variables and one first-order construct financial satisfaction is the main endogenous variable in the proposed structural model.

The structural model is assessed on the basis of the following criteria:

- i) Coefficient of determination (R^2)
- ii) Predictive relevance (Q^2)
- iii) Significance of path coefficients
- iv) Model fit using SRMR

5.9.1 Coefficient of Determination (R^2)

The coefficient of determination (R^2) is a measure of the structural model's predictive power (Rigdon, 2012). To avoid bias towards complex models, adjusted R^2 values can also be reported. Adj- R^2 reduces the value of the regular R^2 after taking into account the

number of non-significant exogenous constructs in the model and sample size. The minimum acceptable value of R^2 depends on the context of the study. The R^2 values in the study ranged between 21.5 to 26.6%. (Table 5.9.1 and figure 5.3) The proposed model is able to explain over 23.3 percent of the variance of investors' perceived investment performance and 21.5 percent of the variance of investment satisfaction through behavioral biases exhibited by individual investors. Simultaneously, the proposed model is also able to explain 26.6 percent of the variance in financial satisfaction of individual investors collectively through PIP, IS, and behavioral biases. These values of R^2 are acceptable from the perspective of behavioral sciences (Hair et al., 2017; Rasoolimanesh et al., 2019). Hence, the predictive capability of the model is established.

5.9.2 Predictive Relevance Q^2

Predictive relevance Q^2 represents how well the path model can predict originally observed values. Q^2 values above zero for an endogenous construct indicate predictive relevance for this particular construct. (Hair et al., 2017). As a general guideline, Q^2 values higher than 0, 0.25, and 0.50 indicate small, medium, and large predictive relevance of the structural model (Hair et al., 2019). Q^2 values of all endogenous constructs in the structural model are reported in table 5.9.1. All these values are above the minimum threshold value of zero, hence, predictive relevance for the structural model is established.

Table 5.9.1 Predictive Power of the Model.

	R-square	R-square adjusted	Q^2 predict
FS	0.266	0.244	0.162
IS	0.215	0.197	0.151
PIP	0.234	0.216	0.180

5.9.3 SRMR

Apart from R^2 and Q^2 values standardized root mean square residual (SRMR) can also be used as a goodness of fit statistic. A value of less than 0.10 or 0.08 is usually considered as a benchmark for good model fit (Hu & Bentler, 1999). The SRMR value for the proposed model in the present study is **0.074** determining the suitable fit for the model.

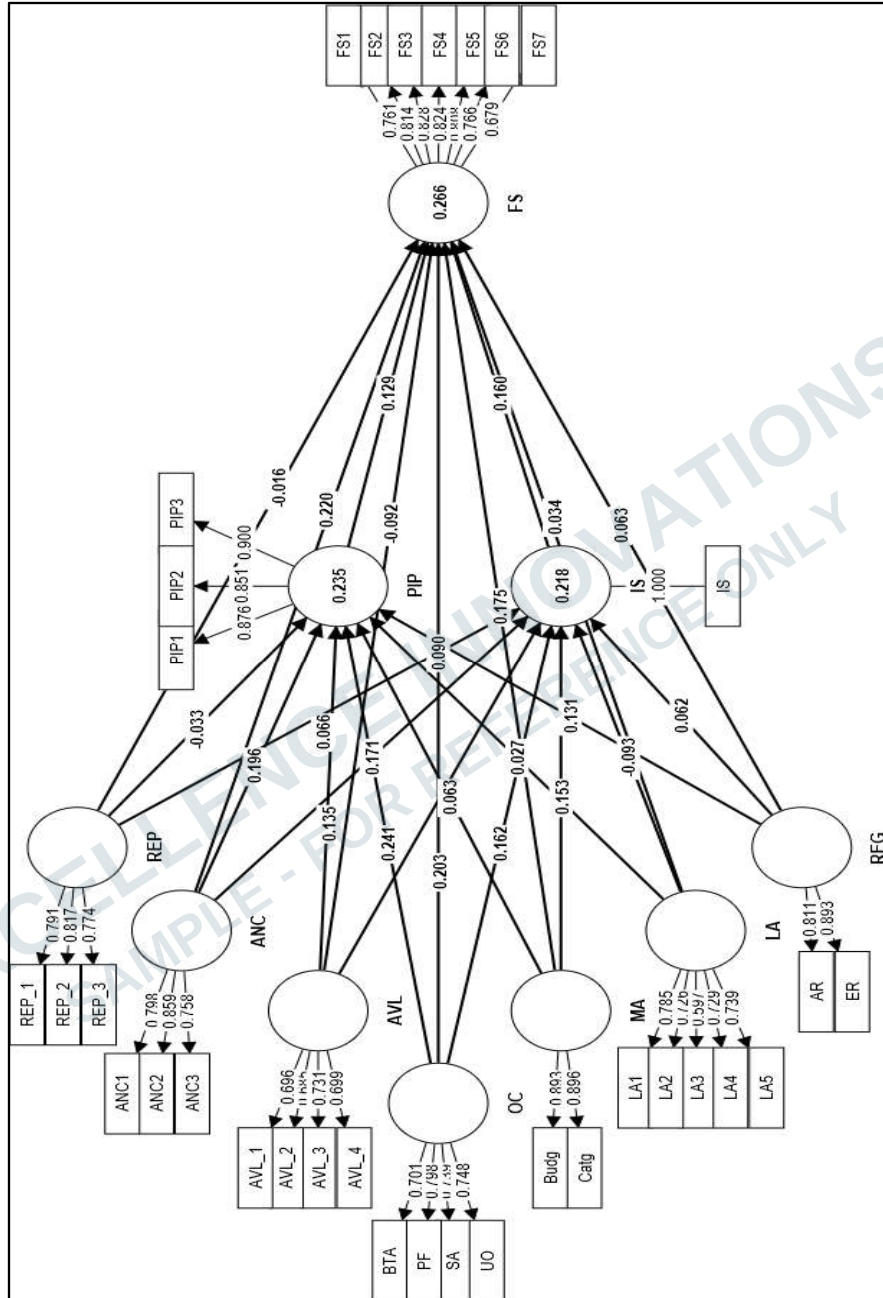


Figure 5.3 Structural model

Source: SmartPLS output

5.9.4 Hypothesis Testing (Significance of path coefficients)

Path coefficient values generally represented as β values fall between the standardized values of +1 and -1. ' β ' Values close to the extremes of either +1 or -1 represent strong positive or negative relationships among the latent variables in the path model and values close to zero represent weak relationships among the underlying constructs. The significance of path coefficients in PLS-SEM is determined with the help of the bootstrapping procedure. 10000 bootstrap samples have been used to obtain results in the present study following the recommendations of Streukens and Leroi-Werelds, 2016 which surely exceeds the previous recommendations of 1000 and 5000 bootstrap samples by Efron and Tishirani (1994) and Preacher and Hayes (2008).

In marketing and behavioral studies, researchers normally assume a significance level of 5% with critical values of 1.96 in the case of a two-tailed test. Along with t-values, P-values are also routinely reported to test the significance levels of path coefficients. Table 5.9.2 reports the statistical significance of all direct research hypotheses in the structural model.

Following are the hypotheses from the structural model.

H3: Behavioral biases have a significant impact on the perceived investment performance of individual investors

H3.1 Overconfidence has a significant impact on perceived investment performance

H3.1 evaluates whether overconfidence bias has a significant impact on the perceived investment performance of individual investors. The results revealed that overconfidence has a significant and positive impact on perceived investment performance ($\beta = .241$, $t = 4.202$, $P < 0.05$). Hence, H3.1 was supported.

H3.2 Availability has a significant impact on perceived investment performance

Availability bias has a significant and positive impact on the perceived investment performance of individual investors ($\beta = 0.136$, $t = 2.246$, $p < 0.05$). Hence, H3.2 was supported by the results obtained from data analysis.

H3.3 Anchoring has a significant impact on perceived investment performance

H3.3 evaluates the impact of anchoring on the perceived investment performance of individual investors. The results reveal that anchoring has a significant and positive

impact on the perceived investment performance of individual investors ($\beta = 0.192$, $t = 2.962$, $P < 0.05$). Hence, H3.3 was supported.

H3.4 Representativeness has a significant impact on perceived investment performance.

H3.4 was not supported by the results obtained from the data ($\beta = -0.032$, $t = 0.505$, $P = 0.614$). Therefore the impact of representativeness bias on perceived investment performance is insignificant.

H3.5 Mental accounting has a significant impact on perceived investment performance

H3.5 evaluates the impact of mental accounting on the perceived investment performance of individual investors. The results revealed that the impact of mental accounting on perceived investment performance is insignificant ($\beta = 0.064$, $t = 1.031$, $P = 0.303$). Hence, H3.5 was not supported.

H3.6 Loss aversion has a significant impact on perceived investment performance

H3.6 was also not supported by the results obtained as the p-value for this hypothesis is greater than 0.05. Therefore, the impact of loss aversion on perceived investment performance is insignificant ($\beta = 0.028$, $t = 0.44$, $P = .66$).

H3.7 Regret has a significant impact on perceived investment performance

H3.7 evaluates the impact of regret on the perceived investment performance of individual investors. The results reveal that the impact of regret on perceived investment performance is positive and significant ($\beta = 0.132$, $t = 1.982$, $P < 0.05$). Hence, H3.7 was supported.

H4: Behavioral biases have a significant impact on the investment satisfaction (IS) of individual investors.

H4.1 Overconfidence has a significant impact on investment satisfaction

H4.1 is supported by the results as the p-value is less than 0.05, providing evidence for the fact that overconfidence has a significant impact on the investment satisfaction of individual investors ($\beta = 0.163$, $t = 2.591$, $p < 0.05$).

H4.2 Availability has a significant impact on investment satisfaction.

H4.2 evaluates the impact of availability bias on the investment satisfaction of individual investors. Results revealed that the hypothesis is significant and availability has a positive and significant impact on the investment satisfaction of individual investors ($\beta = 0.204$, $t = 3.299$, $P < 0.05$).

H4.3 Anchoring has a significant impact on investment satisfaction.

Anchoring bias was found to have a significant and positive impact on the investment satisfaction of individual investors ($\beta = 0.16$, $t = 2.379$, $P < 0.05$). Hence, H4.3 is supported.

H4.4 Representativeness has a significant impact on investment satisfaction

H4.4 was not supported by the results as the p-value < 0.005 . Therefore representativeness bias has no significant impact on the investment satisfaction of individual investors ($\beta = 0.69$, $t = 0.998$, $P = 0.318$).

H4.5 Mental accounting has a significant impact on investment satisfaction.

Mental accounting has a positive and significant association with the investment satisfaction of individual investors ($\beta = 0.154$, $t = 2.373$, $P = < 0.05$). Hence, H4.5 was supported.

H4.6 Loss aversion has a significant impact on investment satisfaction.

The results revealed that there is a negative association between loss aversion and investment satisfaction as the β coefficient is negative, but at the same time this relationship is not significant as p-value > 0.05 ($\beta = -0.092$, $t = 1.309$, $P = 0.191$). Hence, H4.6 was not supported.

H4.7 Regret has a significant impact on investment satisfaction.

H4.7 was not supported as the p-value is greater than 0.05. It means that regret has no significant impact on the investment satisfaction of individual investors ($\beta = 0.064$, $t = 0.91$, $p = 0.363$).

H5: Behavioral biases have a significant impact on the financial satisfaction (FS) of individual investors.

H5.1 Overconfidence has a significant impact on financial satisfaction

H5.1 was not supported ($\beta = 0.088$, $t = 1.293$, $p = 0.196$) the direct effect of overconfidence on financial satisfaction is weak as the impact is passing through the mediating variables in the structural model, Hence overconfidence has no direct impact on the financial satisfaction of individual investors.

H5.2 Availability has a significant impact on financial satisfaction

The impact of availability bias on the financial satisfaction of individual investors is significant ($\beta = 0.220$, $t = 3.792$, $p < 0.05$). Hence H5.2 was supported.

H5.3 Anchoring has a significant impact on financial satisfaction

Anchoring bias has a positive and significant association with the financial satisfaction of individual investors ($\beta = .16$, $t = 2.379$, $p < 0.05$). Hence H5.3 was supported.

H5.4 Representativeness has a significant impact on financial satisfaction

H5.4 was not supported as a P-value > 0.05 ($\beta = -0.015$, $t = 0.196$, $p = 0.844$). However, a negative beta value (β) indicates that representativeness bias has a negative association with the financial satisfaction of individual investors but the association is not statistically significant.

H5.5 Mental accounting has a significant impact on financial satisfaction

The results revealed that mental accounting has a significant and positive impact on the financial satisfaction of individual investors ($\beta = 0.176$, $t = 2.921$, $p < 0.05$). Hence, H5.5 was supported.

H5.6 Loss aversion has a significant impact on financial satisfaction

H5.6 was not supported by the results obtained through empirical analysis of data as the p-value is greater than 0.05 ($\beta = 0.034$, $t = 0.505$, $p = .613$). Hence loss aversion has no significant impact on the financial satisfaction of investors.

H5.7 Regret has a significant impact on financial satisfaction

Regret has no significant impact on the financial satisfaction of individual investors ($\beta = 0.063$, $t = 0.92$, $p = .357$). Hence, H5.7 was not supported.

H6 Perceived investment performance has a significant impact on financial satisfaction

The results obtained through data analysis support ($\beta = 0.129$, $t = 2.106$, $p < 0.05$) the hypothesis that perceived investment performance has a significant and positive impact on financial the satisfaction of individual investors. It indicates that investors who perceive their performance as high have high levels of financial satisfaction. Hence, H6 was supported.

H7 Investment satisfaction has a significant impact on financial satisfaction

The results revealed that the investment satisfaction of individual investors is positively and significantly associated with their levels of financial satisfaction ($\beta = 0.163$, $t = 2.467$, $p < 0.05$). It indicates that individuals who are highly satisfied with their investment performance also have high levels of financial satisfaction in their lives and vice-versa. Hence, H7 was supported.

Table 5.9.2 Statistical significance of path coefficients

Hypothesis	Path	β -Coefficient	t-value	p-value	Result
H3.1	OC -> PIP	0.241	4.202	0	Supported
H3.2	AVL -> PIP	0.136	2.246	0.025	Supported
H3.3	ANC -> PIP	0.192	2.926	0.003	Supported
H3.4	REP -> PIP	-0.032	0.505	0.614	Not supported
H3.5	MA -> PIP	0.064	1.031	0.303	Not supported
H3.6	LA -> PIP	0.028	0.44	0.66	Not supported
H3.7	REG -> PIP	0.132	1.982	0.048	Supported
H4.1	OC -> IS	0.163	2.591	0.01	Supported
H4.2	AVL -> IS	0.204	3.299	0.001	Supported
H4.3	ANC -> IS	0.16	2.379	0.017	Supported
H4.4	REP -> IS	0.069	0.998	0.318	Not supported
H4.5	MA -> IS	0.154	2.373	0.018	Supported
H4.6	LA -> IS	-0.092	1.309	0.191	Not supported
H4.7	REG -> IS	0.064	0.91	0.363	Not supported
H5.1	OC -> FS	0.088	1.293	0.196	Not supported
H5.2	AVL -> FS	0.220	3.792	<0.05	Supported

H5.3	ANC -> FS	0.22	3.712	0	Supported
H5.4	REP -> FS	-0.015	0.196	0.844	Not supported
H5.5	MA -> FS	0.176	2.921	0.003	Supported
H5.6	LA -> FS	0.034	0.505	0.613	Not supported
H5.7	REG -> FS	0.063	0.92	0.357	Not supported
H6	PIP -> FS	0.129	2.106	0.035	Supported
H7	IS -> FS	0.163	2.467	0.014	Supported

* Significant at 1%, ** significant at 5%

Source: Author's Calculations

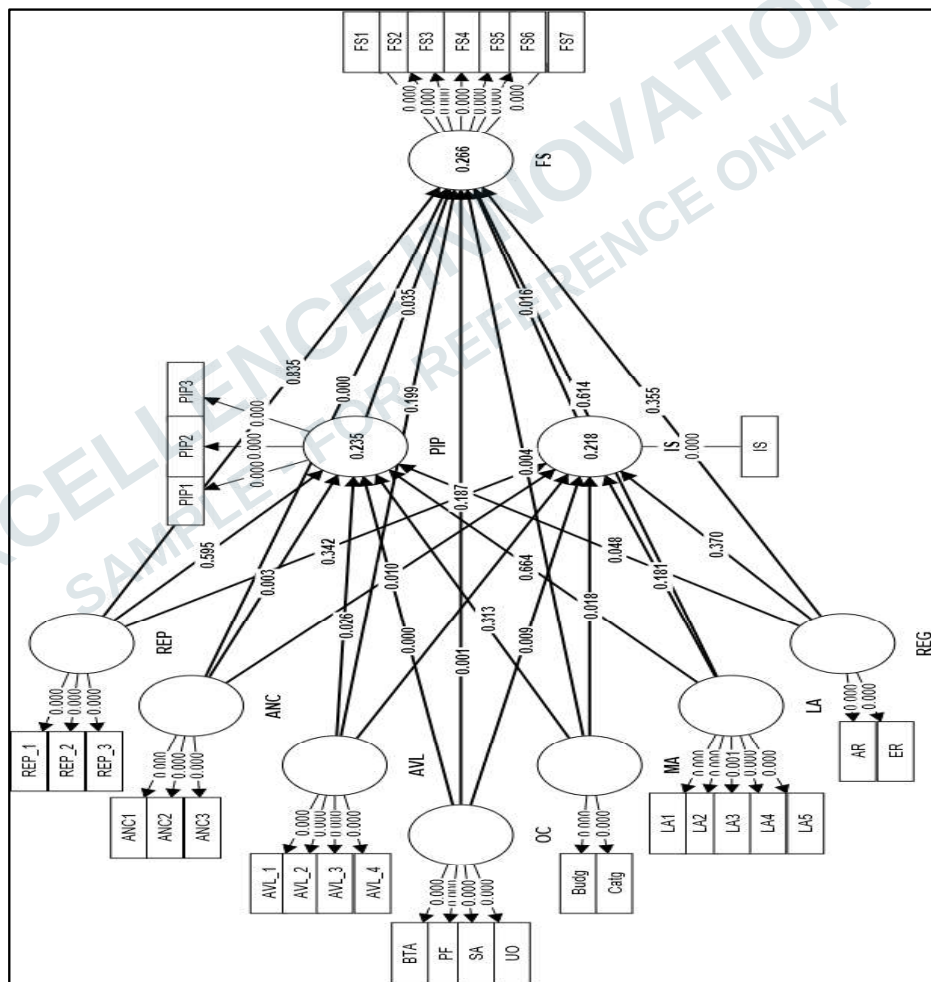


Figure 5.4 Path coefficients

Source: SmartPLS output

5.9.4.1 Mediation Hypothesis

H8: Perceived investment performance mediates the relationship between behavioral biases and financial satisfaction.

H8.1 PIP mediates the relationship between OC and FS

Mediation analysis was performed to assess the mediating role of PIP in the relationship between OC and FS. The results revealed (Table 5.9.3) a significant indirect effect of overconfidence on financial satisfaction through perceived investment performance (H1: $\beta = 0.036$, $t = 2.216$, $p < 0.05$). The total effect of overconfidence on financial satisfaction was significant ($\beta = 0.145$, $t = 2.175$, $p < 0.05$), with the inclusion of the mediator the effect of overconfidence on financial satisfaction becomes insignificant ($\beta = 0.008$, $t = 1.293$, $p = 0.196$). This shows that PIP is fully mediating the relationship between overconfidence on FS. Hence, H8.1 was supported.

H8.2 PIP mediates the relationship between AVL and FS

The effect of availability bias on financial satisfaction through perceived investment performance (table 5.9.3) is found to be insignificant (H8.2: $\beta = 0.018$, $t = 1.405$, $P = 0.160$). Therefore PIP is not mediating the relationship between AVL and FS. Hence H8.2 was not supported

H8.3 PIP mediates the relationship between ANC and FS

The mediation analysis conducted to test the effect of anchoring bias on financial satisfaction through perceived investment performance is found to be insignificant (H8.3: $\beta = 0.018$, $t = 1.405$, $p = 0.160$). Although the total effect of anchoring bias on financial satisfaction is significant ($\beta = 0.27$, $t = 4.627$, $p = 0.000$) and the direct of anchoring bias on financial satisfaction is also significant ($\beta = 0.220$, $t = 3.792$, $p = 0.000$). This suggests that although anchoring bias has a positive and significant impact on the financial satisfaction of individual investors but this effect is not passing through perceived investment performance. Hence H8.3 was not supported (table 5.9.3).

H8.4 PIP mediates the relationship between REP and FS

The impact of representativeness bias on financial satisfaction through perceived investment performance was found to be insignificant (H8.4: $\beta = -0.004$, $t = 0.462$, $P =$

0.644). Therefore PIP is not mediating the relationship between REP and FS. Hence, H8.4 was not supported.

H8.5 PIP mediates the relationship between MA and FS

The impact of mental accounting bias on financial satisfaction through perceived investment performance is found to be insignificant (H8.5: $\beta = 0.008$, $t = 0.922$, $p = 0.356$) but results in table 5.9.3 shows that mental accounting has a direct and significant impact on financial satisfaction in the presence of mediating variables ($\beta = 0.176$, $t = 2.978$, $p = 0.003$), however, this effect is not passing through PIP, therefore PIP is not mediating the relationship between MA and FS. Hence, H8.5 was not supported.

H8.6 PIP mediates the relationship between LA and FS

Perceived investment performance is not mediating the relationship between loss aversion and financial satisfaction as the indirect effect of LA on FS was insignificant and $p\text{-value} > 0.05$ (H8.6: $\beta = 0.004$, $t = 0.462$, $p = 0.701$). Hence, H8.6 was not supported.

H8.7 PIP mediates the relationship between REG and FS

The mediation analysis was conducted to test the mediating role of perceived investment performance between the relationship of regret and financial satisfaction of individual investors the results (table 5.9.3) revealed that PIP doesn't mediate the relationship between REG and FS (H8.7: $\beta = 0.017$, $t = 1.427$, $p = 0.154$). Hence, H8.7 was not supported.

H9: Investment satisfaction mediates the relationship between behavioral biases and the financial satisfaction of individual investors

H9.1 IS mediates the relationship between OC and FS

The impact of overconfidence bias on financial satisfaction through investment satisfaction is found to be significant (H9.1: $\beta = 0.032$, $t = 1.969$, $p < 0.05$). The total effect of overconfidence on financial satisfaction was significant ($\beta = 0.145$, $t = 2.175$, $p < 0.05$), with the inclusion of the mediator the effect of overconfidence on financial satisfaction becomes insignificant ($\beta = 0.106$, $t = 1.541$, $p = 0.123$). This shows that IS

was fully mediating the relationship between overconfidence on FS. Hence, H9.1 was supported.

H9.2 IS mediates the relationship between AVL and FS

Mediation analysis was performed to assess the mediating role of investment satisfaction in the relationship between availability bias and financial satisfaction. The results (table 5.9.3) revealed that availability has an indirect impact on financial satisfaction (H9: $\beta = 0.038$, $t = 2.191$, $P < 0.05$). The total effect of availability bias on financial satisfaction was significant ($\beta = 0.271$, $t = 4.627$, $P < 0.05$), with the inclusion of the mediating variable the effect of availability on financial satisfaction has reduced a bit but it is still significant ($\beta = 0.220$, $t = 3.792$, $P < 0.05$). Therefore investment satisfaction is partially mediating the role between availability bias and financial satisfaction. Hence, H9.2 was supported.

H9.3 IS mediates the relationship between ANC and FS

The impact of anchoring bias on financial satisfaction through investment satisfaction was significant (H9.3: $\beta = 0.045$, $t = 2.119$, $p < 0.05$). The total impact of anchoring bias on financial satisfaction was significant ($\beta = 0.271$, $t = 4.627$, $p < 0.05$) with the inclusion of the mediating variable i.e. investment satisfaction the impact of anchoring on financial satisfaction is still significant ($\beta = 0.220$, $t = 3.792$, $p < 0.05$) which suggest that investment satisfaction is partially mediating the relationship between anchoring and financial satisfaction. Hence, H9.3 was supported.

H9.4 IS mediates the relationship between REP and FS

The impact of representativeness bias on financial satisfaction through investment satisfaction is insignificant (H9.4: $\beta = 0.011$, $t = 0.824$, $p = 0.410$). Therefore investment satisfaction is not mediating the relationship between representativeness and financial satisfaction. Hence, H9.4 was not supported.

H9.5 IS mediates the relationship between MA and FS.

The impact of mental accounting bias on financial satisfaction through investment satisfaction is significant (H9.5: $\beta = 0.035$, $t = 1.989$, $p < 0.05$). The total effect of mental accounting on financial satisfaction is significant ($\beta = 0.209$, $t = 3.632$, $p < 0.05$), and with the inclusion of mediating variable the relationship is still significant ($\beta = 0.176$, t

= 2.978, $P < 0.05$). Therefore investment satisfaction is partially mediating the relationship between mental accounting and financial satisfaction. Hence, H9.5 is not supported.

H9.6 IS mediates the relationship between LA and FS

Investment satisfaction is not mediating the relationship between loss aversion and financial satisfaction as the indirect effect of LA and FS is insignificant as $p\text{-value} > 0.05$ (H9.6: $\beta = -0.015$, $t = 1.120$, $p = 0.263$). Hence, H9.6 was not supported.

H9.7 IS mediates the relationship between REG and FS

The impact of regret on financial satisfaction through investment satisfaction is insignificant (H9.7: $\beta = 0.011$, $t = 0.911$, $p = 0.362$). Thus, IS was not mediating the relationship between LA and FS. Hence, H9.7 was not supported.

Table 5.9.3 Mediation Analysis Results

Relationship	Direct Effect			Indirect effect			Conclusion
	β	t-value	p-value	β	t-value	p-value	
H8.1: OC -> PIP -> FS	0.088	1.293	0.196	0.057	2.216	<0.05	Full mediation
H8.2: AVL -> PIP -> FS	-	1.262	0.207	0.018	1.405	0.160	No mediation
H8.3: ANC -> PIP -> FS	0.16	2.379	<0.05	0.018	1.405	0.160	No mediation
H8.4: REP -> PIP -> FS	-	0.505	0.614	-	0.462	0.644	No mediation
H8.5: REP -> PIP -> FS	0.176	2.978	<0.05	0.008	0.922	0.356	No mediation
H8.6: LA -> PIP -> FS	0.034	0.492	0.623	0.004	0.462	0.701	No Mediation

H8.7: REG -> PIP -> FS	0.063	0.898	0.369	0.017	1.427	0.154	No mediation
H9.1: OC -> IS -> FS	0.106	1.541	0.123	0.032	1.969	<0.05	Full mediation
H9.2: AVL -> IS -> FS	0.220	3.792	<.05	0.033	2.032	<0.05	Partial mediation
H9.3: ANC -> IS -> FS	0.220	3.792	<0.05	0.045	2.119	<0.05	Partial mediation
H9.4: REP -> IS -> FS	0.069	0.989	0.323	0.011	0.824	0.410	No mediation
H9.5: MA -> IS -> FS	0.176	2.978	<0.05	0.034	1.989	<0.05	Partial mediation
H9.6: LA -> IS -> FS	0.034	0.492	0.623	-	1.120	0.263	No mediation
H9.7: REG -> IS > FS	0.064	0.911	0.362	0.011	0.824	0.410	No mediation

* Significant at 1%, ** significant at 5%

Source: Author's Calculations

5.10 Multi-Group Analysis

From the preliminary analysis of the sample characteristics, it is known that data structures are heterogeneous in terms of various socio-demographic variables and investor sophistication measures. In order to capture the effect of this heterogeneity arising from these variables multigroup analysis technique has been used in this section of the study. The categorical variables which influence the relationships in the PLS path model are known as categorical moderator variables. The main objective of the multigroup analysis is to identify the impact of these categorical moderators on the relationships in the PLS path model. Multigroup analysis in the context of PLS-SEM is called PLS-SEM Multigroup Analysis or PLS-MGA. PLS-MGA helps us to assess moderation on all the relationships in the path model simultaneously instead of standard moderation that examines a single relationship at a time. (Hair et al., 2017).

5.10.1 Moderation Effects of Gender Using PLS-MGA

The moderation effects of gender on hypothesized relationships were estimated through the multigroup analysis technique. For this purpose, the sample size was divided into two groups Male (n = 220) and Female (n = 87). The models were estimated for two groups separately and differences in the path coefficients were evaluated and outcomes were assessed using Henseler-MGA nonparametric technique.

Table 5.10.1 shows the specific PLS-SEM results and their differences. The results show that the two segments were distinct. In hypotheses, H3.2 and H3.3, availability and anchoring bias has a positive and significant impact on the perceived investment performance of male investors, but they do not have a significant impact on the PIP of female investors. Similarly, In H3.6, loss aversion has a significant impact on the PIP of female investors but this effect was not significant in the male category of investors. However, these differences are not significant. H3.4 and H3.7 reveal very interesting results that, the impact of representativeness on PIP (H3.4) is negative and significant ($\beta = -0.104$, $P < 0.05$) for male investors and positive for female investors ($\beta = 0.311$, $P < 0.05$) while the impact of regret on PIP is positive and significant for male investors ($\beta = 0.173$, $P < 0.05$) and negative and significant for female investors ($\beta = -0.134$, $P < 0.05$). As far as the impact of behavioral biases on investment satisfaction is concerned, overconfidence and mental accounting have no impact on IS (H4.1 and H4.5) of male investors but it has a positive and significant impact on IS of female investors. Availability and Anchoring have a positive impact on the IS (H4.2 and H4.3) for male investors but these biases are not impacting the IS for female investors. With regard to the impact of behavioral biases on financial satisfaction, mental accounting has no significant impact on the FS (H5.5) of male investors but it has a positive and significant impact on FS ($\beta = 0.386$, $P < 0.05$) for female investors. **Thus Gender is moderating the hypothesized relationships H3.4, H3.7, and H5.5 in the proposed model.** The R^2 values of the two models also substantiate these results. Behavioral biases are explaining a 33.7% variation in PIP for female investors and only 26.6% for male investors. Similarly, a 33.5% variation in IS was explained by behavioral biases for female investors but it was only 20.7% for male investors. The overall impact of behavioral biases, PIP, and IS on FS is 40.1% for females and only 27.2% for male investors.

Table 5.10.1: Moderation effects of Gender

	Male (β)	Female (β)	(Male-Female)	p-value
H3.1: OC -> PIP	0.266**	0.204**	0.062	0.591
H3.2: AVL -> PIP	0.169**	-0.088	0.257	0.092
H3.3: ANC -> PIP	0.179**	0.182	-0.003	0.99
H3.4: REP -> PIP	-0.104**	0.311**	-0.415**	0.005**
H3.5: MA -> PIP	0.069	-0.028	0.097	0.426
H3.6: LA -> PIP	0.019	0.238**	-0.218	0.142
H3.7: REG -> PIP	0.173**	-0.134**	0.307**	0.012**
H4.1: OC -> IS	0.122	0.229**	-0.106	0.424
H4.2: AVL -> IS	0.23**	0.083	0.147	0.285
H4.3: ANC -> IS	0.208**	-0.035	0.243	0.092
H4.4: REP -> IS	0.029	0.21	-0.181	0.227
H4.5: MA -> IS	0.116	0.262**	-0.146	0.281
H4.6: LA -> IS	-0.072	0.145	-0.217	0.19
H4.7: REG -> IS	0.079	-0.074	0.153	0.234
H5.1: OC -> FS	0.071	0.191	-0.12	0.451
H5.2: AVL -> FS	-0.102	-0.072	-0.03	0.865
H5.3: ANC -> FS	0.232**	0.253	-0.02	0.886
H5.4: REP -> FS	0	0.061	-0.061	0.703
H5.5: MA -> FS	0.029	0.386**	-0.360	0.017**
H5.6: LA -> FS	0.048	-0.137	0.185	0.217
H5.7: REG -> FS	0.039	0.122	-0.083	0.519
H6: PIP -> FS	0.156**	0.057	0.099	0.443
H7: IS -> FS	0.184**	0.025	0.159	0.254
R²				
PIP	26.6	33.7		
IS	20.7	33.5		
FS	27.2	40.1		

* Significant at 1%, ** significant at 5%

Source: Prepared by the researcher through Smart-PLS output

5.10.2 Moderation Effects of Marital Status Using PLS-MGA

To estimate the moderating effects of the marital status of respondents on the hypothesized relationships sample is divided into two groups unmarried investors (n = 133) and married investors (n = 174). Table 5.10.2 shows the results of the estimated models for the two groups separately and their differences have been evaluated using Heneseler MGA nonparametric technique. **The results revealed that marital status is only moderating the relationship between regret and the perceived investment performance of individual investors i.e. hypothesis H3.7.** Regret has a positive and significant impact on the PIP ($\beta = 0.295$, $P < 0.05$) of unmarried investors but it has a negative and significant impact on the PIP of married investors ($\beta = -0.026$, $P < 0.05$). With regard to the impact of behavioral biases on investment satisfaction, anchoring and mental accounting have a positive and significant impact on the IS (H4.3 and H4.5) of married investors but these effects are not significant in the case of unmarried investors. Similarly in H5.3 and H5.5, the impact of anchoring and mental accounting is also significant on financial satisfaction in the case of married investors only. In H5.1 overconfidence has a significant impact on FS, for unmarried investors and not for married investors. In terms of R^2 , the total variance in PIP explained by behavioral biases is less for unmarried investors ($R^2 = 21.6$) as compared to married investors ($R^2 = 31.7$). Variation in investment satisfaction explained by behavioral biases is also less for unmarried investors ($R^2 = 21.5$) than married investors ($R^2 = 27.2$). Similarly, variation in financial satisfaction explained by its independent variables is also less for unmarried investors ($R^2 = 26.4$) in comparison to married investors ($R^2 = 30.1$)

Table 5.10.2: Moderation effects of Marital Status

	Unmarried	Married	difference	p value
H3.1: OC -> PIP	0.224**	0.264**	-0.04	0.749
H3.2: AVL -> PIP	0.12	0.134	-0.014	0.915
H3.3: ANC -> PIP	0.11	0.275**	-0.166	0.222
H3.4: REP -> PIP	-0.127	0.075	-0.201	0.126
H3.5: MA -> PIP	0.045	0.064	-0.019	0.881
H3.6: LA -> PIP	0.044	0.034	0.01	0.937
H3.7: REG -> PIP	0.295**	-0.026**	0.321**	0.013**
H4.1: OC -> IS	0.252	0.089	0.163	0.21

H4.2: AVL -> IS	0.241**	0.172**	0.069	0.58
H4.3: ANC -> IS	0.085	0.228**	-0.142	0.291
H4.4: REP -> IS	0.098	0.047	0.051	0.731
H4.5: MA -> IS	0.102	0.181**	-0.079	0.563
H4.6: LA -> IS	-0.042	-0.135	0.093	0.515
H4.7: REG -> IS	-0.005	0.147	-0.152	0.285
H5.1: OC -> FS	0.101**	0.063	0.038	0.804
H5.2: AVL -> FS	-0.025	-0.159	0.133	0.401
H5.3: ANC -> FS	0.166	0.335**	-0.169	0.164
H5.4: REP -> FS	0.006	-0.038	0.043	0.793
H5.5: MA -> FS	0.132	0.232**	-0.1	0.444
H5.6: LA -> FS	0.011	0.022	-0.011	0.938
H5.7: REG -> FS	0.091	0.058	0.033	0.834
H6: PIP -> FS	0.161	0.081	0.08	0.546
H7: IS -> FS	0.197	0.12	0.077	0.585
R²				
PIP	21.6	31.7		
IS	21.5	27.2		
FS	26.4	30.1		

* Significant at 1%, ** significant at 5%

Source: Prepared by the researcher through Smart-PLS output

5.10.3 Moderating effect of Age using PLS-MGA

To assess the moderating effects of respondents' age on the hypothesized relationships, again the sample is split into two age categories young investors who are below 30 years of age (n = 132) and mature investors who are above 30 years of age. (n = 175).

Results presented in table 5.10.3 revealed that age is only moderating the relationship between regret and perceived investment performance of individual investors i.e. hypothesis H3.7. Regret has a positive and significant impact on the perceived investment performance of young investors ($\beta = 0.259$, $p < 0.05$), while it has a negative and significant impact on the perceived investment performance of mature investors who are above 30 years of age ($\beta = -0.031$, $p < 0.05$). In hypothesis H3.1 overconfidence has a stronger impact on the PIP of mature investors as compared

to young investors. Similarly in H5.3 anchoring has a stronger impact on the FS of young investors as compared to mature investors, but H3.1 and H5.3 are insignificant as $p\text{-value} > 0.05$. In contrast to mature investors, young investors' IS is significantly impacted by overconfidence and availability (H4.1 and H4.2). In H4.3 and H4.5 the impact of anchoring and mental accounting on investment satisfaction is significant for mature investors but not for young investors. Similarly, with regard to the impact of behavioral biases on FS, the impact of mental accounting and IS is also significant for mature investors but not for young investors (H5.5 and H7). However, all these differences are insignificant as $p\text{-values}$ in all the cases are greater than 0.05.

Table 5.10.3 Moderation effects of Age

	Below 30	Above 30	Below 30 - Above 30	p-value
H3.1: OC -> PIP	0.199**	0.309**	-0.11	0.359
H3.2: AVL -> PIP	0.135	0.137	-0.001	0.981
H3.3: ANC -> PIP	0.077	0.3**	-0.222	0.097
H3.4: REP -> PIP	-0.041	0.001	-0.042	0.736
H3.5: MA -> PIP	0.058	0.079	-0.021	0.89
H3.6: LA -> PIP	0.029	0.011	0.019	0.907
H3.7: REG -> PIP	0.259**	-0.031**	0.29**	0.027**
H4.1: OC -> IS	0.212**	0.131	0.081	0.52
H4.2: AVL -> IS	0.229**	0.146	0.083	0.508
H4.3: ANC -> IS	0.072	0.243**	-0.171	0.221
H4.4: REP -> IS	0.136	0	0.136	0.321
H4.5: MA -> IS	0.098	0.206**	-0.109	0.41
H4.6: LA -> IS	0.007	-0.17	0.177	0.259
H4.7: REG -> IS	-0.013	0.138	-0.151	0.309
H5.1: OC -> FS	0.004	0.138	-0.134	0.361
H5.2: AVL -> FS	-0.133	-0.025	-0.107	0.454
H5.3: ANC -> FS	0.237**	0.221**	0.017	0.895
H5.4: REP -> FS	0.042	-0.028	0.07	0.648
H5.5: MA -> FS	0.108	0.266**	-0.159	0.205
H5.6: LA -> FS	0.013	0.025	-0.013	0.921
H5.7: REG -> FS	0.074	0.022	0.052	0.708

H6: PIP -> FS	0.141	0.09	0.051	0.688
H7: IS -> FS	0.149	0.196**	-0.047	0.741

* Significant at 1%, ** significant at 5%

Source: Prepared by the researcher through Smart-PLS output

5.10.4 Moderating effects of Income using PLS-MGA

To assess the moderating impact of income on the hypothesized relationships, respondents are divided into three categories: those earning less than 5 lakh rupees per year, those earning between 5 lakh and 10 lakh, and those earning more than 10 lakh rupees. Results from table 5.10.4 suggest that Income does not moderate any of the relationships in the structural model. However, some inferences can still be drawn from the data. In H3.1 Overconfidence has a strong positive impact on the PIP of investors earning between 5 to 10 lakh rupees as compared to investors earning less than 5 lakh. Anchoring has a significant impact on the PIP of the higher-income group (H3.2) investors as compared to lower-income group investors. Similarly, in H5.5 and H7 mental accounting and investment satisfaction has a significant impact on financial satisfaction only for investors earning between 5 to 10 lakhs. However, these differences are not significant. Additionally in H3.7 impact of regret on PIP is significant only for investors earning less than 5 lakh and not for the other category, in H4.2 and H4.3 impact of availability and anchoring on investment satisfaction is also significant only for the lower-income category investors, however, these difference are not significant to conclude anything conclusive from the empirical results.

Table 5.10.4 Moderation effects of Income

	Below 5 lakh	5 to 10 lakhs	5-10 - below 5	p-value
H3.1: OC -> PIP	0.194**	0.306**	0.111	0.444
H3.2: AVL -> PIP	0.198**	0.18	-0.018	0.949
H3.3: ANC -> PIP	0.145	0.225**	0.081	0.599
H3.4: REP -> PIP	0.035	-0.065	-0.1	0.505
H3.5: MA -> PIP	-0.002	0.056	0.058	0.701
H3.6: LA -> PIP	0.082	-0.095	-0.177	0.238
H3.7: REG -> PIP	0.205**	0.163	-0.042	0.768
H4.1: OC -> IS	0.191**	0.315**	0.124	0.423

H4.2: AVL -> IS	0.266**	0.183	-0.083	0.568
H4.3: ANC -> IS	0.211**	0.097	-0.114	0.475
H4.4: REP -> IS	0.086	0.047	-0.039	0.815
H4.5: MA -> IS	0.131	0.107	-0.024	0.871
H4.6: LA -> IS	-0.071	-0.092	-0.02	0.919
H4.7: REG -> IS	-0.049	0.045	0.094	0.553
H5.1: OC -> FS	0.057	0.085	0.028	0.873
H5.2: AVL -> FS	-0.062	-0.033	0.029	0.865
H5.3: ANC -> FS	0.274**	0.084	-0.19	0.176
H5.4: REP -> FS	0.089	-0.078	-0.167	0.325
H5.5: MA -> FS	0.088	0.262**	0.175	0.258
H5.6: LA -> FS	0.107	-0.093	-0.2	0.245
H5.7: REG -> FS	0.023	0.111	0.088	0.592
H6: PIP -> FS	0.128	0.179	0.05	0.714
H7: IS -> FS	0.075	0.241**	0.165	0.294

* Significant at 1%, ** significant at 5%

Source: Prepared by the researcher through Smart-PLS output

5.10.5 Moderating effects of Investment experience using PLS-MGA

To estimate the moderating effects of investment experience on hypothesized relationships respondents are divided into two categories those who have investment experience of fewer than 5 years are termed as less experienced investors and those who have investment experience of more than 5 years are termed as more experienced investors. The sample consists of 194 less experienced investors and 113 more experienced investors. The results of the estimated models for the two groups are shown individually in Table 5.10.4, and the Heneseler MGA nonparametric technique has been used to assess the differences between the groups. The results show that investment experience is moderating the relationships between overconfidence and investment satisfaction (H4.1). Overconfidence has a positive impact on the IS of more experienced investors while it has a negative impact on the IS of less experienced investors.

Table 5.10.5 Moderation effects of Investment Experience

	Less Exp.	More Exp.	Less Exp. - More Exp.	p-value
H3.1: OC -> PIP	0.074	0.041	-0.063	0.584
H3.2: AVL -> PIP	0.185	0.214	0.049	0.743
H3.3: ANC -> PIP	0.257	-0.011	0.179	0.219
H3.4: REP -> PIP	-0.097	-0.019	-0.031	0.807
H3.5: MA -> PIP	0.085	0.201	0.081	0.525
H3.6: LA -> PIP	0.121	0.128	-0.054	0.715
H3.7: REG -> PIP	0	0.189	-0.116	0.374
H4.1: OC -> IS	-0.082	0.218	-0.269**	0.046**
H4.2: AVL -> IS	0.196	0.215	0.093	0.479
H4.3: ANC -> IS	0.263	0.17	-0.02	0.786
H4.4: REP -> IS	-0.082	-0.074	0.033	0.824
H4.5: MA -> IS	0.094	0.098	-0.006	0.974
H4.6: LA -> IS	0.157	0.171	-0.009	0.956
H4.7: REG -> IS	0.002	0.056	-0.189	0.181
H5.1: OC -> FS	0.084	0.004	-0.086	0.603
H5.2: AVL -> FS	0.215	0.278	-0.078	0.632
H5.3: ANC -> FS	0.281	0.102	-0.03	0.805
H5.4: REP -> FS	-0.042	-0.012	0.3	0.051
H5.5: MA -> FS	0.114	0.23	-0.015	0.935
H5.6: LA -> FS	0.176	0.02	0.129	0.383
H5.7: REG -> FS	0.067	0.153	-0.004	0.96
H6: PIP -> FS	0.071	-0.058	0.156	0.315
H7: IS -> FS	0.177	0.128	-0.115	0.394

* Significant at 1%, ** significant at 5%

Source: Prepared by the researcher through Smart-PLS output

5.10.6 Moderating effects of Trading Frequency using PLS-MGA

To assess the moderating impact of trading frequency on the hypothesized relationships, respondents are grouped into active and passive investors based on how frequently they trade in stock markets. Investors who trade their stocks multiple times within a year are categorized as active investors (n = 257) and investors who prefer to

hold their stocks for longer than one year are categorized as passive investors (n = 50). The results of the multi-group analysis presented in table 5.10.6 show that trading frequency has a moderating impact on the relationship between mental accounting and investment satisfaction (H4.5). Mental accounting has a stronger positive impact on the investment satisfaction of passive investors when compared with active investors.

Table 5.10.6 Moderating Effects of Trading Frequency

	Active	Passive	Active - Passive	p-value
H3.1: OC -> PIP	0.221	0.214	0.008	0.97
H3.2: AVL -> PIP	0.179	-0.102	0.281	0.099
H3.3: ANC -> PIP	0.237	-0.041	0.278	0.185
H3.4: REP -> PIP	-0.044	0.372	-0.416	0.348
H3.5: MA -> PIP	0.036	0.059	-0.023	0.896
H3.6: LA -> PIP	0.033	0.246	-0.214	0.287
H3.7: REG -> PIP	0.105	0.199	-0.094	0.5
H4.1: OC -> IS	0.157	0.199	-0.043	0.803
H4.2: AVL -> IS	0.242	0.206	0.036	0.924
H4.3: ANC -> IS	0.208	-0.241	0.449	0.104
H4.4: REP -> IS	0.05	0.077	-0.027	0.861
H4.5: MA -> IS	0.098	0.438	-0.34**	0.042**
H4.6: LA -> IS	-0.044	-0.182	0.138	0.543
H4.7: REG -> IS	0.043	0.036	0.007	0.976
H5.1: OC -> FS	0.063	0.156	-0.093	0.557
H5.2: AVL -> FS	-0.062	-0.157	0.095	0.636
H5.3: ANC -> FS	0.232	0.244	-0.012	0.886
H5.4: REP -> FS	0.019	0.137	-0.118	0.74
H5.5: MA -> FS	0.186	-0.01	0.196	0.26
H5.6: LA -> FS	0.009	0.121	-0.112	0.615
H5.7: REG -> FS	0.105	-0.183	0.288	0.127
H6: PIP -> FS	0.117	0.11	0.007	0.914
H7: IS -> FS	0.12	0.434	-0.314	0.088

* Significant at 1%, ** significant at 5%

Source: Prepared by the researcher through Smart-PLS output

CHAPTER 6

FINDINGS AND CONCLUSION

The present chapter summarizes the major findings of the study on behavioral biases and their impact on individual investors in the Delhi-NCR region. The answers to all of the research objectives formulated in the first chapter have been incorporated into this chapter. The chapter discusses the major findings and draws conclusions from them. In addition, the chapter discussed the study's practical and theoretical contributions, as well as its limitations and the scope for future research.

6.1 Sample Composition of respondents

According to the demographic profile of investors, married men with postgraduate degrees who are predominantly employed in private service make up the bulk of respondents. The average age of the respondent is 33 years, earning an annual income between 2.5 lakh rupees to 5 lakh rupees. The gender gap in the number of respondents participating in the survey can be attributed to the patriarchal nature of Indian society where male members of the households still have the exclusive power to make financial decisions (Baker et al., 2018). Also, the average annual income of the respondents is higher than the national average annual income of approximately 1.50 lakh rupees for the FY 2022 (Ohri, 2022). Sophistication measures of the investors revealed that the majority of the respondents have an investment experience of around 2-5 years in stock markets with an investment amount ranging from 1 lakh to 5 lakh rupees diversified across 2 to 5 firms, which they normally trade within a period of three months.

6.2 Impact levels of Behavioral Biases

Representativeness is the most common behavioral bias, with the highest mean, influencing the investment decisions of Delhi-NCR investors. Then comes overconfidence, loss aversion, and anchoring. These findings are consistent with those of Chandra and Kumar (2012), who found that representativeness was the most impactful on individual investors in India, followed by overconfidence, anchoring, and gambler's fallacy. The present study also found that the mean values of mental accounting, regret, and availability are lower when compared to other biases, this indicates that these factors are less dominant in the investment decisions of Delhi-NCR investors.

6.3 Demographics and Behavioral Biases (Objective 1)

6.3.1 Gender and Behavioral biases

The results of the t-test indicate that males are more overconfident than female investors in the Delhi-NCR region these results are consistent with the studies of Barber and Odean, (2001), Bhandari and Deaves (2006), Bakar and Yi (2015), and Kumar and Goyal (2016). With respect to gender, results of the study also revealed that females are more loss averse and more prone to mental accounting bias than male investors in the Delhi-NCR region which are in accordance with the findings of Bajtelsmit and Bernasek (1996), Arora and Kumari (2015), and Prasad and Mohta, (2012).

6.3.2 Age and Behavioral Biases

According to the findings of ANOVA and Welch's F, elder investors over 40 years of age are more likely than younger investors under 40 years to exhibit overconfidence, representativeness, and mental accounting. This age-related increase in the levels of behavioral biases can be attributed to the declining cognitive abilities of investors as they grow old (Bruine de Bruin et al., 2012). Additionally, it gets more difficult and expensive as investors age to keep up with the rapidly evolving financial products and investment prospects, especially when they are faced with cognitively demanding tasks (Pak & Chatterjee, 2016; Korniotis & Kumar, 2011). In the Indian context Baker et al. (2018), and Prasad et al. (2014) also found significant associations between age and behavioral biases.

6.3.3 Education and Behavioral Biases

Among the behavioral biases overconfidence and anchoring are found to have strong associations with the education of investors. Graduate investors are more prone to overconfidence and anchoring bias than postgraduate investors. This suggests that overconfidence and anchoring decrease with higher education. These findings are in line with the findings of Novokmet and Zalic (2017) and Beblo et al. (2017) which concluded that learning and education help in mitigating overconfidence and anchoring respectively. However, these are in contradiction with the findings of Bhandari and Deaves (2006), Deaves et al. (2010), Mishra and Metilda (2015), and Baker et al. (2018) which shows that overconfidence increases with the level of education among investors.

6.3.4 Occupation and Behavioral Biases

Results of ANOVA and Welch's F indicate that depending upon the type of occupation, investors tend to exhibit different levels of overconfidence in financial decision-making. Self-employed investors who are mostly entrepreneurs and professionals are more overconfident than investors who are still pursuing higher education and working in the government or private sector. This may be because entrepreneurs are risk-takers, they have more positive beliefs about the future success of their business which makes them more optimistic and consequently more overconfident compared to other categories of investors. These findings are consistent with the findings of Rietveld et al. (2013) and Joo and Durri (2017) which showed that self-employed individuals are more overconfident than individuals who are in service. In India Mushinada and Veluri (2019), Baker et al. (2018), and Prosad et al. (2014) concluded that overconfidence is significantly associated with the occupation of respondents.

6.3.5 Income and Behavioral Biases

ANOVA test results revealed that investors belonging to various income categories differed in terms of overconfidence, mental accounting, and loss aversion bias. Overconfidence and mental accounting are higher in higher-income groups and lower in lower-income groups, whereas, loss aversion is higher in investors belonging to lower-income groups and lower in investors belonging to higher-income groups. These findings are consistent with the findings of Chandra (2009), Lin (2011), Chandra and Kumar (2012), Isidore and Christie (2018), Kansal and Singh (2018), and Baker et al. (2018) which showed that investors with high-income categories are competent and trade more frequently in the stock market which makes them more overconfident and increases their mental accounting bias as compared to investors in the lower income categories. Concerning loss aversion, investors in lower-income groups are more loss averse perhaps because they do not want to risk their already meager income, whereas investors in higher-income groups are less loss averse because they have the extra room to take more risk.

6.4 Investor Sophistication and Behavioral Biases (Objective 1)

6.4.1 Investment Experience and Behavioral Biases

The results of Welch's F revealed that overconfidence is increasing with the investment experience of investors of Delhi-NCR. Overconfidence levels in experienced investors (with more than ten years of experience) are significantly higher than in novice investors. These findings are in line with the findings of Oberlechner and Osler (2009), Chen et al. (2007), and Kansal and Singh (2018). This finding could be explained by the fact that increased investment experience increases a person's ability to spot more profitable opportunities, creating an illusion of success and resulting in higher levels of overconfidence bias in investors with more investment experience.

6.4.2 Trading Frequency and Behavioral Biases

The empirical findings suggest that trading frequency is positively related to the availability bias of investors in the Delhi-NCR region. The more frequently a person makes purchase and sale decisions, the more susceptible he is to availability bias. Intraday traders have the highest availability bias, while long-term investors have the lowest. This could be because intraday traders are less cautious than investors who trade less frequently. They rely on readily available information to make quick decisions and discussing their trading decisions with friends, family, and colleagues relieves them of psychological stress (Prosad et al., 2014). Mental accounting has been found to have a negative relationship with trading frequency. Mental accounting levels are higher in investors who trade less frequently and lower in investors who trade more frequently. This can be explained by the fact that since intraday traders are more casual in their decision-making as it is a routine job for them thus they do less mental accounting than traders who are more cautious in their investment decisions and invest less frequently.

6.4.3 Number of Stocks in Portfolio and Behavioral Biases

The number of stocks in an investor's stock portfolio has been found to have a positive relationship with investors' regret aversion bias. The more stocks in a portfolio, the more a person regrets his mistakes and, as a result, becomes more regret averse. This could be because as the number of stocks in an investor's portfolio grows, so does the amount at stake, making a person more cautious and risk-averse, and thus more regret-averse.

6.5 Behavioral Biases and Perceived Investment Performance (Objective 2)

6.5.1 Overconfidence and Perceived Investment performance

Overconfidence has a positive and significant impact on the perceived investment performance of individual investors. This observation may be due to the fact that overconfident investors trade more aggressively than their rational counterparts' do, which enables them to better take advantage of risky profit opportunities and generate higher returns (Hirshleifer & Luo, 2001). Similar findings were made by Javed et al. (2017), ul Abdin et al. (2017), and Le Luong and Thi Thu Ha (2011), who found that overconfidence has a significant and positive impact on the perceived investment performance of individual investors. Additionally, Oberlechner and Osler (2008) noted that the overconfidence-induced illusion of success boosts investors' self-esteem and keeps them motivated to continue in the market. Research by De Long et al. (1991) also supported the idea that overconfident investors hold riskier investments and hence earn larger returns than other investors. These results, however, are at odds with those of Odean (1999), Barber and Odean (2000), and Ahamd and Shah (2020), who demonstrated that overconfidence lowers individual investors' investing performance and returns.

6.5.2 Availability and Perceived Investment Performance

Availability has a positive and significant impact on the perceived investment performance of individual investors. This suggests that availability bias helps investors to take better financial decisions and thus contributes to better investment performance. These findings are consistent with the findings of Javed et al. (2017), Alrabadi et al. (2018), ul Abdin et al. (2017), and Khan (2015). However, most of the research studies by Keller et al. (2006), Clark (2014), Hadi (2017), Tversky and Kahneman (1974), and Massa and Simonov (2005) suggested that the availability heuristic causes decision-makers to limit their investment opportunities, which prevents them from diversifying their investment portfolio, selecting investments based on retrievability rather than a thorough analysis of the options, allocating assets appropriately, and selecting alternative investments when appropriate.

6.5.3 Anchoring and Perceived Investment Performance

Anchoring has a positive and significant impact on the perceived investment performance of individual investors. These findings are consistent with the findings of Aziz and Khan (2016), Ishfaq and Anjum (2015), Menike et al. (2015), Ranjbar et al. (2014), Obara (2015), and Malik et al. (2022).

6.5.4 Regret and Perceived Investment Performance

Regret has a positive and significant impact on the perceived investment performance of individual investors. In the opinion of the researcher regret averse investors use feedback from other participants to avoid risks so as not to regret later in case of anticipated regret and in case of experienced regret, the pain of regret leads to subsequent changes in asset allocation, as a result, they tend to buy assets that performed well in the past and sell those that perform poorly. Thus, disciplined investing by regret-averse investors helps them to improve their investment performance. The results are consistent with the findings of Aziz and Khan (2016) and Zouaoui and Bellouma (2018) who also found a positive impact of regret on the investment performance of investors in Pakistan and Tunisia. Cao et al. (2021) also showed that prospect theory variables including regret have a favorable impact on investment results. Dodonova and Khoroshilov (2005) showed that regret-averse investors may be able to earn positive stock returns in the short-run and negative stock returns in the long run. However, the result is in contrast to that of Le Luong and Thi Thu Ha (2011), Silwal and Bajracharya (2021), and Kengatharan and Kengatharan (2014), who found that regret had a detrimental effect on investment performance. In order to minimize regret, investors increase their awareness and consideration, invest in more secure and creditworthy assets, and make wiser decisions (Bailey and Kinerson, 2005; Copur, 2015, p. 153).

6.6 Behavioral Biases and Investment Satisfaction (Objective 3)

6.6.1 Overconfidence and Investment satisfaction

The results of the study suggest that overconfidence has a significant and positive effect on the satisfaction of investors from their investment performance. As per the opinion of the researcher the possible reason for this finding is that overconfidence is a bias reflected through excessive optimism and the excessive illusion of success. People who

are overconfident typically have high expectations for their own abilities and efforts. When an investor has confidence in their ability to make wise financial decisions, they are more likely to select solutions that will help them reach their investment goals and increase their level of investment satisfaction. Chen and Koufaris (2014) took satisfaction as the decision-making process's primary end result and found that overconfident participants also demonstrated higher levels of satisfaction.

6.6.2 Availability and Investment satisfaction

The availability bias has a positive and significant impact on the levels of investment satisfaction of investors in India's NCR region. The findings are consistent with those of Pandey and Jessica (2019) and Gavrilakis and Floros (2021), who found that heuristics such as availability have a positive effect on investment satisfaction in the real estate sector in India and Private Investors in Greece, respectively. According to these studies, biases are not always harmful; they occasionally enable individual investors to select the best course of action from a wide range of options and enable them to make less costly errors, aiding in the development of satisfying behavior.

6.6.3 Anchoring and Investment satisfaction

Anchoring has a positive and significant impact on the investment satisfaction of individual investors of Delhi-NCR. Again the outcomes support Pandey and Jessica's (2019), and Gavrilakis and Floros's (2021) observation that heuristics such as anchoring have a beneficial impact on the investment satisfaction of investors in India as well as in Greece.

6.6.4 Mental accounting and investment satisfaction

Mental accounting has a positive and significant impact on individual investors of Delhi-NCR. The researcher believes that this is the case because with mental accounting the investors are in a better position to keep a track of their investment in different financial assets and can exercise greater self-control while maintaining risky portfolios. Investors divide their investments into distinct mental accounts, and investment decisions are made to satisfy each of these distinct mental accounts. (Zahera & Bansal, 2018)

6.7 Behavioral Biases and Financial Satisfaction (Objective 4)

6.7.1 Availability and Financial Satisfaction

Availability has a significant positive impact on the financial satisfaction of individual investors of Delhi-NCR. The majority of private investors aren't expert stock traders, and they don't live off of stock market profits; rather, stocks comprise a small portion of their overall investment portfolio, which could be one explanation for this conclusion. Because of this, it is impossible for them to consider all of the information available in the market when making financial decisions; instead, they rely on information that is readily available to them and use the availability heuristic inadvertently. This not only saves them time and energy due to the complex information integration, but it can also produce better results than sophisticated financial models (Gigerenzer, 2008). Hence, when investors achieve desired outcomes with less time-consuming tasks and fact-checking, their overall financial satisfaction increases. Further, this saved time and energy by making efficient use of available information that could be devoted to solving other meaningful purposes in life leading to better life satisfaction.

6.7.2 Anchoring and Financial Satisfaction

Anchoring has a positive and significant impact on the financial satisfaction of individual investors of Delhi-NCR. This finding may be explained by the fact that anchoring aids investors in choosing the best possible action among multiple alternative actions available within a quick time frame. Without anchoring bias, decision-making will be delayed since investors won't have any easily available "benchmarks" or "anchors" on which they can base their decisions. As we all know, the stock market is a place where investors must make quick decisions regarding numerous investment possibilities and methods. Decision-makers can use previously defined anchors, in this case, to quickly and profitably take advantage of lucrative chances, which will increase their earnings and financial satisfaction.

6.6.3 Mental accounting and Financial Satisfaction

Mental accounting has a positive and significant impact on the financial satisfaction of individual investors residing in Delhi-NCR. The researcher believes that this may be the case because mental accounting involves the task of categorization of money into different categories according to the sources and uses of funds. This provides them with maximum information with minimum effort when needed, and helps investors to fulfill their financial objectives which also improves their financial satisfaction. The task of budgeting in mental accounting helps investors to keep a track of their spending in different categories belonging to life's needs, thus mental accounting gives them mental satisfaction when they have sufficient budget in each mental account, which helps them to improve their overall financial satisfaction (Sahi, 2017; Mogilner, 2008)

6.8 Mediation Effect of Perceived Investment Performance and Investment Satisfaction (Objective 5)

6.8.1 Perceived investment performance fully mediates the relationship between overconfidence and financial satisfaction. This indicates that overconfidence has a significant impact on PIP, which in turn has a significant impact on the financial satisfaction levels of individual investors. This may be because overconfident investors are more optimistic and trade more aggressively than rational investors which leads to higher investment performance and higher investment performance implies greater income for investors that increases their overall solvency and helps in satisfying all their life's needs leading to higher financial satisfaction among individual investors of Delhi-NCR. Vera-Toscano et al. (2006) and Seghieri et al. (2006) in their respective studies have established the role of higher income in achieving higher levels of financial satisfaction.

6.8.2 Investment satisfaction fully mediates the relationship between overconfidence and financial satisfaction. According to the researcher, this may be the result of overconfidence having a favorable impact on individual investors' satisfaction with their investments because overconfident investors believe they are better than others at making sound financial decisions, increasing the likelihood of their financial independence (Hu et al., 2021) and, as a result, their overall financial satisfaction.

6.8.3 Investment satisfaction partially mediates the relationship between availability and financial satisfaction. The positive mediating effect of investment satisfaction between availability bias and financial satisfaction can be explained using evolutionary psychology. The availability heuristic is a natural tendency that emerges as a result of humans' limited capacity to access all types of information. As a result, humans act decisively on easily accessible information which contributes to their investment satisfaction which in turn, contributes to their financial satisfaction.

6.8.4 Investment satisfaction partially mediates the relationship between anchoring and financial satisfaction. Again, from the standpoint of evolutionary psychology, anchoring can be seen as innate human characteristics that cause decision-makers to act quickly on the basis of already available anchors learned from previous behaviors, thereby assisting investors in financial markets to have better investment satisfaction and, as a result, better financial satisfaction.

6.8.4 Investment satisfaction partially mediates the relationship between mental accounting and financial satisfaction. According to the researcher, this finding results from mental accounting acting as a self-controlling mechanism, economizing the investor's thinking and assisting them in keeping better track of their investments, thus contributing to investment satisfaction and, ultimately, financial satisfaction of investors.

Thus, perceived investment performance and investment satisfaction serve as mediators between behavioral biases and financial satisfaction among Delhi-NCR investors. These mediators are more than just transmitters of behavioral biases' influence; they are the foundation of the stability of the relationship between behavioral biases and financial satisfaction.

6.9 Moderating effects of the Demographic and Investor Sophistication Variables on Hypothesized Relationships (Objective 6)

6.9.1 Impact of gender on hypothesized relationships

The results of the multi-group analysis suggest that gender has a moderating effect on the relationships between representativeness and PIP, regret and PIP, and mental

accounting and FS. Regret has a positive impact on the PIP of male investors, while it has a negative impact on the PIP of female investors. According to Villanueva-Moya and Expósito (2022), after experiencing regret, women internalize a greater fear of negative evaluation than men, because women's decisions are usually directed by others, whereas men make self-oriented decisions, lowering women's overall well-being. This fact may have had a negative impact on women investors' perceived investment performance. Mental accounting has no significant impact on the FS of male investors, but it has a strong positive impact on the FS of Female investors. This finding has resulted because female investors are more prone to mental accounting than male investors, since males do less mental accounting it has no impact on the levels of their financial satisfaction, and women being more susceptible to mental accounting has a strong impact on the levels of their financial satisfaction.

6.9.2 Impact of marital status on hypothesized relationships

The results revealed that the marital status of the respondents has a significant impact on the relationship between regret and PIP. Regret has a positive impact on the PIP of unmarried investors while it has a negative impact on the PIP of married investors. This finding could be explained by the fact that married investors are typically risk averse; they cannot afford to take on the additional financial risk because they have a family to care for. If they experience regret, married investors may withdraw from risky securities and prefer to invest in low-risk assets, which typically have lower returns than risky assets. Unmarried investors, on the other hand, can take additional risks to earn superior returns, which may have a positive impact on unmarried investors' perceived investment performance.

6.9.3 Impact of age on hypothesized relationships

To identify the moderation effects of age on hypothesized relationships, investors are divided into two age groups below 30 years of age and above 30 years of age. The results of the multi-group analysis show that age does not have a significant impact on hypothesized relationships except for the relationship between regret and PIP. Regret has a positive impact on the PIP for investors who are below 30 years of age, but it has a negative impact on investors who are above 30 years of age. Again, the findings show that young investors are adventurous and risk-takers, so when they experience regret, they do not back down and continue to invest in profitable opportunities, which may

result in regret having a positive impact on the PIP of young investors, whereas mature investors have a low-risk appetite, so when they experience regret, they become more cautious and refrain from investing in risky yet profitable opportunities, which results in a negative impact on the PIP of mature investors.

6.9.4 Impact of income on hypothesized relationships

The results of the multi-group analysis revealed that income does not have moderating effect on any of the hypothesized relationships in the proposed model.

6.9.5 Impact of investment experience on hypothesized relationships

Investment experience moderates the relationship between overconfidence and investment satisfaction. Overconfidence positively affects the IS of more experienced investors, while it has a negative effect on the IS of less experienced investors. This could be because more experienced investors are more overconfident, so they trade more aggressively and feel a sense of accomplishment in their trades, which keeps them satisfied with their investment performance. Less experienced investors, on the other hand, are less overconfident, and as a result, they may not be in a position to take advantage of profitable opportunities in time, resulting in lower-than-expected returns and thus remaining dissatisfied with their investment performance.

6.9.6 Impact of trading frequency on hypothesized relationships

Trading frequency is moderating the relationship between mental accounting and investment satisfaction. Based on trading frequency investors are categorized into active and passive investors. Mental accounting has a stronger impact on the investment satisfaction of passive investors as compared to active investors. This finding is due to the fact that passive investors are more prone to mental accounting because they trade less frequently, are more cautious in their investment decisions, and do a lot of mental accounting, which may have resulted in mental accounting positively influencing investment satisfaction. Active investors, on the other hand, trade so frequently that they do not spend time thinking about their trades and are less prone to mental accounting; thus, the impact of mental accounting on investment satisfaction is weaker for active investors than for passive investors.

6.10 Conclusion

The study provided a thorough and in-depth examination of the behavioral biases of Indian individual investors. An integrated research model developed for the study is used to investigate the factors (socio-demographic and investor sophistication variables) that influence these behavioral biases as well as those that are affected by these behavioral biases in terms of performance and satisfaction variables. Thus, the current study attempted to provide a comprehensive view of the underlying mechanisms of behavioral biases and their consequences in the Indian context.

The changing environment of Indian financial markets, evolving financial market instruments, and the vulnerability of Indian financial consumers all contributed to the need for this research. The study focused on research areas that had been largely ignored by previous research studies in the existing literature, and as a result, it attempted to add to the existing behavioral finance literature in a limited manner. Since India is a country with people from diverse social, cultural, and economical backgrounds the finding of the present study becomes more relevant and applicable. The study analysed data in two phases. First, it measured the impact of different socio-demographics and sophistication variables on behavioral biases and then in the second phase, it analysed the impact of behavioral biases on the financial well-being of individual investors.

The present study captured the current state of behavioral biases of Indian investors. The research examined the presence of behavioral biases using a sample of individual investors in Delhi-NCR. According to the survey findings, Indian investors exhibit a variety of behavioral biases, including overconfidence, representativeness, loss aversion, anchoring, mental accounting, regret, and availability. Therefore, the study's results are consistent with the idea that individual investors do not always make rational decisions. Instead, making financial decisions is influenced by emotions, heuristics, and other biases. It has been observed that behavioral biases are influenced by various demographic and investor sophistication variables. The study's findings show that gender, age, education, occupation, and income are the most important demographic variables influencing individual investors' behavioral biases. In terms of gender, the findings show that males appear to be more overconfident in their stock market knowledge than females, and females are more sensitive to losses than male investors. Moreover, older investors are more likely to exhibit overconfidence,

representativeness, and mental accounting than younger investors. An important finding of the study is that higher education reduces the chances of investors being biased in their decisions, and postgraduate investors are less likely to be overconfident and anchored in their financial decisions. Self-employed persons appear to be more overconfident than salaried-class investors. With regard to the income of the respondents, evidence suggests that higher-income group people are more prone to overconfidence and mental accounting, and lower-income group people are more inclined towards loss aversion. Another interesting observation is that investor sophistication variables such as investment experience, trading frequency, and the number of stocks in the portfolio also influence the degree of behavioral biases exhibited by Indian individual investors. Investment experience contributes to the overconfidence bias, whereas trading frequency increases availability bias among investors and the number of stocks in the portfolio influences the degree of regret aversion displayed by a person. Overall, the evidence confirms that individual investors in India are susceptible to different behavioral biases and demographic and investor sophistication variables are related to these biases.

The present study also extends the current knowledge base about the relationships between behavioral biases, perceived investment performance, investment satisfaction, and financial satisfaction. Overconfidence availability, anchoring, and regret are found to have a positive and significant impact on the perceived investment performance of individual investors. Further, heuristics and mental accounting bias have a significant and positive impact on the investment satisfaction and financial satisfaction of individual investors in Delhi-NCR. Moreover, it is also found that the effect of behavioral biases on financial satisfaction is passing through investment performance and investment satisfaction, i.e. these two variables are playing the role of significant mediators in the relationship between behavioral biases and financial satisfaction which is one of the most important findings of the present research.

Overall the study concludes that psychological biases should not always be considered as risk factors because sometimes they have a flip side that can be beneficial for the financial well-being of individual investors. The current research emphasizes the fact that in real financial settings, investors must act quickly with known probabilities and utilities, multiple goals, and poorly defined problems drive investors to choose satisfying solutions rather than the best ones. In such complex situations, the human

mind turns to heuristics and biases like a handyman's toolbox to help itself choose the best course of action from the many options and enable it to go for the less costly errors, helping to achieve better investment performance and satisficing behavior.

6.11 Contributions and Implications of the study

An extensive and thorough analysis was used to arrive at the findings of the current study. Our research made a modest contribution to the body of knowledge while attempting to bridge the gap in the existing literature on behavioral finance. Although there are certain limits, this study has attempted to draw conclusions that could be highly helpful to those involved in the stock markets. Regardless of these limitations, this study will undoubtedly be informative to readers, individual investors, financial professionals, researchers, and other stakeholders in this field as discussed below:-

Implications for individual investors

- The results of the study indicate that behavioral biases have a significant impact on the perceived investment performance and investment satisfaction of individual investors which ultimately affects their overall financial satisfaction. Individual investors should always try to identify the influence of any potential behavioral biases within their personality and should select appropriate investment tools by recognizing their behavioral biases in order to have the upper hand in all of their financial decisions and to further improve their investment performance and returns.
- The results of the study also validated the impact of heterogeneity in demographic variables and investor sophistication measures on behavioral biases of individual investors and hypothesized relationships among variables. These findings provide valuable insights to individual investors to make investment decisions according to their demographic and sophistication characteristics.
- Although the study suggested that heuristics and biases have a positive impact on individual investors' investment performance and financial satisfaction, investors should remember that heuristics are a double-edged sword and that disregarding them can negatively impact their investment returns and financial satisfaction. In order to make better investment decisions and advance the field of finance, the researcher would like to suggest that investors should not solely

rely on cognitive heuristics and sentiments when making investments. Instead, they should perform a proper analysis of investment opportunities, develop quantitative investment criteria, and establish investment objectives and constraints.

- Understanding the behavioral aspects of human psychology can give individual investors a competitive edge to survive and grow in a dynamic market environment, the research's findings also assist retail investors in justifying their investment decisions and dispelling their doubts about market psychology.

Implications for financial advisors and brokerage firms: The findings are also valuable to various financial advisors and brokerage firms that help investors obtain higher returns.

- A good financial advisor is a mix of a psychologist and an economist. By incorporating the research's findings into their thinking, financial advisors can develop relationships with their clients, which is crucial for being competent advisors.
- Financial advisors can offer their clients specialized services based on their demographic and sophistication characteristics, particularly when they have clients from various racial and ethnic origins. Brokerage firms can also plan awareness campaigns to educate their clients about the importance of taking background factors into account when making investing decisions.
- The results of this study also improve advisers' capacity to develop plans that will help clients meet their financial goals. Additionally, it enables advisors to create behaviorally modified portfolios in accordance with the behavioral biases ingrained in their psychology.
- The current study also enables practitioners and advisors to recognize their own mistakes in addition to those of their clients. It helps them predict individual investor behavior more accurately in light of changing market sentiments, enabling them to suggest better stocks to their clients.

Implications for academics: There are several important implications of this study for academics.

- The study increases our understanding of numerous behavioral biases including overconfidence, mental accounting, and regret by establishing them as second-

order constructs of their antecedents for the first time in the context of Indian research studies in the field of behavioral finance.

- The majority of behavioral finance literature to date has focused on the direct connections between behavioral biases and financial satisfaction or investment performance; however, the current study has successfully established the mediating roles of perceived investment performance and investment satisfaction in the relationship between behavioral biases and financial satisfaction. Consequently, the study brought to light the crucial significance that perceived investment performance and investment satisfaction play in determining an investor's level of financial satisfaction.
- Further, additional behavioral biases can be examined using the integrated model that was established for the study.
- Finally, very few studies have been conducted in India that examines the critical role that behavioral biases play in determining financial satisfaction. As a result, the study broadens the knowledge of Indian researchers and academicians for future research in this field.

6.12 Limitations of the study

- The study was carried out in India's national capital region (NCR), where investor trading activity, per capita income, and education levels are all higher than elsewhere in the nation, limiting the relevance of our findings to this region only.
- The study was done on a sample of just 307 respondents due to time and budget constraints, which reduced the generalizability of results even though it fulfilled the required criteria. Also, the study's scope was limited to the equity investments segment of financial markets.
- The present study collected primary data from respondents regarding their financial behavior. In stressful market environments, respondents may be reluctant to acknowledge their biases and may give socially desirable answers that may differ from their true responses.
- The current study is based on cross-sectional data, which captures the respondents' mental state at a certain point in time. Responses may change in reaction to changing market conditions.

- The study uses pre-defined scales to assess behavioral biases and heuristics. Thus, there is a measurement weakness in our study.

6.13 Scope for Future Research

The current study opens up a wide range of research areas that future research studies can investigate in order to contribute to the field of behavioral finance.

- To increase the generalizability of the findings, the study might be carried out in other regions of the nation. Future studies can be carried out in Mumbai or other major Indian metropolises to better understand the behavior of Indian investors because Mumbai serves as the country's financial capital and is home to the Bombay Stock Exchange (BSE) and the National Stock Exchange, two of the world's largest stock exchanges.
- The study can be extended to include other developing nations' economies so that their circumstances can be compared to those of India. Such comparative analysis can be useful in revealing cross-cultural variations in investor behavior and contribute to the body of knowledge already available on behavioral finance.
- To gain a deeper knowledge of retail investors' investment behavior, a comprehensive study that includes a larger sample size across all financial market categories, such as commodity markets, mutual funds, and derivatives, can be carried out.
- The sample of the present study is composed of students, government and corporate employees, professionals, and entrepreneurs. Future research studies can be conducted to focus only on professional investors to make the study more relevant.
- To solve the problem of measurement weakness present study can be replicated using micro-trading data of individual investors to capture their real behavior in actual market conditions.
- The proposed model in the study investigated the impact of seven important behavioral biases (overconfidence, availability, anchoring, representativeness, mental accounting, loss aversion, and regret) on the investment performance and financial well-being of individual investors. The study can be further extended to find the impact of other behavioral biases on these dependent

variables and interrelationships between different psychological biases can also be analysed.

- In the current study, perceived investment performance and investment satisfaction are two mediating variables used to examine the effect of behavioral biases on investors' financial satisfaction. To gain a comprehensive picture of investor behavior, future studies can add additional mediating variables to the model, such as fundamental and technical anomalies, risk perception, and locus of control.

EXCELLENCE INNOVATIONS
SAMPLE - FOR REFERENCE ONLY

APPENDICES

APPENDIX-I (TABLES AND FIGURES)

Appendix 1.1 Tukey HSD and Tamhane's Post Hoc Test

Multiple Comparisons						
Dependent Variable		(I) Age categories	(J) Age categories	Mean Difference (I-J)	Std. Error	Sig.
Mean OC	Tukey HSD	18-30	31-40	-0.08539	0.09947	0.667
			Above 40	-0.28907	0.12444	0.054
		31-40	18-30	0.08539	0.09947	0.667
			Above 40	-0.20369	0.12664	0.244
		Above 40	18-30	0.28907	0.12444	0.054
	Tamhane		31-40	0.20369	0.12664	0.244
		18-30	31-40	-0.08539	0.10452	0.8
			Above 40	-.28907*	0.10468	0.019
		31-40	18-30	0.08539	0.10452	0.8
			Above 40	-0.20369	0.1051	0.155
Mean REP	Tukey HSD	Above 40	18-30	.28907*	0.10468	0.019
			31-40	0.20369	0.1051	0.155
		18-30	31-40	0.20373	0.1163	0.188
			Above 40	-0.10021	0.1455	0.77
		31-40	18-30	-0.20373	0.1163	0.188
	Tamhane		Above 40	-0.30394	0.14808	0.102
		Above 40	18-30	0.10021	0.1455	0.77
			31-40	0.30394	0.14808	0.102
		18-30	31-40	0.20373	0.12049	0.252
			Above 40	-0.10021	0.12954	0.825
	Tukey HSD	31-40	18-30	-0.20373	0.12049	0.252
			Above 40	-0.30394	0.12722	0.054
		Above 40	18-30	0.10021	0.12954	0.825
			31-40	0.30394	0.12722	0.054

Mean AVL	Tukey	18-30	31-40	-0.05752	0.15878	0.93
	HSD		Above 40	-0.07436	0.19863	0.926
		31-40	18-30	0.05752	0.15878	0.93
			Above 40	-0.01684	0.20215	0.996
		Above 40	18-30	0.07436	0.19863	0.926
			31-40	0.01684	0.20215	0.996
	Tamhane	18-30	31-40	-0.05752	0.16108	0.978
			Above 40	-0.07436	0.18977	0.972
		31-40	18-30	0.05752	0.16108	0.978
			Above 40	-0.01684	0.18094	1
		Above 40	18-30	0.07436	0.18977	0.972
			31-40	0.01684	0.18094	1
Mean ANC	Tukey	18-30	31-40	-0.03711	0.11765	0.947
	HSD		Above 40	-0.00239	0.14718	1
		31-40	18-30	0.03711	0.11765	0.947
			Above 40	0.03472	0.14979	0.971
		Above 40	18-30	0.00239	0.14718	1
			31-40	-0.03472	0.14979	0.971
	Tamhane	18-30	31-40	-0.03711	0.11837	0.985
			Above 40	-0.00239	0.14441	1
		31-40	18-30	0.03711	0.11837	0.985
			Above 40	0.03472	0.14257	0.993
		Above 40	18-30	0.00239	0.14441	1
			31-40	-0.03472	0.14257	0.993
Mean MA	Tukey	18-30	31-40	0.01451	0.1623	0.996
	HSD		Above 40	-.51077*	0.20304	0.033
		31-40	18-30	-0.01451	0.1623	0.996
			Above 40	-.52528*	0.20664	0.031
		Above 40	18-30	.51077*	0.20304	0.033
			31-40	.52528*	0.20664	0.031
	Tamhane	18-30	31-40	0.01451	0.16663	1
			Above 40	-.51077*	0.18693	0.021
		31-40	18-30	-0.01451	0.16663	1
			Above 40	-.52528*	0.1875	0.018
		Above 40	18-30	.51077*	0.18693	0.021

			31-40	.52528*	0.1875	0.018
Mean LA	Tukey HSD	18-30	31-40	0.0256	0.13498	0.98
			Above 40	0.10024	0.16886	0.824
		31-40	18-30	-0.0256	0.13498	0.98
			Above 40	0.07464	0.17186	0.901
		Above 40	18-30	-0.10024	0.16886	0.824
			31-40	-0.07464	0.17186	0.901
	Tamhane	18-30	31-40	0.0256	0.13794	0.997
			Above 40	0.10024	0.15782	0.894
		31-40	18-30	-0.0256	0.13794	0.997
			Above 40	0.07464	0.15572	0.95
		Above 40	18-30	-0.10024	0.15782	0.894
			31-40	-0.07464	0.15572	0.95
Mean REG	Tukey HSD	18-30	31-40	-0.01775	0.11823	0.988
			Above 40	-0.06968	0.14791	0.885
		31-40	18-30	0.01775	0.11823	0.988
			Above 40	-0.05193	0.15053	0.937
		Above 40	18-30	0.06968	0.14791	0.885
			31-40	0.05193	0.15053	0.937
	Tamhane	18-30	31-40	-0.01775	0.12062	0.998
			Above 40	-0.06968	0.13888	0.944
		31-40	18-30	0.01775	0.12062	0.998
			Above 40	-0.05193	0.13468	0.973
		Above 40	18-30	0.06968	0.13888	0.944
			31-40	0.05193	0.13468	0.973
* The mean difference is significant at the 0.05 level.						

Appendix 1.2 Tukey HSD Post Hoc Tests

Multiple Comparisons					
Tukey HSD					
Dependent Variable	(I) Education	(J) Education	Mean Difference (I-J)	Std. Error	Sig.
meanOC	Undergraduate	Graduate	-.58226*	0.19618	0.009
		Post graduate	-0.30082	0.19179	0.261

	Graduate	Undergraduate	.58226*	0.19618	0.009
		Post graduate	.28144*	0.09293	0.008
	Post graduate	Undergraduate	0.30082	0.19179	0.261
		Graduate	-.28144*	0.09293	0.008
meanREP	Undergraduate	Graduate	-0.33174	0.23355	0.332
		Post graduate	-0.20638	0.22832	0.638
	Graduate	Undergraduate	0.33174	0.23355	0.332
		Post graduate	0.12536	0.11063	0.494
	Post graduate	Undergraduate	0.20638	0.22832	0.638
		Graduate	-0.12536	0.11063	0.494
meanAVL	Undergraduate	Graduate	-0.04981	0.31738	0.987
		Post graduate	0.04584	0.31028	0.988
	Graduate	Undergraduate	0.04981	0.31738	0.987
		Post graduate	0.09565	0.15035	0.8
	Post graduate	Undergraduate	-0.04584	0.31028	0.988
		Graduate	-0.09565	0.15035	0.8
meanANC	Undergraduate	Graduate	-.64224*	0.2319	0.016
		Post graduate	-0.43569	0.22671	0.134
	Graduate	Undergraduate	.64224*	0.2319	0.016
		Post graduate	0.20655	0.10985	0.146
	Post graduate	Undergraduate	0.43569	0.22671	0.134
		Graduate	-0.20655	0.10985	0.146
meanMA	Undergraduate	Graduate	-0.48515	0.32738	0.301
		Post graduate	-0.42237	0.32006	0.385
	Graduate	Undergraduate	0.48515	0.32738	0.301
		Post graduate	0.06279	0.15508	0.914
	Post graduate	Undergraduate	0.42237	0.32006	0.385
		Graduate	-0.06279	0.15508	0.914
meanLA	Undergraduate	Graduate	0.02682	0.26921	0.995
		Post graduate	0.19294	0.26318	0.744
	Graduate	Undergraduate	-0.02682	0.26921	0.995
		Post graduate	0.16612	0.12753	0.395
	Post graduate	Undergraduate	-0.19294	0.26318	0.744
		Graduate	-0.16612	0.12753	0.395
meanREG	Undergraduate	Graduate	-0.11327	0.23592	0.881

		Post graduate	0.02184	0.23064	0.995
	Graduate	Undergraduate	0.11327	0.23592	0.881
		Post graduate	0.1351	0.11176	0.449
	Post graduate	Undergraduate	-0.02184	0.23064	0.995
		Graduate	-0.1351	0.11176	0.449
* The mean difference is significant at the 0.05 level.					

Appendix 1.3 Tukey HSD Post Hoc Tests

Multiple Comparisons					
Tukey HSD					
Dependent Variable	(I) Profession	(J) Profession	Mean Difference (I-J)	Std. Error	Sig.
meanOC	Students/Scholars	Govt/Semi-govt	-0.17096	0.14172	0.623
		Private Service	-.34333*	0.12446	0.031
		Self-employed	-.44689*	0.153	0.02
	Govt/Semi-govt	Students/Scholars	0.17096	0.14172	0.623
		Private Service	-0.17237	0.11625	0.449
		Self-employed	-0.27593	0.14641	0.237
	Private Service	Students/Scholars	.34333*	0.12446	0.031
		Govt/Semi-govt	0.17237	0.11625	0.449
		Self-employed	-0.10356	0.12977	0.855
	Self-employed	Students/Scholars	.44689*	0.153	0.02
		Govt/Semi-govt	0.27593	0.14641	0.237
		Private Service	0.10356	0.12977	0.855
meanREP	Students/Scholars	Govt/Semi-govt	-0.13089	0.16843	0.865
		Private Service	-0.13195	0.14792	0.809
		Self-employed	-0.03636	0.18185	0.997
	Govt/Semi-govt	Students/Scholars	0.13089	0.16843	0.865
		Private Service	-0.00106	0.13817	1
		Self-employed	0.09453	0.174	0.948
	Private Service	Students/Scholars	0.13195	0.14792	0.809
		Govt/Semi-govt	0.00106	0.13817	1
		Self-employed	0.09559	0.15424	0.926

	Self-employed	Students/Scholars	0.03636	0.18185	0.997
		Govt/Semi-govt	-0.09453	0.174	0.948
		Private Service	-0.09559	0.15424	0.926
meanAVL	Students/Scholars	Govt/Semi-govt	-0.18575	0.2278	0.847
		Private Service	-0.22156	0.20006	0.685
		Self-employed	-0.01586	0.24594	1
	Govt/Semi-govt	Students/Scholars	0.18575	0.2278	0.847
		Private Service	-0.0358	0.18686	0.998
		Self-employed	0.16989	0.23533	0.888
	Private Service	Students/Scholars	0.22156	0.20006	0.685
		Govt/Semi-govt	0.0358	0.18686	0.998
		Self-employed	0.20569	0.20859	0.757
	Self-employed	Students/Scholars	0.01586	0.24594	1
		Govt/Semi-govt	-0.16989	0.23533	0.888
		Private Service	-0.20569	0.20859	0.757
meanANC	Students/Scholars	Govt/Semi-govt	0.14403	0.16906	0.829
		Private Service	0.08235	0.14847	0.945
		Self-employed	0.11837	0.18252	0.916
	Govt/Semi-govt	Students/Scholars	-0.14403	0.16906	0.829
		Private Service	-0.06168	0.13868	0.971
		Self-employed	-0.02566	0.17465	0.999
	Private Service	Students/Scholars	-0.08235	0.14847	0.945
		Govt/Semi-govt	0.06168	0.13868	0.971
		Self-employed	0.03601	0.15481	0.996
	Self-employed	Students/Scholars	-0.11837	0.18252	0.916
		Govt/Semi-govt	0.02566	0.17465	0.999
		Private Service	-0.03601	0.15481	0.996
meanMA	Students/Scholars	Govt/Semi-govt	-0.24518	0.23534	0.725
		Private Service	-0.23352	0.20668	0.671
		Self-employed	0.03497	0.25409	0.999
	Govt/Semi-govt	Students/Scholars	0.24518	0.23534	0.725
		Private Service	0.01166	0.19306	1
		Self-employed	0.28016	0.24313	0.657
	Private Service	Students/Scholars	0.23352	0.20668	0.671
		Govt/Semi-govt	-0.01166	0.19306	1

		Self-employed	0.26849	0.21551	0.598
	Self-employed	Students/Scholars	-0.03497	0.25409	0.999
		Govt/Semi-govt	-0.28016	0.24313	0.657
		Private Service	-0.26849	0.21551	0.598
meanLA	Students/Scholars	Govt/Semi-govt	0.24928	0.19361	0.572
		Private Service	0.17123	0.17004	0.745
		Self-employed	0.26019	0.20903	0.599
	Govt/Semi-govt	Students/Scholars	-0.24928	0.19361	0.572
		Private Service	-0.07805	0.15882	0.961
		Self-employed	0.0109	0.20002	1
	Private Service	Students/Scholars	-0.17123	0.17004	0.745
		Govt/Semi-govt	0.07805	0.15882	0.961
		Self-employed	0.08896	0.17729	0.959
	Self-employed	Students/Scholars	-0.26019	0.20903	0.599
		Govt/Semi-govt	-0.0109	0.20002	1
		Private Service	-0.08896	0.17729	0.959
meanREG	Students/Scholars	Govt/Semi-govt	-0.11174	0.16965	0.912
		Private Service	-0.1735	0.14899	0.65
		Self-employed	-0.0282	0.18316	0.999
	Govt/Semi-govt	Students/Scholars	0.11174	0.16965	0.912
		Private Service	-0.06176	0.13917	0.971
		Self-employed	0.08354	0.17526	0.964
	Private Service	Students/Scholars	0.1735	0.14899	0.65
		Govt/Semi-govt	0.06176	0.13917	0.971
		Self-employed	0.1453	0.15535	0.786
	Self-employed	Students/Scholars	0.0282	0.18316	0.999
		Govt/Semi-govt	-0.08354	0.17526	0.964
		Private Service	-0.1453	0.15535	0.786
* The mean difference is significant at the 0.05 level.					

Appendix 1.4 Tukey HSD Post Hoc Tests

Multiple Comparisons					
Tukey HSD					
Dependent Variable	(I) Annual Income	(J) Annual Income	Mean Difference (I-J)	Std. Error	Sig.
Mean OC	0 - 2.5 Lakhs	2.5 - 5 lakhs	0.20061	0.13776	0.592
		5 - 7.5 lakhs	0.08104	0.14647	0.981
		7.5- 10 lakhs	-0.1625	0.14902	0.811
		more than 10 lakhs	-0.1854	0.13949	0.673
	2.5 - 5 lakhs	0 - 2.5 Lakhs	-0.20061	0.13776	0.592
		5 - 7.5 lakhs	-0.11957	0.15055	0.932
		7.5- 10 lakhs	-0.36311	0.15303	0.126
		more than 10 lakhs	-0.386	0.14377	0.059
	5 - 7.5 lakhs	0 - 2.5 Lakhs	-0.08104	0.14647	0.981
		2.5 - 5 lakhs	0.11957	0.15055	0.932
		7.5- 10 lakhs	-0.24354	0.16092	0.555
		more than 10 lakhs	-0.26643	0.15214	0.404
	7.5- 10 lakhs	0 - 2.5 Lakhs	0.1625	0.14902	0.811
		2.5 - 5 lakhs	0.36311	0.15303	0.126
		5 - 7.5 lakhs	0.24354	0.16092	0.555
		more than 10 lakhs	-0.0229	0.1546	1
	more than 10 lakhs	0 - 2.5 Lakhs	0.1854	0.13949	0.673
		2.5 - 5 lakhs	0.386	0.14377	0.059
		5 - 7.5 lakhs	0.26643	0.15214	0.404
		7.5- 10 lakhs	0.0229	0.1546	1
Mean REP	0 - 2.5 Lakhs	2.5 - 5 lakhs	0.02242	0.14387	1
		5 - 7.5 lakhs	0.15736	0.15296	0.842
		7.5- 10 lakhs	0.11	0.15563	0.955
		more than 10 lakhs	0.03397	0.14568	0.999
	2.5 - 5 lakhs	0 - 2.5 Lakhs	-0.02242	0.14387	1
		5 - 7.5 lakhs	0.13493	0.15722	0.912
		7.5- 10 lakhs	0.08758	0.15982	0.982
		more than 10 lakhs	0.01154	0.15014	1

	5 - 7.5 lakhs	0 - 2.5 Lakhs	-0.15736	0.15296	0.842
		2.5 - 5 lakhs	-0.13493	0.15722	0.912
		7.5- 10 lakhs	-0.04736	0.16805	0.999
		more than 10 lakhs	-0.12339	0.15888	0.937
	7.5- 10 lakhs	0 - 2.5 Lakhs	-0.11	0.15563	0.955
		2.5 - 5 lakhs	-0.08758	0.15982	0.982
		5 - 7.5 lakhs	0.04736	0.16805	0.999
		more than 10 lakhs	-0.07603	0.16145	0.99
	more than 10 lakhs	0 - 2.5 Lakhs	-0.03397	0.14568	0.999
		2.5 - 5 lakhs	-0.01154	0.15014	1
		5 - 7.5 lakhs	0.12339	0.15888	0.937
		7.5- 10 lakhs	0.07603	0.16145	0.99
Mean AVL	0 - 2.5 Lakhs	2.5 - 5 lakhs	0.32273	0.21137	0.546
		5 - 7.5 lakhs	0.23396	0.22473	0.836
		7.5- 10 lakhs	0.115	0.22865	0.987
		more than 10 lakhs	0.1254	0.21403	0.977
	2.5 - 5 lakhs	0 - 2.5 Lakhs	-0.32273	0.21137	0.546
		5 - 7.5 lakhs	-0.08877	0.23099	0.995
		7.5- 10 lakhs	-0.20773	0.2348	0.902
		more than 10 lakhs	-0.19733	0.22059	0.899
	5 - 7.5 lakhs	0 - 2.5 Lakhs	-0.23396	0.22473	0.836
		2.5 - 5 lakhs	0.08877	0.23099	0.995
		7.5- 10 lakhs	-0.11896	0.2469	0.989
		more than 10 lakhs	-0.10857	0.23343	0.99
	7.5- 10 lakhs	0 - 2.5 Lakhs	-0.115	0.22865	0.987
		2.5 - 5 lakhs	0.20773	0.2348	0.902
		5 - 7.5 lakhs	0.11896	0.2469	0.989
		more than 10 lakhs	0.0104	0.2372	1
	more than 10 lakhs	0 - 2.5 Lakhs	-0.1254	0.21403	0.977
		2.5 - 5 lakhs	0.19733	0.22059	0.899
		5 - 7.5 lakhs	0.10857	0.23343	0.99
		7.5- 10 lakhs	-0.0104	0.2372	1
Mean ANC	0 - 2.5 Lakhs	2.5 - 5 lakhs	0.25212	0.17085	0.579
		5 - 7.5 lakhs	0.00855	0.18165	1
		7.5- 10 lakhs	.51667*	0.18482	0.043

		more than 10 lakhs	0.10746	0.173	0.972
	2.5 - 5 lakhs	0 - 2.5 Lakhs	-0.25212	0.17085	0.579
		5 - 7.5 lakhs	-0.24357	0.18671	0.689
		7.5- 10 lakhs	0.26455	0.18979	0.632
		more than 10 lakhs	-0.14466	0.1783	0.927
	5 - 7.5 lakhs	0 - 2.5 Lakhs	-0.00855	0.18165	1
		2.5 - 5 lakhs	0.24357	0.18671	0.689
		7.5- 10 lakhs	0.50811	0.19957	0.083
		more than 10 lakhs	0.09891	0.18868	0.985
	7.5- 10 lakhs	0 - 2.5 Lakhs	-.51667	0.18482	0.043
		2.5 - 5 lakhs	-0.26455	0.18979	0.632
		5 - 7.5 lakhs	-0.50811	0.19957	0.083
		more than 10 lakhs	-0.40921	0.19173	0.208
	more than 10 lakhs	0 - 2.5 Lakhs	-0.10746	0.173	0.972
		2.5 - 5 lakhs	0.14466	0.1783	0.927
		5 - 7.5 lakhs	-0.09891	0.18868	0.985
		7.5- 10 lakhs	0.40921	0.19173	0.208
Mean MA	0 - 2.5 Lakhs	2.5 - 5 lakhs	-0.03273	0.21444	1
		5 - 7.5 lakhs	-0.02887	0.228	1
		7.5- 10 lakhs	-.68500*	0.23198	0.028
		more than 10 lakhs	-0.06159	0.21714	0.999
	2.5 - 5 lakhs	0 - 2.5 Lakhs	0.03273	0.21444	1
		5 - 7.5 lakhs	0.00386	0.23435	1
		7.5- 10 lakhs	-0.65227	0.23822	0.051
		more than 10 lakhs	-0.02886	0.2238	1
	5 - 7.5 lakhs	0 - 2.5 Lakhs	0.02887	0.228	1
		2.5 - 5 lakhs	-0.00386	0.23435	1
		7.5- 10 lakhs	-0.65613	0.2505	0.069
		more than 10 lakhs	-0.03272	0.23683	1
	7.5- 10 lakhs	0 - 2.5 Lakhs	.68500*	0.23198	0.028
		2.5 - 5 lakhs	0.65227	0.23822	0.051
		5 - 7.5 lakhs	0.65613	0.2505	0.069
		more than 10 lakhs	0.62341	0.24065	0.075
	more than 10 lakhs	0 - 2.5 Lakhs	0.06159	0.21714	0.999
		2.5 - 5 lakhs	0.02886	0.2238	1

		5 - 7.5 lakhs	0.03272	0.23683	1
		7.5- 10 lakhs	-0.62341	0.24065	0.075
Mean LA	0 - 2.5 Lakhs	2.5 - 5 lakhs	.64703*	0.1755	0.002
		5 - 7.5 lakhs	0.27608	0.1866	0.577
		7.5- 10 lakhs	.61200*	0.18985	0.012
		more than 10 lakhs	0.42654	0.17771	0.118
	2.5 - 5 lakhs	0 - 2.5 Lakhs	-.64703*	0.1755	0.002
		5 - 7.5 lakhs	-0.37095	0.1918	0.302
		7.5- 10 lakhs	-0.03503	0.19496	1
		more than 10 lakhs	-0.22049	0.18316	0.749
	5 - 7.5 lakhs	0 - 2.5 Lakhs	-0.27608	0.1866	0.577
		2.5 - 5 lakhs	0.37095	0.1918	0.302
		7.5- 10 lakhs	0.33592	0.20501	0.474
		more than 10 lakhs	0.15046	0.19382	0.937
	7.5- 10 lakhs	0 - 2.5 Lakhs	-.61200*	0.18985	0.012
		2.5 - 5 lakhs	0.03503	0.19496	1
		5 - 7.5 lakhs	-0.33592	0.20501	0.474
		more than 10 lakhs	-0.18546	0.19695	0.88
	more than 10 lakhs	0 - 2.5 Lakhs	-0.42654	0.17771	0.118
		2.5 - 5 lakhs	0.22049	0.18316	0.749
		5 - 7.5 lakhs	-0.15046	0.19382	0.937
		7.5- 10 lakhs	0.18546	0.19695	0.88
Mean REG	0 - 2.5 Lakhs	2.5 - 5 lakhs	0.35867	0.16295	0.182
		5 - 7.5 lakhs	0.39703	0.17325	0.15
		7.5- 10 lakhs	0.34933	0.17627	0.277
		more than 10 lakhs	0.30629	0.165	0.343
	2.5 - 5 lakhs	0 - 2.5 Lakhs	-0.35867	0.16295	0.182
		5 - 7.5 lakhs	0.03836	0.17807	1
		7.5- 10 lakhs	-0.00933	0.18101	1
		more than 10 lakhs	-0.05238	0.17006	0.998
	5 - 7.5 lakhs	0 - 2.5 Lakhs	-0.39703	0.17325	0.15
		2.5 - 5 lakhs	-0.03836	0.17807	1
		7.5- 10 lakhs	-0.0477	0.19034	0.999
		more than 10 lakhs	-0.09075	0.17995	0.987
	7.5- 10 lakhs	0 - 2.5 Lakhs	-0.34933	0.17627	0.277

		2.5 - 5 lakhs	0.00933	0.18101	1
		5 - 7.5 lakhs	0.0477	0.19034	0.999
		more than 10 lakhs	-0.04305	0.18286	0.999
	more than 10 lakhs	0 - 2.5 Lakhs	-0.30629	0.165	0.343
		2.5 - 5 lakhs	0.05238	0.17006	0.998
		5 - 7.5 lakhs	0.09075	0.17995	0.987
		7.5- 10 lakhs	0.04305	0.18286	0.999
* The mean difference is significant at the 0.05 level.					

Appendix 1.5 Tamhane's Post Hoc Test

Multiple Comparisons					
Tamhane					
Dependent Variable	(I) Investment Experience	(J) Investment Experience	Mean Difference (I-J)	Std. Error	Sig.
Mean OC	Since last 2 years	2-5 years	-0.10393	0.11981	0.947
		5-10 years	-0.1227	0.13232	0.928
		More than 10 years	-.37182*	0.13498	0.041
	2-5 years	Since last 2 years	0.10393	0.11981	0.947
		5-10 years	-0.01877	0.11679	1
		More than 10 years	-0.26789	0.11979	0.157
	5-10 years	Since last 2 years	0.1227	0.13232	0.928
		2-5 years	0.01877	0.11679	1
		More than 10 years	-0.24912	0.1323	0.322
Mean REP	More than 10 years	Since last 2 years	.37182*	0.13498	0.041
		2-5 years	0.26789	0.11979	0.157
		5-10 years	0.24912	0.1323	0.322
	Since last 2 years	2-5 years	0.04283	0.13709	1
		5-10 years	0.12245	0.15074	0.961
		More than 10 years	-0.04457	0.15788	1
	2-5 years	Since last 2 years	-0.04283	0.13709	1
		5-10 years	0.07963	0.14253	0.994
		More than 10 years	-0.08739	0.15006	0.993
	5-10 years	Since last 2 years	-0.12245	0.15074	0.961

		2-5 years	-0.07963	0.14253	0.994
		More than 10 years	-0.16702	0.16263	0.889
	More than 10 years	Since last 2 years	0.04457	0.15788	1
		2-5 years	0.08739	0.15006	0.993
		5-10 years	0.16702	0.16263	0.889
Mean AVL	Since last 2 years	2-5 years	0.24887	0.17382	0.633
		5-10 years	0.30563	0.19841	0.553
		More than 10 years	0.09528	0.25017	0.999
	2-5 years	Since last 2 years	-0.24887	0.17382	0.633
		5-10 years	0.05676	0.19238	1
		More than 10 years	-0.15359	0.24542	0.99
	5-10 years	Since last 2 years	-0.30563	0.19841	0.553
		2-5 years	-0.05676	0.19238	1
		More than 10 years	-0.21035	0.26341	0.965
	More than 10 years	Since last 2 years	-0.09528	0.25017	0.999
		2-5 years	0.15359	0.24542	0.99
		5-10 years	0.21035	0.26341	0.965
Mean ANC	Since last 2 years	2-5 years	-0.3227	0.13667	0.11
		5-10 years	-0.33977	0.14201	0.103
		More than 10 years	-0.3567	0.18821	0.319
	2-5 years	Since last 2 years	0.3227	0.13667	0.11
		5-10 years	-0.01707	0.13025	1
		More than 10 years	-0.034	0.1795	1
	5-10 years	Since last 2 years	0.33977	0.14201	0.103
		2-5 years	0.01707	0.13025	1
		More than 10 years	-0.01693	0.1836	1
	More than 10 years	Since last 2 years	0.3567	0.18821	0.319
		2-5 years	0.034	0.1795	1
		5-10 years	0.01693	0.1836	1
Mean MA	Since last 2 years	2-5 years	0.03784	0.18155	1
		5-10 years	0.15494	0.21009	0.976
		More than 10 years	-0.08243	0.25547	1
	2-5 years	Since last 2 years	-0.03784	0.18155	1
		5-10 years	0.1171	0.19988	0.993
		More than 10 years	-0.12027	0.24714	0.997

	5-10 years	Since last 2 years	-0.15494	0.21009	0.976
		2-5 years	-0.1171	0.19988	0.993
		More than 10 years	-0.23737	0.2688	0.943
	More than 10 years	Since last 2 years	0.08243	0.25547	1
		2-5 years	0.12027	0.24714	0.997
		5-10 years	0.23737	0.2688	0.943
Mean LA	Since last 2 years	2-5 years	0.36335	0.15605	0.119
		5-10 years	0.32791	0.15098	0.174
		More than 10 years	0.05759	0.18562	1
	2-5 years	Since last 2 years	-0.36335	0.15605	0.119
		5-10 years	-0.03544	0.16149	1
		More than 10 years	-0.30576	0.19426	0.533
	5-10 years	Since last 2 years	-0.32791	0.15098	0.174
		2-5 years	0.03544	0.16149	1
		More than 10 years	-0.27032	0.19022	0.647
	More than 10 years	Since last 2 years	-0.05759	0.18562	1
		2-5 years	0.30576	0.19426	0.533
		5-10 years	0.27032	0.19022	0.647
Mean RG	Since last 2 years	2-5 years	0.07447	0.13393	0.994
		5-10 years	-0.04241	0.14284	1
		More than 10 years	-0.19434	0.17115	0.836
	2-5 years	Since last 2 years	-0.07447	0.13393	0.994
		5-10 years	-0.11688	0.14409	0.961
		More than 10 years	-0.26881	0.1722	0.545
	5-10 years	Since last 2 years	0.04241	0.14284	1
		2-5 years	0.11688	0.14409	0.961
		More than 10 years	-0.15193	0.17922	0.953
	More than 10 years	Since last 2 years	0.19434	0.17115	0.836
		2-5 years	0.26881	0.1722	0.545
		5-10 years	0.15193	0.17922	0.953
* The mean difference is significant at the 0.05 level.					

Appendix 1.6 Tukey HSD and Tamhane's Post Hoc Test

Multiple Comparisons					
Dependent Variable		(I) Investment frequency	(J) Investment Frequency	Mean Difference (I-J)	Sig.
Mean OC	Tukey HSD	Intraday	0 - 3 months	0.12528	0.874
			3 - 12 months	0.03878	0.999
			12 - 36 months	0.03214	1
			36 months or more	0.09167	0.988
		0 - 3 months	Intraday	-0.12528	0.874
			3 - 12 months	-0.0865	0.952
			12 - 36 months	-0.09314	0.99
			36 months or more	-0.03361	1
		3 - 12 months	Intraday	-0.03878	0.999
			0 - 3 months	0.0865	0.952
			12 - 36 months	-0.00664	1
			36 months or more	0.05288	0.998
		12 - 36 months	Intraday	-0.03214	1
			0 - 3 months	0.09314	0.99
			3 - 12 months	0.00664	1
			36 months or more	0.05952	0.999
		36 months or more	Intraday	-0.09167	0.988
			0 - 3 months	0.03361	1
			3 - 12 months	-0.05288	0.998
			12 - 36 months	-0.05952	0.999
	Tamhane	Intraday	0 - 3 months	0.12528	0.991
			3 - 12 months	0.03878	1
			12 - 36 months	0.03214	1
			36 months or more	0.09167	1
		0 - 3 months	Intraday	-0.12528	0.991
			3 - 12 months	-0.0865	0.998
			12 - 36 months	-0.09314	1
			36 months or more	-0.03361	1
		3 - 12 months	Intraday	-0.03878	1

			0 - 3 months	0.0865	0.998
			12 - 36 months	-0.00664	1
			36 months or more	0.05288	1
		12 - 36 months	Intraday	-0.03214	1
			0 - 3 months	0.09314	1
			3 - 12 months	0.00664	1
			36 months or more	0.05952	1
		36 months or more	Intraday	-0.09167	1
			0 - 3 months	0.03361	1
			3 - 12 months	-0.05288	1
			12 - 36 months	-0.05952	1
Mean REP	Tukey	Intraday	0 - 3 months	0.22377	0.455
	HSD		3 - 12 months	0.20737	0.612
			12 - 36 months	-0.10536	0.988
			36 months or more	0.16394	0.913
		0 - 3 months	Intraday	-0.22377	0.455
			3 - 12 months	-0.0164	1
			12 - 36 months	-0.32913	0.472
			36 months or more	-0.05984	0.997
		3 - 12 months	Intraday	-0.20737	0.612
			0 - 3 months	0.0164	1
			12 - 36 months	-0.31273	0.562
			36 months or more	-0.04344	0.999
		12 - 36 months	Intraday	0.10536	0.988
			0 - 3 months	0.32913	0.472
			3 - 12 months	0.31273	0.562
			36 months or more	0.26929	0.802
		36 months or more	Intraday	-0.16394	0.913
			0 - 3 months	0.05984	0.997
			3 - 12 months	0.04344	0.999
			12 - 36 months	-0.26929	0.802
	Tamhane	Intraday	0 - 3 months	0.22377	0.665
			3 - 12 months	0.20737	0.843
			12 - 36 months	-0.10536	1
			36 months or more	0.16394	0.97

		0 - 3 months	Intraday	-0.22377	0.665
			3 - 12 months	-0.0164	1
			12 - 36 months	-0.32913	0.746
			36 months or more	-0.05984	1
		3 - 12 months	Intraday	-0.20737	0.843
			0 - 3 months	0.0164	1
			12 - 36 months	-0.31273	0.83
			36 months or more	-0.04344	1
		12 - 36 months	Intraday	0.10536	1
			0 - 3 months	0.32913	0.746
			3 - 12 months	0.31273	0.83
			36 months or more	0.26929	0.932
		36 months or more	Intraday	-0.16394	0.97
			0 - 3 months	0.05984	1
			3 - 12 months	0.04344	1
			12 - 36 months	-0.26929	0.932
Mean AVL	Tukey	Intraday	0 - 3 months	.73330*	0.002
	HSD		3 - 12 months	.60288*	0.034
			12 - 36 months	.97560*	0.015
			36 months or more	.92716*	0.008
		0 - 3 months	Intraday	-.73330*	0.002
			3 - 12 months	-0.13041	0.948
			12 - 36 months	0.2423	0.918
			36 months or more	0.19386	0.939
		3 - 12 months	Intraday	-.60288*	0.034
			0 - 3 months	0.13041	0.948
			12 - 36 months	0.37271	0.725
			36 months or more	0.32427	0.737
		12 - 36 months	Intraday	-.97560*	0.015
			0 - 3 months	-0.2423	0.918
			3 - 12 months	-0.37271	0.725
			36 months or more	-0.04844	1
		36 months or more	Intraday	-.92716*	0.008
			0 - 3 months	-0.19386	0.939
			3 - 12 months	-0.32427	0.737

			12 - 36 months	0.04844	1
	Tamhane	Intraday	0 - 3 months	.73330*	0.007
			3 - 12 months	0.60288	0.058
			12 - 36 months	0.9756	0.087
			36 months or more	.92716*	0.015
		0 - 3 months	Intraday	-.73330*	0.007
			3 - 12 months	-0.13041	0.996
			12 - 36 months	0.2423	0.998
			36 months or more	0.19386	0.996
		3 - 12 months	Intraday	-0.60288	0.058
			0 - 3 months	0.13041	0.996
			12 - 36 months	0.37271	0.954
			36 months or more	0.32427	0.886
		12 - 36 months	Intraday	-0.9756	0.087
			0 - 3 months	-0.2423	0.998
			3 - 12 months	-0.37271	0.954
			36 months or more	-0.04844	1
		36 months or more	Intraday	-.92716*	0.015
			0 - 3 months	-0.19386	0.996
			3 - 12 months	-0.32427	0.886
			12 - 36 months	0.04844	1
Mean ANC	Tukey	Intraday	0 - 3 months	0.14608	0.896
	HSD		3 - 12 months	0.075	0.993
			12 - 36 months	0.2119	0.925
			36 months or more	-0.19368	0.919
		0 - 3 months	Intraday	-0.14608	0.896
			3 - 12 months	-0.07108	0.989
			12 - 36 months	0.06583	0.999
			36 months or more	-0.33976	0.496
		3 - 12 months	Intraday	-0.075	0.993
			0 - 3 months	0.07108	0.989
			12 - 36 months	0.1369	0.983
			36 months or more	-0.26868	0.747
		12 - 36 months	Intraday	-0.2119	0.925
			0 - 3 months	-0.06583	0.999

			3 - 12 months	-0.1369	0.983
			36 months or more	-0.40558	0.639
		36 months or more	Intraday	0.19368	0.919
			0 - 3 months	0.33976	0.496
			3 - 12 months	0.26868	0.747
			12 - 36 months	0.40558	0.639
	Tamhane	Intraday	0 - 3 months	0.14608	0.996
			3 - 12 months	0.075	1
			12 - 36 months	0.2119	0.997
			36 months or more	-0.19368	0.994
		0 - 3 months	Intraday	-0.14608	0.996
			3 - 12 months	-0.07108	1
			12 - 36 months	0.06583	1
			36 months or more	-0.33976	0.555
		3 - 12 months	Intraday	-0.075	1
			0 - 3 months	0.07108	1
			12 - 36 months	0.1369	1
			36 months or more	-0.26868	0.836
		12 - 36 months	Intraday	-0.2119	0.997
			0 - 3 months	-0.06583	1
			3 - 12 months	-0.1369	1
			36 months or more	-0.40558	0.793
		36 months or more	Intraday	0.19368	0.994
			0 - 3 months	0.33976	0.555
			3 - 12 months	0.26868	0.836
			12 - 36 months	0.40558	0.793
Mean MA	Tukey	Intraday	0 - 3 months	0.10238	0.986
	HSD		3 - 12 months	-0.08397	0.995
			12 - 36 months	-.94524*	0.029
			36 months or more	-0.14023	0.988
		0 - 3 months	Intraday	-0.10238	0.986
			3 - 12 months	-0.18636	0.851
			12 - 36 months	-1.04762*	0.005
			36 months or more	-0.24261	0.888
		3 - 12 months	Intraday	0.08397	0.995

			0 - 3 months	0.18636	0.851
			12 - 36 months	-.86126*	0.048
			36 months or more	-0.05626	1
		12 - 36 months	Intraday	.94524*	0.029
			0 - 3 months	1.04762*	0.005
			3 - 12 months	.86126*	0.048
			36 months or more	0.80501	0.177
		36 months or more	Intraday	0.14023	0.988
			0 - 3 months	0.24261	0.888
			3 - 12 months	0.05626	1
			12 - 36 months	-0.80501	0.177
	Tamhane	Intraday	0 - 3 months	0.10238	1
			3 - 12 months	-0.08397	1
			12 - 36 months	-.94524*	0.002
			36 months or more	-0.14023	1
		0 - 3 months	Intraday	-0.10238	1
			3 - 12 months	-0.18636	0.973
			12 - 36 months	-1.04762*	0
			36 months or more	-0.24261	0.995
		3 - 12 months	Intraday	0.08397	1
			0 - 3 months	0.18636	0.973
			12 - 36 months	-.86126*	0.003
			36 months or more	-0.05626	1
		12 - 36 months	Intraday	.94524*	0.002
			0 - 3 months	1.04762*	0
			3 - 12 months	.86126*	0.003
			36 months or more	0.80501	0.138
		36 months or more	Intraday	0.14023	1
			0 - 3 months	0.24261	0.995
			3 - 12 months	0.05626	1
			12 - 36 months	-0.80501	0.138
Mean LA	Tukey	Intraday	0 - 3 months	-0.09221	0.982
	HSD		3 - 12 months	0.11692	0.968
			12 - 36 months	-0.15048	0.981
			36 months or more	0.20782	0.91

		0 - 3 months	Intraday	0.09221	0.982
			3 - 12 months	0.20914	0.66
			12 - 36 months	-0.05826	0.999
			36 months or more	0.30003	0.652
		3 - 12 months	Intraday	-0.11692	0.968
			0 - 3 months	-0.20914	0.66
			12 - 36 months	-0.2674	0.845
			36 months or more	0.09089	0.995
		12 - 36 months	Intraday	0.15048	0.981
			0 - 3 months	0.05826	0.999
			3 - 12 months	0.2674	0.845
			36 months or more	0.35829	0.765
		36 months or more	Intraday	-0.20782	0.91
			0 - 3 months	-0.30003	0.652
			3 - 12 months	-0.09089	0.995
			12 - 36 months	-0.35829	0.765
	Tamhane	Intraday	0 - 3 months	-0.09221	1
			3 - 12 months	0.11692	1
			12 - 36 months	-0.15048	1
			36 months or more	0.20782	0.995
		0 - 3 months	Intraday	0.09221	1
			3 - 12 months	0.20914	0.838
			12 - 36 months	-0.05826	1
			36 months or more	0.30003	0.856
		3 - 12 months	Intraday	-0.11692	1
			0 - 3 months	-0.20914	0.838
			12 - 36 months	-0.2674	0.969
			36 months or more	0.09089	1
		12 - 36 months	Intraday	0.15048	1
			0 - 3 months	0.05826	1
			3 - 12 months	0.2674	0.969
			36 months or more	0.35829	0.928
		36 months or more	Intraday	-0.20782	0.995
			0 - 3 months	-0.30003	0.856
			3 - 12 months	-0.09089	1

			12 - 36 months	-0.35829	0.928
Mean REG	Tukey	Intraday	0 - 3 months	0.09459	0.973
	HSD		3 - 12 months	0.24077	0.599
			12 - 36 months	-0.20905	0.915
			36 months or more	-0.00149	1
		0 - 3 months	Intraday	-0.09459	0.973
			3 - 12 months	0.14618	0.839
			12 - 36 months	-0.30364	0.678
			36 months or more	-0.09609	0.989
		3 - 12 months	Intraday	-0.24077	0.599
			0 - 3 months	-0.14618	0.839
			12 - 36 months	-0.44982	0.327
			36 months or more	-0.24226	0.781
		12 - 36 months	Intraday	0.20905	0.915
			0 - 3 months	0.30364	0.678
			3 - 12 months	0.44982	0.327
			36 months or more	0.20755	0.945
		36 months or more	Intraday	0.00149	1
			0 - 3 months	0.09609	0.989
			3 - 12 months	0.24226	0.781
			12 - 36 months	-0.20755	0.945
	Tamhane	Intraday	0 - 3 months	0.09459	1
			3 - 12 months	0.24077	0.817
			12 - 36 months	-0.20905	0.992
			36 months or more	-0.00149	1
		0 - 3 months	Intraday	-0.09459	1
			3 - 12 months	0.14618	0.957
			12 - 36 months	-0.30364	0.833
			36 months or more	-0.09609	1
		3 - 12 months	Intraday	-0.24077	0.817
			0 - 3 months	-0.14618	0.957
			12 - 36 months	-0.44982	0.365
			36 months or more	-0.24226	0.948
		12 - 36 months	Intraday	0.20905	0.992
			0 - 3 months	0.30364	0.833

			3 - 12 months	0.44982	0.365
			36 months or more	0.20755	0.997
		36 months or more	Intraday	0.00149	1
			0 - 3 months	0.09609	1
			3 - 12 months	0.24226	0.948
			12 - 36 months	-0.20755	0.997
* The mean difference is significant at the 0.05 level.					

Appendix 1.7 Tukey HSD Post Hoc Tests

Multiple Comparisons					
Tukey HSD					
Dependent Variable	(I) Number of stocks	(J) Number of stocks	Mean Difference (I-J)	Std. Error	Sig.
Mean OC	One	2-5	-0.15645	0.17411	0.897
		5-10	-0.0822	0.17725	0.99
		10-20	-0.10697	0.1869	0.979
		More than 20	-0.37326	0.19249	0.299
	2-5	One	0.15645	0.17411	0.897
		5-10	0.07425	0.11842	0.971
		10-20	0.04948	0.13242	0.996
		More than 20	-0.21681	0.1402	0.533
	5-10	One	0.0822	0.17725	0.99
		2-5	-0.07425	0.11842	0.971
		10-20	-0.02477	0.13653	1
		More than 20	-0.29106	0.14408	0.259
	10-20	One	0.10697	0.1869	0.979
		2-5	-0.04948	0.13242	0.996
		5-10	0.02477	0.13653	1
		More than 20	-0.26629	0.15579	0.43
	More than 20	One	0.37326	0.19249	0.299
		2-5	0.21681	0.1402	0.533
		5-10	0.29106	0.14408	0.259
		10-20	0.26629	0.15579	0.43
Mean REP	One	2-5	0.0008	0.20419	1

		5-10	-0.11632	0.20787	0.981
		10-20	-0.22985	0.21918	0.832
		More than 20	-0.22859	0.22574	0.849
	2-5	One	-0.0008	0.20419	1
		5-10	-0.11712	0.13888	0.917
		10-20	-0.23065	0.1553	0.573
		More than 20	-0.22939	0.16442	0.631
	5-10	One	0.11632	0.20787	0.981
		2-5	0.11712	0.13888	0.917
		10-20	-0.11353	0.16011	0.954
		More than 20	-0.11226	0.16898	0.964
	10-20	One	0.22985	0.21918	0.832
		2-5	0.23065	0.1553	0.573
		5-10	0.11353	0.16011	0.954
		More than 20	0.00127	0.18271	1
	More than 20	One	0.22859	0.22574	0.849
		2-5	0.22939	0.16442	0.631
		5-10	0.11226	0.16898	0.964
		10-20	-0.00127	0.18271	1
Mean AVL	One	2-5	0.02003	0.27629	1
		5-10	0.07974	0.28127	0.999
		10-20	0.40694	0.29657	0.646
		More than 20	0.07876	0.30544	0.999
	2-5	One	-0.02003	0.27629	1
		5-10	0.05971	0.18792	0.998
		10-20	0.3869	0.21013	0.352
		More than 20	0.05873	0.22248	0.999
	5-10	One	-0.07974	0.28127	0.999
		2-5	-0.05971	0.18792	0.998
		10-20	0.3272	0.21664	0.557
		More than 20	-0.00097	0.22863	1
	10-20	One	-0.40694	0.29657	0.646
		2-5	-0.3869	0.21013	0.352
		5-10	-0.3272	0.21664	0.557
		More than 20	-0.32817	0.24722	0.674

	More than 20	One	-0.07876	0.30544	0.999
		2-5	-0.05873	0.22248	0.999
		5-10	0.00097	0.22863	1
		10-20	0.32817	0.24722	0.674
Mean ANC	One	2-5	-0.17007	0.20503	0.921
		5-10	-0.26477	0.20873	0.711
		10-20	-0.32074	0.22008	0.591
		More than 20	-0.30155	0.22667	0.672
	2-5	One	0.17007	0.20503	0.921
		5-10	-0.0947	0.13945	0.961
		10-20	-0.15067	0.15594	0.87
		More than 20	-0.13148	0.1651	0.932
	5-10	One	0.26477	0.20873	0.711
		2-5	0.0947	0.13945	0.961
		10-20	-0.05597	0.16077	0.997
		More than 20	-0.03678	0.16967	1
	10-20	One	0.32074	0.22008	0.591
		2-5	0.15067	0.15594	0.87
		5-10	0.05597	0.16077	0.997
		More than 20	0.01919	0.18346	1
	More than 20	One	0.30155	0.22667	0.672
		2-5	0.13148	0.1651	0.932
		5-10	0.03678	0.16967	1
		10-20	-0.01919	0.18346	1
Mean MA	One	2-5	0.0022	0.28738	1
		5-10	0.06426	0.29256	0.999
		10-20	-0.03091	0.30848	1
		More than 20	-0.12418	0.3177	0.995
	2-5	One	-0.0022	0.28738	1
		5-10	0.06206	0.19546	0.998
		10-20	-0.03311	0.21857	1
		More than 20	-0.12639	0.23141	0.982
	5-10	One	-0.06426	0.29256	0.999
		2-5	-0.06206	0.19546	0.998
		10-20	-0.09517	0.22534	0.993

		More than 20	-0.18844	0.23781	0.933
	10-20	One	0.03091	0.30848	1
		2-5	0.03311	0.21857	1
		5-10	0.09517	0.22534	0.993
		More than 20	-0.09328	0.25714	0.996
	More than 20	One	0.12418	0.3177	0.995
		2-5	0.12639	0.23141	0.982
		5-10	0.18844	0.23781	0.933
		10-20	0.09328	0.25714	0.996
Mean LA	One	2-5	-0.40176	0.23371	0.424
		5-10	-0.02702	0.23792	1
		10-20	-0.22527	0.25087	0.898
		More than 20	-0.32619	0.25837	0.714
	2-5	One	0.40176	0.23371	0.424
		5-10	0.37475	0.15896	0.13
		10-20	0.17649	0.17775	0.858
		More than 20	0.07558	0.18819	0.995
	5-10	One	0.02702	0.23792	1
		2-5	-0.37475	0.15896	0.13
		10-20	-0.19826	0.18325	0.816
		More than 20	-0.29917	0.1934	0.533
	10-20	One	0.22527	0.25087	0.898
		2-5	-0.17649	0.17775	0.858
		5-10	0.19826	0.18325	0.816
		More than 20	-0.10091	0.20912	0.989
	More than 20	One	0.32619	0.25837	0.714
		2-5	-0.07558	0.18819	0.995
		5-10	0.29917	0.1934	0.533
		10-20	0.10091	0.20912	0.989
Mean REG	One	2-5	-0.11579	0.20349	0.979
		5-10	-0.03588	0.20716	1
		10-20	0.12157	0.21843	0.981
		More than 20	-0.44967	0.22496	0.269
	2-5	One	0.11579	0.20349	0.979
		5-10	0.0799	0.1384	0.978

		10-20	0.23735	0.15477	0.541
		More than 20	-0.33389	0.16386	0.251
	5-10	One	0.03588	0.20716	1
		2-5	-0.0799	0.1384	0.978
		10-20	0.15745	0.15956	0.861
		More than 20	-0.41379	0.16839	0.103
	10-20	One	-0.12157	0.21843	0.981
		2-5	-0.23735	0.15477	0.541
		5-10	-0.15745	0.15956	0.861
		More than 20	-.57124*	0.18208	0.016
	More than 20	One	0.44967	0.22496	0.269
		2-5	0.33389	0.16386	0.251
		5-10	0.41379	0.16839	0.103
		10-20	.57124*	0.18208	0.016
* The mean difference is significant at the 0.05 level.					

Appendix II

Questionnaire on Individual Investors' Behaviour

Dear Respondent,

I am a research scholar at the Department of Commerce and Business Studies, Jamia Millia Islamia (A Central University). As a part of my Ph.D. curriculum, I am conducting a survey on retail investors to understand their investment behavior and investment pattern in general.

I humbly invite you to participate in this survey. The information provided by you will be used only for academic purposes and your responses will be kept confidential and anonymous. It will hardly take 10-12 minutes to fill up this form. I really appreciate your contribution and time.

Section-I

(Behavioral biases)

Please answer the following questions by circling your preferred response where: 1= Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4= Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree

1	I feel that on average my investments perform better than the stock market	1	2	3	4	5	6	7
2	I feel more confident in my own investment opinions over those of financial analysts and advisors	1	2	3	4	5	6	7
3	I am responsible for all my past profitable investments	1	2	3	4	5	6	7
4	I am responsible for all my past failures	1	2	3	4	5	6	7
5	I do not change my investment, even if market is not supporting my investment decisions	1	2	3	4	5	6	7
6	I stick with a consistent marketing strategy even if the market is volatile	1	2	3	4	5	6	7
7	I am Satisfied regarding past investing decision making	1	2	3	4	5	6	7

8	I always feel optimistic about the future returns of my investments	1	2	3	4	5	6	7
9	I usually invest in familiar stocks.	1	2	3	4	5	6	7
10	I consider the past performance of the stocks before investing in it	1	2	3	4	5	6	7
11	I believe that through detailed analysis of past performance future value of a share in stock market can be determined	1	2	3	4	5	6	7
12	If in each of the last six months, the Nifty-50 Index value increased, I would expect the value of the Index to decrease in the next month.	1	2	3	4	5	6	7
13	I prefer to sell stocks on the days when the value of the stock market index decreases.	1	2	3	4	5	6	7
14	I prefer to buy stocks on the days when the value of the stock market index increases.”	1	2	3	4	5	6	7
15	I consider the information from my close friends and relatives as the reliable reference for my investment decisions	1	2	3	4	5	6	7
16	I prefer to invest in local stocks than international stocks because the information of local stocks is more available	1	2	3	4	5	6	7
17	I keep my money into separate accounts based on the source of the money	1	2	3	4	5	6	7
18	I split my money into separate account heads based on the use that I would put it for (e.g., children's education, marriage, and retirement)	1	2	3	4	5	6	7
19	When I receive income, I first put some money aside for saving and investments.	1	2	3	4	5	6	7
20	I have a pre-established monthly budget for investments.	1	2	3	4	5	6	7
21	Whenever I make a choice, I'm curious about what would have happened if I had chosen differently.	1	2	3	4	5	6	7

22	After making a choice, I try to get information about how the other alternatives turned out and feel bad if another alternative has done better than the alternative I have chosen.”	1	2	3	4	5	6	7
23	If I make a choice and it turns out well, I still feel like something of a failure if I find out that another choice would have turned out better.	1	2	3	4	5	6	7
24	Once I make a decision, I don’t look back.	1	2	3	4	5	6	7
25	When making a decision, I think much more about what might be lost than what might be gained.	1	2	3	4	5	6	7
26	The pain of losing money matters more than the pleasure of gaining the same amount of money	1	2	3	4	5	6	7
27	I feel nervous when I have to make a decision that may lead to loss	1	2	3	4	5	6	7
28	Experiencing a major loss stays in my mind longer than experiencing a major gain.	1	2	3	4	5	6	7
29	The suffering that comes with losses can be fully offset by the pleasure that comes from gains.	1	2	3	4	5	6	7
30	I compare the current stock price with its recent 52-week high and low price to justify my stock purchase	1	2	3	4	5	6	7
31	I usually forecast the future stock prices based on recent stock price	1	2	3	4	5	6	7
32	I usually consider the purchase price of the stock as reference point for trading	1	2	3	4	5	6	7
33	The purchase price of a security is a not big factor to be considered while selling it	1	2	3	4	5	6	7

Section –II

(Perceived Investment performance and Satisfaction measures)

The statements below will help you to think about and assess your satisfaction with the present financial situation. Please answer the following by circling your preferred response where:

1 = Highly Dissatisfied, 2 = Dissatisfied, 3 = Somewhat Dissatisfied, 4 = Undecided, 5 = Somewhat Satisfied, 6 = Satisfied, 7 = Highly Satisfied

34	Present level of savings	1	2	3	4	5	6	7
35	Ability to handle family's financial emergencies(e.g., medical expenses)	1	2	3	4	5	6	7
36	Money available for future needs (house, children's education, marriage, own retirement, etc.)	1	2	3	4	5	6	7
37	Ability to manage money to protect from inflation	1	2	3	4	5	6	7
38	Ability to save taxes/tax planning	1	2	3	4	5	6	7
39	Ability to pay back the amount of money owed (on debts, loans, credit card payments due, etc.)	1	2	3	4	5	6	7
40	Present level of income	1	2	3	4	5	6	7
41	I feel satisfied with my investment decisions in the last year (including selling, buying, choosing and deciding on stock volumes)	1	2	3	4	5	6	7

Please answer the following questions by circling your preferred response where: 1= Strongly Disagree, 2 = Disagree, 3 = Somewhat Disagree, 4 = Neither Agree nor Disagree, 5 = Somewhat Agree, 6 = Agree, 7 = Strongly Agree

42	The rate of return of my recent stock investment meets my Investment expectations	1	2	3	4	5	6	7
43	My rate of return is return is equal to or higher than the average return rate of the market.	1	2	3	4	5	6	7
44	I do not care about the effects of the financial market on my return, as long as I am able to beat inflation	1	2	3	4	5	6	7

Section – III

(Demographics and Stock portfolio details)

	Stock portfolio details	
45	Please specify which type of securities are you most comfortable in investing	
	1	Only stocks
	2	Stocks and mutual funds both
	3	Derivatives and commodities market
	4	High grade corporate bonds
	5	Others (Please specify)
46	Number of stocks in stock portfolio? -----	
47	What is your current investment amount in stocks? -----	
48	For how long have you been investing?	
	1	Less than 1 year
	2	1-3 years
	3	3-5 years
	4	5-7 years
	5	More than 7 years
49	How frequently do you invest in equity markets?	
	1	Intraday
	2	0-3 months
	3	3-12 months
	4	12-36 months
	5	36 months or more

50	Age _____

51	Gender	
	1	Male
	2	Female
	3	Other
52	Marital Status	
	1	Single
	2	Married
53	Educational Qualification	
	1	Undergraduate
	2	Graduate
	3	Post Graduate
54	Profession (Please specify the industry in which you work)	

55	Annual Income	
	1	0-2.5 lakhs
	2	2.5-5 lakhs
	3	5-7.5 lakhs
	4	7.5-10 lakhs
	5	More than 10 lakhs

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APPENDICES

APPENDIX-I (TABLES AND FIGURES)

Appendix 1.1 Tukey HSD and Tamhane's Post Hoc Test

Multiple Comparisons						
Dependent Variable		(I) Age categories	(J) Age categories	Mean Difference (I-J)	Std. Error	Sig.
Mean OC	Tukey HSD	18-30	31-40	-0.08539	0.09947	0.667
			Above 40	-0.28907	0.12444	0.054
		31-40	18-30	0.08539	0.09947	0.667
			Above 40	-0.20369	0.12664	0.244
		Above 40	18-30	0.28907	0.12444	0.054
	Tamhane		31-40	0.20369	0.12664	0.244
		18-30	31-40	-0.08539	0.10452	0.8
			Above 40	-.28907*	0.10468	0.019
		31-40	18-30	0.08539	0.10452	0.8
			Above 40	-0.20369	0.1051	0.155
Mean REP	Tukey HSD	Above 40	18-30	.28907*	0.10468	0.019
			31-40	0.20369	0.1051	0.155
		18-30	31-40	0.20373	0.1163	0.188
			Above 40	-0.10021	0.1455	0.77
		31-40	18-30	-0.20373	0.1163	0.188
	Tamhane		Above 40	-0.30394	0.14808	0.102
		Above 40	18-30	0.10021	0.1455	0.77
			31-40	0.30394	0.14808	0.102
		18-30	31-40	0.20373	0.12049	0.252
			Above 40	-0.10021	0.12954	0.825
	Tukey HSD	31-40	18-30	-0.20373	0.12049	0.252
			Above 40	-0.30394	0.12722	0.054
		Above 40	18-30	0.10021	0.12954	0.825
			31-40	0.30394	0.12722	0.054

Mean AVL	Tukey	18-30	31-40	-0.05752	0.15878	0.93
	HSD		Above 40	-0.07436	0.19863	0.926
		31-40	18-30	0.05752	0.15878	0.93
			Above 40	-0.01684	0.20215	0.996
		Above 40	18-30	0.07436	0.19863	0.926
			31-40	0.01684	0.20215	0.996
	Tamhane	18-30	31-40	-0.05752	0.16108	0.978
			Above 40	-0.07436	0.18977	0.972
		31-40	18-30	0.05752	0.16108	0.978
			Above 40	-0.01684	0.18094	1
		Above 40	18-30	0.07436	0.18977	0.972
			31-40	0.01684	0.18094	1
Mean ANC	Tukey	18-30	31-40	-0.03711	0.11765	0.947
	HSD		Above 40	-0.00239	0.14718	1
		31-40	18-30	0.03711	0.11765	0.947
			Above 40	0.03472	0.14979	0.971
		Above 40	18-30	0.00239	0.14718	1
			31-40	-0.03472	0.14979	0.971
	Tamhane	18-30	31-40	-0.03711	0.11837	0.985
			Above 40	-0.00239	0.14441	1
		31-40	18-30	0.03711	0.11837	0.985
			Above 40	0.03472	0.14257	0.993
		Above 40	18-30	0.00239	0.14441	1
			31-40	-0.03472	0.14257	0.993
Mean MA	Tukey	18-30	31-40	0.01451	0.1623	0.996
	HSD		Above 40	-.51077*	0.20304	0.033
		31-40	18-30	-0.01451	0.1623	0.996
			Above 40	-.52528*	0.20664	0.031
		Above 40	18-30	.51077*	0.20304	0.033
			31-40	.52528*	0.20664	0.031
	Tamhane	18-30	31-40	0.01451	0.16663	1
			Above 40	-.51077*	0.18693	0.021
		31-40	18-30	-0.01451	0.16663	1
			Above 40	-.52528*	0.1875	0.018
		Above 40	18-30	.51077*	0.18693	0.021

			31-40	.52528*	0.1875	0.018
Mean LA	Tukey	18-30	31-40	0.0256	0.13498	0.98
	HSD		Above 40	0.10024	0.16886	0.824
		31-40	18-30	-0.0256	0.13498	0.98
			Above 40	0.07464	0.17186	0.901
		Above 40	18-30	-0.10024	0.16886	0.824
			31-40	-0.07464	0.17186	0.901
	Tamhane	18-30	31-40	0.0256	0.13794	0.997
			Above 40	0.10024	0.15782	0.894
		31-40	18-30	-0.0256	0.13794	0.997
			Above 40	0.07464	0.15572	0.95
		Above 40	18-30	-0.10024	0.15782	0.894
			31-40	-0.07464	0.15572	0.95
Mean REG	Tukey	18-30	31-40	-0.01775	0.11823	0.988
	HSD		Above 40	-0.06968	0.14791	0.885
		31-40	18-30	0.01775	0.11823	0.988
			Above 40	-0.05193	0.15053	0.937
		Above 40	18-30	0.06968	0.14791	0.885
			31-40	0.05193	0.15053	0.937
	Tamhane	18-30	31-40	-0.01775	0.12062	0.998
			Above 40	-0.06968	0.13888	0.944
		31-40	18-30	0.01775	0.12062	0.998
			Above 40	-0.05193	0.13468	0.973
		Above 40	18-30	0.06968	0.13888	0.944
			31-40	0.05193	0.13468	0.973
* The mean difference is significant at the 0.05 level.						

Appendix 1.2 Tukey HSD Post Hoc Tests

Multiple Comparisons					
Tukey HSD					
Dependent Variable	(I) Education	(J) Education	Mean Difference (I-J)	Std. Error	Sig.
meanOC	Undergraduate	Graduate	-.58226*	0.19618	0.009
		Post graduate	-0.30082	0.19179	0.261



**INTERNATIONAL JOURNAL OF
MANAGEMENT, IT AND ENGINEERING**
(IJMRA Publications) ISSN: 2249-0558 UGC Approved No 46823
Publication Certificate



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Delhi, India*

For the publication of research paper entitled:

Endowment Effect as a Function of Gender and Age: Mediating Role of Loss Aversion

In Volume 9 Issue 05 May 2019 with Impact factor 7.119 UGC Approved Journal No 46823



2249-0558

Shabana

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Managing Editor

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Double-Blind Peer Reviewed Refereed Open Access International Journal - Included in the International Serial Directories

Endowment Effect as a Function of Gender and Age: Mediating Role of Loss Aversion

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Abstract

Investment decisions of individual investors are influenced by many psychological biases and variation in their demography further increases the complexities of these decisions. The purpose of the paper is to investigate the role of age and gender in determining a hard-wired emotional bias in the mind of investors i.e. the endowment effect. It also explores the mediating role of loss aversion between age, gender, and endowment effect of individual investors in India. Snowball and convenience sampling methods are employed to collect data from respondents. A total of 200 investors were contacted, out of which 155 responses were considered useful for further analysis. Since the data are cross-sectional we used AMOS-21 to perform Confirmatory Factor Analysis (CFA) and Path Analysis to examine the relationship between variables. Findings of the study suggest that female investors are more loss averse and levels of their endowment effect are also higher as compared to their male counterparts. Evidence from the study also indicates that as the age of the respondents is increasing their endowment effect and loss aversion are also increasing. Data also revealed that loss aversion does not play a mediating role between gender, age, and endowment effect of Indian individual investors.



Endowment Effect as a Function of Gender and Age: Mediating Role of Loss Aversion

1. Introduction

Investment decision-making is a complex process that requires allocating financial resources to different assets with the objective of getting the highest possible returns while undertaking a minimum amount of risk. A relatively new discipline of behavioral finance explained to us that investors are not solely guided by the factors of risk and return, rather there are many psychological aspects and behavioral biases that unconsciously affect the investment decisions of individual investors. Varied demographic characteristics of the investor population further accentuate the complexities that arise because of deep-seated behavioral biases in the minds of investors. (Baker et.al, 2018; Prosad et.al, 2015). Loss aversion and the Endowment effect are two such biases that originate from a paper titled "Prospect theory: An analysis of decision under risk" by Kahneman and Tversky (1979). In the classical research papers that demonstrate the endowment effect, it is always seen as evidence for loss aversion around a reference point.(Kahneman et.al, 1990; Kahneman et. al, 1991; Knetch & Wong, 2009). This study is an attempt to examine the role of age and gender in determining the endowment effect of an individual investor and the mediating role of loss aversion between demographic variables and the endowment effect. We test our theoretical model using structural equation modeling on the primary data collected from 155 individual investors in the Indian stock market. The results of the study indicate that the gender and age of investors do have a positive and significant impact on the levels of loss aversion and the endowment effect of Indian individual investors. Female investors are more loss averse and levels of their endowment effect are also higher as compared to their male counterparts. Evidence from the study also indicates that as the age of the respondents is increasing their endowment effect and loss aversion are also increasing. Data also revealed that loss aversion does not play a mediating role between gender, age, and endowment effect of Indian individual investors.

2. Literature survey and hypotheses development

The endowment effect is the tendency of people to attach additional value to the things they own simply because they belong to them (Ericson & Fuster, 2014). Thaler, (1980) through their exchange experiment with university students demonstrated that goods that are included

in one's endowment are valued more highly than identical goods not held in the endowment and coined the term endowment effect (Reb & Connolly, 2007). Later on Kahneman, Knetsch, and Thaler (1991) extended this work and demonstrated the endowment effect through their experiments that are popularly known as the valuation paradigm. In the valuation paradigm, the minimum amount of money that sellers are willing to accept (WTA) is higher than the minimum amount of money that buyers are willing to pay (WTP) to acquire a good. This creates a gap between WTA and WTP which has many economic consequences such as increased inefficiencies and irregularities in the market and reluctance to trade. Thus endowment effect rejects many important assumptions of standard finance.

Loss Aversion: Kahneman and Tversky (1979) described loss aversion as "the aggravation that one experiences in losing a sum of money appear to be greater than the pleasure associated with gaining the same amount of money". The phenomenon emerged from the prospect theory in the form of an "S" Shaped value function passing through a reference point. The observations suggest that people are more sensitive to losses than to gains resulting in a utility function that is steeper for losses than for gains (Kobberling & Wakker, 2005)

Gender, Age, and Loss Aversion: A large body of academic literature suggests that investment pattern differs across gender, females are believed to be more risk-averse and consequently more loss averse than males. Prasad and Mohta, (2012) conducted an empirical survey on 128 Indian investors and found out that female investors are more loss averse in comparison to males. Arora and Kumari, (2015) showed the mediating role of loss aversion between gender, age, and financial risk-taking and found out that gender and age are important determinants of loss aversion and regret aversion, females were found to be more loss averse than males and age was positively related to loss aversion. Johnson et.al, (2006) found that younger respondents in the sample have lower levels of loss aversion as compared to older respondents in their study. Hjorth and Fosgerau, (2011) showed that loss aversion increases with age and decreases with the level of education. Gatcher et.al, (2007) found that loss aversion, in the form of a gap between valuation measures increases with age and income. Thus, past literature provides enough evidence for the fact that age and gender are

important factors in explaining levels of loss aversion in an individual investor. Therefore we form the following hypotheses.

H1 There is a significant relationship between Gender and loss aversion

H2 There is a significant relationship between age and loss aversion

Gender, Age, and Endowment Effect

Harbaugh et.al (2001) in their experimental design tried to relate the endowment effect with age and experience, they found that increase in age does not decrease the levels of endowment in an individual even though the investor becomes more experienced with getting and giving up the goods. Dommer and Swaminathan, (2013) found that men and women have different interpretations of what ownership signifies in an endowment effect context. Wieland et.al (2014) explored gender differences in endowment effect in different countries and found out that when a choice is framed as a willingness to pay (WTP) task, women are willing to pay less than men. However, when a choice is framed as a willingness to accept (WTA) task, women will not accept less than men, giving rise to gender differences in endowment effect across gender. Bao and Gang, (2016) suggest that the endowment effect is weaker in young investors as compared to old investors.

H3 There is a significant relationship between gender and the endowment effect

H4 There is a significant relationship between age and the endowment effect

Loss Aversion and Endowment Effect

From the very beginning, the phenomenon of the endowment effect has been linked to loss aversion. The endowment effect was seen as a manifestation of loss aversion. The pain of giving up a good would be felt as more aversive than gaining from the opportunity of acquiring an alternative good (Kahneman et.al, 1990; Kahneman et. al, 1991; Knetch & Wong, 2009)

According to prospect theory losses hurt us more than the gains make us happy. When we sell something it can be viewed as a loss of possession and when we buy something it is viewed as a gain of a new possession, and because of loss aversion people want more compensation for losing an item than buyers who are willing to acquire it, resulting in a

greater discrepancy between WTA-WTP, giving rise to the endowment effect (Dommer and Swaminathan, 2013). Considering the above fact, this paper tries to find the mediating effect of loss aversion on the relationship between demographic variables and the endowment effect of individual investors in India. Thus we form the following hypotheses.

H5 There is a significant relationship between loss aversion and the endowment effect.

H6 There is a mediating effect of loss aversion between gender and the endowment effect

H7 There is a mediating effect of loss aversion between age and the endowment effect.

Figure 1: Hypothesized model.

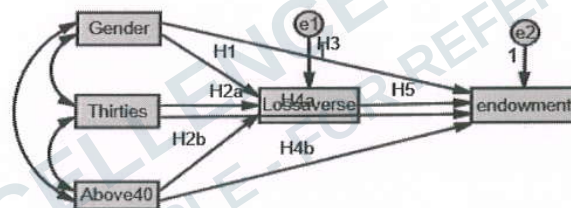


Figure-1

3. Research Design and Methodology

Sampling

The target population for the study consists of individual investors investing in the Indian stock market. The sample area from which the data are collected is Delhi- NCR. Snowball and convenience sampling methods are employed to collect data from respondents. A total of 200 investors were contacted, out of which 170 people filled the survey, after checking for validation, 155 responses were considered useful for further analysis. It has been documented

that there is no specific rule for determining sample size in the case of behavioral studies (Osborne & Costello, 2004). Since the data are cross-sectional we used AMOS-21 to perform Confirmatory Factor Analysis (CFA) and Path Analysis to examine the relationship between variables.

Questionnaire

A self-administered questionnaire was developed containing items related to demography and behavioral biases concerning Indian individual investors. Every construct and item of the study have been identified with extensive literature review and validated by experts from academics.

The questionnaire consists of two sections. Section 'A' deals with respondents' demographic profiles, while section B focuses on behavioral biases using a five-point Likert scale. To assess loss aversion a four-item scale was used which was taken from M. Zat and U. Khan, (2017). Any scale to measure the endowment effect was not found in the literature, therefore it was developed for the study. Four items were finalized to obtain a self-reported view of the endowment effect, which were further evaluated by domain experts for the possibility of reducing or clubbing the items.

4. Data Analysis and Interpretation

Age and Gender are taken as exogenous variables while Loss aversion and Endowment effect are taken as endogenous variables. Path analysis was conducted using Amos to find path coefficients of all the variables. The conceptual model provides for the following relationships

$$LA_i = B_0 + B_1 D_{i, \text{Gender}} + B_2 D_{i, \text{Age}} + e$$

$$EE_i = B_0 + B_1 D_{i, \text{Gender}} + B_2 D_{i, \text{Age}} + e$$

$$EE_i = B_0 + B_1 LA_i + e$$

Where, LA_i is the loss aversion score for respondent i calculated from loss aversion scale. EE_i is the endowment effect score for respondent i calculated from endowment effect scale. D_i gender is a dummy variable taking the value of unity if the respondent is female and the



value of zero if the respondent is male. DiAge is a dummy variable taking the value 1 for the reference category and zero for others.

Table 1 shows the mean and standard deviation of endogenous variables.

	Gender		Age		
	Males	Females	18-30	31-40	Above 40
Loss	N = 113	N = 42	N = 87	N = 47	N = 21
Aversion	M = 3.63 (0.849)	M = 4.3 (0.109)	M = 3.35 (.844)	M = 4.27 (.412)	M = 4.7 (.232)
Endowment	M = 2.65	M = 3.63	M = 2.75	M = 2.94	M = 3.96
Effect	(1.016)	(.504)	(.980)	(.970)	(.948)

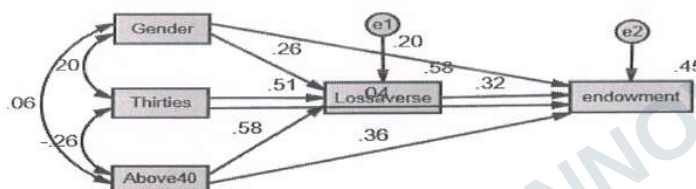
Model Testing

Structural equation modeling is an advance tool of research methodology that assist the researcher to analyze several regression equations simultaneously. It is accepted as dominant multivariate technique in social sciences. We conducted model testing in two steps first, we measured the effect of all independent variables in dependent variables. In the second step, we estimated total, direct and indirect effect in the presence of mediating variable using AMOS Graphics 21. We estimated mediating effect based on bootstrap procedures with in conventional covariance structural framework.

A structural equation model generated through AMOS was used to test the relationships. A Good fitting model is accepted if the value of the CMIN/df is < 5, the goodness of the fit (GFI) indices (Hair et al, 2010); the Tucker and Lewis (1973) index (TLI); the Confirmatory Fit Index (CFI) (Bentler, 1990) is > 0.90 (Hair et al., 2010) In addition an adequate- fitting model is accepted if the AMOS computed value the standardized root mean square residual (RMR) is < 0.05, and the root mean square error approximation (RMSEA) is between 0.05 and 0.08 (Hair et al., 2010). The fit indices for the model shown in table 2 fell within the acceptable range: CMIN/df = 2.321, GFI = 0.914, TLI = 0.911, CFI = 0.940, SRMR = 0.053, RMSEA= 0.093

The squared multiple correlation was 0.583 for loss aversion, this shows that gender and age of investors explain about 58% variance in loss aversion, and the squared multiple correlation for endowment effect is 0.446, which shows that almost 44% variation in endowment effect is explained by age and gender of investors in the present model.

Figure 2: Structural model



The study assessed the impact of demographic variables (age and gender) on loss aversion and the endowment effect of individual investors in India. The impact of gender on loss aversion is significant (H1: $b = 0.248$, $p < 0.05$) and a positive coefficient implies that females have higher levels of loss aversion as compared to males. Age also has a significant impact on the loss aversion of investors (H2a: $b = 0.480$, $p < 0.05$; H2b: $b = 0.584$, $p < 0.05$), the positive coefficient here indicates that investors in the reference category (18-30 age group) have lower levels of loss aversion as compared to investors in their thirties or above 40 years of age, hence, data confirms H1 and H2 in the model. The impact of gender and age on the endowment effect without the presence of loss aversion i.e. H3 and H4 were also supported by the results obtained from the data analysis (H3: $b = 0.274$, $p < 0.05$; H4a: $b = 0.190$, $p < 0.05$; H4b: $b = 0.518$, $p < 0.05$). Loss aversion also has a significant impact on the endowment effect supporting H5 in the structural model (H5: $b = 0.258$, $p < 0.05$).

Table 2 shows the impact of independent variables on dependent variables without mediating variables.

Hypothesized relationship	Standardized Estimates	T-Values	P-values	Decision
Endowment effect <- Gender	0.274	3.632	< 0.05	Supported
Endowment effect <- Thirties	0.190	2.500	< 0.05	Supported
Endowment Effect <- Above 40	0.518	6.039	< 0.05	Supported

Table 3 shows the direct effect of independent variables on dependent variables in the presence of mediating variable

Hypothesized relationship	Standardized Estimates	T-Values	P-values	Decision
Loss aversion <- Gender	0.248	3.719	< 0.05	Supported
Loss aversion <- Thirties	0.480	6.758	< 0.05	Supported
Loss aversion <- Above 40	0.548	7.757	< 0.05	Supported
Endowment effect <- Gender	0.209	2.679	< 0.05	Supported
Endowment effect <- Thirties	0.067	0.735	0.462	Not Supported
Endowment Effect <- Above 40	0.377	3.751	< 0.05	Supported
Endowment effect <- Loss aversion	0.258	2.216	< 0.05	Supported

R- square

Loss aversion	0.583
Endowment effect	0.446

CMIN/df = 2.321, GFI = 0.914, TLI = 0.911, CFI = 0.940, SRMR = 0.053, RMSEA = 0.093

Mediation Analysis

The study assessed the mediating role of loss aversion on the relationship between gender and age of investors on the endowment effect. The study revealed the indirect impact of gender on the endowment effect was not significant ($b = 0.109$, $P = 0.073$) hence, H6 was not supported. However, the direct effect of gender on the endowment effect in the presence of mediating variable was found to be significant ($b = 0.355$, $P = 0.001$). Therefore, we can say that loss aversion does not play a mediating role between gender and the endowment effect. Also, the age of investors does not have an impact on the endowment effect via loss aversion as the indirect effect was not significant for both categories of age (thirties group: $b = 0.203$, $p = 0.095$; above 40 age group: $b = 0.311$, $p = 0.097$) hence, H7 was also supported, therefore, we conclude that loss aversion does not play a mediating role between age and endowment effect of investors. The mediation analysis summary is presented in Table – 3

Table 4: Direct and indirect effects of independent variables on dependent variables

Relationship	Direct Effect	Indirect effect	Confidence Interval		P Value	Conclusion
			Upper	Lower		
Gender-> LA -> EE	0.355 (.001)	0.109	0.285	-0.012	0.073	No Mediation
Thirties -> LA -> EE	0.110 (.364)	0.203	0.425	-0.044	0.095	No Mediation
Above40 - > LA -> EE	0.831 (.001)	0.311	0.651	-0.074	0.097	No Mediation

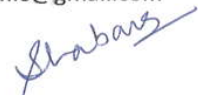
5. Discussion and conclusions

In this article, we set out to deepen our understanding of whether the age and gender of investors affect their levels of the endowment effect and loss aversion among Indian individual investors. The results of the study indicate that females are more loss averse

and the levels of their endowment effects are also higher as compared to male investors in the Indian context. These findings are consistent with the findings of Prasad and Mohta, (2012); Arora and Kumari, (2015); and Dommer and Swaminathan, (2013). Data also revealed that the age of investors is positively and significantly related to the levels of loss aversion and the endowment effect among Indian investors these findings are also consistent with the findings of Hjorth and Fosgerau, (2011); Harbaugh et.al (2001); and Bao and Gang, (2016). With regard to the mediating role of loss aversion between demographics and the endowment effect evidence from the study suggest that loss aversion does not mediate the relationship between age, gender, and endowment effect of Indian retail investors this gives us a chance to think about the alternative explanations to the endowment effect apart from loss aversion. Various pieces of research in the past suggest that the endowment effect can no longer solely be attributed to a traditional loss aversion account. There are new alternative theories such as Motivated Taste Change Theory, Cognitive Perspective and Query Theory, Attachment aversion to bad deals, and Neuroeconomics that suggest evolutionary, strategic, and more basic cognitive origins of the endowment effect. (Isoni et.al, 2011; Ericson and Fuster, 2014; Morewedge and Giblin, 2015) The study has many implications for financial advisors and financial educators. Financial advisors can make themselves more effective by understanding their client's investment decision-making process. Moreover, since demographic variables are closely related to behavioral biases different strategies can be formulated to serve the needs of the client. Future researchers should undertake additional studies with a larger sample size to increase the generalizability of results. Researchers may also include new variables which can influence investment decisions and can extend this study in different contexts.

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CHAPTER 6

FINDINGS AND CONCLUSION

The present chapter summarizes the major findings of the study on behavioral biases and their impact on individual investors in the Delhi-NCR region. The answers to all of the research objectives formulated in the first chapter have been incorporated into this chapter. The chapter discusses the major findings and draws conclusions from them. In addition, the chapter discussed the study's practical and theoretical contributions, as well as its limitations and the scope for future research.

6.1 Sample Composition of respondents

According to the demographic profile of investors, married men with postgraduate degrees who are predominantly employed in private service make up the bulk of respondents. The average age of the respondent is 33 years, earning an annual income between 2.5 lakh rupees to 5 lakh rupees. The gender gap in the number of respondents participating in the survey can be attributed to the patriarchal nature of Indian society where male members of the households still have the exclusive power to make financial decisions (Baker et al., 2018). Also, the average annual income of the respondents is higher than the national average annual income of approximately 1.50 lakh rupees for the FY 2022 (Ohri, 2022). Sophistication measures of the investors revealed that the majority of the respondents have an investment experience of around 2-5 years in stock markets with an investment amount ranging from 1 lakh to 5 lakh rupees diversified across 2 to 5 firms, which they normally trade within a period of three months.

6.2 Impact levels of Behavioral Biases

Representativeness is the most common behavioral bias, with the highest mean, influencing the investment decisions of Delhi-NCR investors. Then comes overconfidence, loss aversion, and anchoring. These findings are consistent with those of Chandra and Kumar (2012), who found that representativeness was the most impactful on individual investors in India, followed by overconfidence, anchoring, and gambler's fallacy. The present study also found that the mean values of mental accounting, regret, and availability are lower when compared to other biases, this indicates that these factors are less dominant in the investment decisions of Delhi-NCR investors.

6.3 Demographics and Behavioral Biases (Objective 1)

6.3.1 Gender and Behavioral biases

The results of the t-test indicate that males are more overconfident than female investors in the Delhi-NCR region these results are consistent with the studies of Barber and Odean, (2001), Bhandari and Deaves (2006), Bakar and Yi (2015), and Kumar and Goyal (2016). With respect to gender, results of the study also revealed that females are more loss averse and more prone to mental accounting bias than male investors in the Delhi-NCR region which are in accordance with the findings of Bajtelsmit and Bernasek (1996), Arora and Kumari (2015), and Prasad and Mohta, (2012).

6.3.2 Age and Behavioral Biases

According to the findings of ANOVA and Welch's F, elder investors over 40 years of age are more likely than younger investors under 40 years to exhibit overconfidence, representativeness, and mental accounting. This age-related increase in the levels of behavioral biases can be attributed to the declining cognitive abilities of investors as they grow old (Bruine de Bruin et al., 2012). Additionally, it gets more difficult and expensive as investors age to keep up with the rapidly evolving financial products and investment prospects, especially when they are faced with cognitively demanding tasks (Pak & Chatterjee, 2016; Korniotis & Kumar, 2011). In the Indian context Baker et al. (2018), and Prasad et al. (2014) also found significant associations between age and behavioral biases.

6.3.3 Education and Behavioral Biases

Among the behavioral biases overconfidence and anchoring are found to have strong associations with the education of investors. Graduate investors are more prone to overconfidence and anchoring bias than postgraduate investors. This suggests that overconfidence and anchoring decrease with higher education. These findings are in line with the findings of Novokmet and Zalic (2017) and Beblo et al. (2017) which concluded that learning and education help in mitigating overconfidence and anchoring respectively. However, these are in contradiction with the findings of Bhandari and Deaves (2006), Deaves et al. (2010), Mishra and Metilda (2015), and Baker et al. (2018) which shows that overconfidence increases with the level of education among investors.

6.3.4 Occupation and Behavioral Biases

Results of ANOVA and Welch's F indicate that depending upon the type of occupation, investors tend to exhibit different levels of overconfidence in financial decision-making. Self-employed investors who are mostly entrepreneurs and professionals are more overconfident than investors who are still pursuing higher education and working in the government or private sector. This may be because entrepreneurs are risk-takers, they have more positive beliefs about the future success of their business which makes them more optimistic and consequently more overconfident compared to other categories of investors. These findings are consistent with the findings of Rietveld et al. (2013) and Joo and Durri (2017) which showed that self-employed individuals are more overconfident than individuals who are in service. In India Mushinada and Veluri (2019), Baker et al. (2018), and Prosad et al. (2014) concluded that overconfidence is significantly associated with the occupation of respondents.

6.3.5 Income and Behavioral Biases

ANOVA test results revealed that investors belonging to various income categories differed in terms of overconfidence, mental accounting, and loss aversion bias. Overconfidence and mental accounting are higher in higher-income groups and lower in lower-income groups, whereas, loss aversion is higher in investors belonging to lower-income groups and lower in investors belonging to higher-income groups. These findings are consistent with the findings of Chandra (2009), Lin (2011), Chandra and Kumar (2012), Isidore and Christie (2018), Kansal and Singh (2018), and Baker et al. (2018) which showed that investors with high-income categories are competent and trade more frequently in the stock market which makes them more overconfident and increases their mental accounting bias as compared to investors in the lower income categories. Concerning loss aversion, investors in lower-income groups are more loss averse perhaps because they do not want to risk their already meager income, whereas investors in higher-income groups are less loss averse because they have the extra room to take more risk.

6.4 Investor Sophistication and Behavioral Biases (Objective 1)

6.4.1 Investment Experience and Behavioral Biases

The results of Welch's F revealed that overconfidence is increasing with the investment experience of investors of Delhi-NCR. Overconfidence levels in experienced investors (with more than ten years of experience) are significantly higher than in novice investors. These findings are in line with the findings of Oberlechner and Osler (2009), Chen et al. (2007), and Kansal and Singh (2018). This finding could be explained by the fact that increased investment experience increases a person's ability to spot more profitable opportunities, creating an illusion of success and resulting in higher levels of overconfidence bias in investors with more investment experience.

6.4.2 Trading Frequency and Behavioral Biases

The empirical findings suggest that trading frequency is positively related to the availability bias of investors in the Delhi-NCR region. The more frequently a person makes purchase and sale decisions, the more susceptible he is to availability bias. Intraday traders have the highest availability bias, while long-term investors have the lowest. This could be because intraday traders are less cautious than investors who trade less frequently. They rely on readily available information to make quick decisions and discussing their trading decisions with friends, family, and colleagues relieves them of psychological stress (Prosad et al., 2014). Mental accounting has been found to have a negative relationship with trading frequency. Mental accounting levels are higher in investors who trade less frequently and lower in investors who trade more frequently. This can be explained by the fact that since intraday traders are more casual in their decision-making as it is a routine job for them thus they do less mental accounting than traders who are more cautious in their investment decisions and invest less frequently.

6.4.3 Number of Stocks in Portfolio and Behavioral Biases

The number of stocks in an investor's stock portfolio has been found to have a positive relationship with investors' regret aversion bias. The more stocks in a portfolio, the more a person regrets his mistakes and, as a result, becomes more regret averse. This could be because as the number of stocks in an investor's portfolio grows, so does the amount at stake, making a person more cautious and risk-averse, and thus more regret-averse.

6.5 Behavioral Biases and Perceived Investment Performance (Objective 2)

6.5.1 Overconfidence and Perceived Investment performance

Overconfidence has a positive and significant impact on the perceived investment performance of individual investors. This observation may be due to the fact that overconfident investors trade more aggressively than their rational counterparts' do, which enables them to better take advantage of risky profit opportunities and generate higher returns (Hirshleifer & Luo, 2001). Similar findings were made by Javed et al. (2017), ul Abdin et al. (2017), and Le Luong and Thi Thu Ha (2011), who found that overconfidence has a significant and positive impact on the perceived investment performance of individual investors. Additionally, Oberlechner and Osler (2008) noted that the overconfidence-induced illusion of success boosts investors' self-esteem and keeps them motivated to continue in the market. Research by De Long et al. (1991) also supported the idea that overconfident investors hold riskier investments and hence earn larger returns than other investors. These results, however, are at odds with those of Odean (1999), Barber and Odean (2000), and Ahamd and Shah (2020), who demonstrated that overconfidence lowers individual investors' investing performance and returns.

6.5.2 Availability and Perceived Investment Performance

Availability has a positive and significant impact on the perceived investment performance of individual investors. This suggests that availability bias helps investors to take better financial decisions and thus contributes to better investment performance. These findings are consistent with the findings of Javed et al. (2017), Alrabadi et al. (2018), ul Abdin et al. (2017), and Khan (2015). However, most of the research studies by Keller et al. (2006), Clark (2014), Hadi (2017), Tversky and Kahneman (1974), and Massa and Simonov (2005) suggested that the availability heuristic causes decision-makers to limit their investment opportunities, which prevents them from diversifying their investment portfolio, selecting investments based on retrievability rather than a thorough analysis of the options, allocating assets appropriately, and selecting alternative investments when appropriate.

6.5.3 Anchoring and Perceived Investment Performance

Anchoring has a positive and significant impact on the perceived investment performance of individual investors. These findings are consistent with the findings of Aziz and Khan (2016), Ishfaq and Anjum (2015), Menike et al. (2015), Ranjbar et al. (2014), Obara (2015), and Malik et al. (2022).

6.5.4 Regret and Perceived Investment Performance

Regret has a positive and significant impact on the perceived investment performance of individual investors. In the opinion of the researcher regret averse investors use feedback from other participants to avoid risks so as not to regret later in case of anticipated regret and in case of experienced regret, the pain of regret leads to subsequent changes in asset allocation, as a result, they tend to buy assets that performed well in the past and sell those that perform poorly. Thus, disciplined investing by regret-averse investors helps them to improve their investment performance. The results are consistent with the findings of Aziz and Khan (2016) and Zouaoui and Bellouma (2018) who also found a positive impact of regret on the investment performance of investors in Pakistan and Tunisia. Cao et al. (2021) also showed that prospect theory variables including regret have a favorable impact on investment results. Dodonova and Khoroshilov (2005) showed that regret-averse investors may be able to earn positive stock returns in the short-run and negative stock returns in the long run. However, the result is in contrast to that of Le Luong and Thi Thu Ha (2011), Silwal and Bajracharya (2021), and Kengatharan and Kengatharan (2014), who found that regret had a detrimental effect on investment performance. In order to minimize regret, investors increase their awareness and consideration, invest in more secure and creditworthy assets, and make wiser decisions (Bailey and Kinerson, 2005; Copur, 2015, p. 153).

6.6 Behavioral Biases and Investment Satisfaction (Objective 3)

6.6.1 Overconfidence and Investment satisfaction

The results of the study suggest that overconfidence has a significant and positive effect on the satisfaction of investors from their investment performance. As per the opinion of the researcher the possible reason for this finding is that overconfidence is a bias reflected through excessive optimism and the excessive illusion of success. People who

are overconfident typically have high expectations for their own abilities and efforts. When an investor has confidence in their ability to make wise financial decisions, they are more likely to select solutions that will help them reach their investment goals and increase their level of investment satisfaction. Chen and Koufaris (2014) took satisfaction as the decision-making process's primary end result and found that overconfident participants also demonstrated higher levels of satisfaction.

6.6.2 Availability and Investment satisfaction

The availability bias has a positive and significant impact on the levels of investment satisfaction of investors in India's NCR region. The findings are consistent with those of Pandey and Jessica (2019) and Gavrilakis and Floros (2021), who found that heuristics such as availability have a positive effect on investment satisfaction in the real estate sector in India and Private Investors in Greece, respectively. According to these studies, biases are not always harmful; they occasionally enable individual investors to select the best course of action from a wide range of options and enable them to make less costly errors, aiding in the development of satisfying behavior.

6.6.3 Anchoring and Investment satisfaction

Anchoring has a positive and significant impact on the investment satisfaction of individual investors of Delhi-NCR. Again the outcomes support Pandey and Jessica's (2019), and Gavrilakis and Floros's (2021) observation that heuristics such as anchoring have a beneficial impact on the investment satisfaction of investors in India as well as in Greece.

6.6.4 Mental accounting and investment satisfaction

Mental accounting has a positive and significant impact on individual investors of Delhi-NCR. The researcher believes that this is the case because with mental accounting the investors are in a better position to keep a track of their investment in different financial assets and can exercise greater self-control while maintaining risky portfolios. Investors divide their investments into distinct mental accounts, and investment decisions are made to satisfy each of these distinct mental accounts. (Zahera & Bansal, 2018)

6.7 Behavioral Biases and Financial Satisfaction (Objective 4)

6.7.1 Availability and Financial Satisfaction

Availability has a significant positive impact on the financial satisfaction of individual investors of Delhi-NCR. The majority of private investors aren't expert stock traders, and they don't live off of stock market profits; rather, stocks comprise a small portion of their overall investment portfolio, which could be one explanation for this conclusion. Because of this, it is impossible for them to consider all of the information available in the market when making financial decisions; instead, they rely on information that is readily available to them and use the availability heuristic inadvertently. This not only saves them time and energy due to the complex information integration, but it can also produce better results than sophisticated financial models (Gigerenzer, 2008). Hence, when investors achieve desired outcomes with less time-consuming tasks and fact-checking, their overall financial satisfaction increases. Further, this saved time and energy by making efficient use of available information that could be devoted to solving other meaningful purposes in life leading to better life satisfaction.

6.7.2 Anchoring and Financial Satisfaction

Anchoring has a positive and significant impact on the financial satisfaction of individual investors of Delhi-NCR. This finding may be explained by the fact that anchoring aids investors in choosing the best possible action among multiple alternative actions available within a quick time frame. Without anchoring bias, decision-making will be delayed since investors won't have any easily available "benchmarks" or "anchors" on which they can base their decisions. As we all know, the stock market is a place where investors must make quick decisions regarding numerous investment possibilities and methods. Decision-makers can use previously defined anchors, in this case, to quickly and profitably take advantage of lucrative chances, which will increase their earnings and financial satisfaction.

6.6.3 Mental accounting and Financial Satisfaction

Mental accounting has a positive and significant impact on the financial satisfaction of individual investors residing in Delhi-NCR. The researcher believes that this may be the case because mental accounting involves the task of categorization of money into different categories according to the sources and uses of funds. This provides them with maximum information with minimum effort when needed, and helps investors to fulfill their financial objectives which also improves their financial satisfaction. The task of budgeting in mental accounting helps investors to keep a track of their spending in different categories belonging to life's needs, thus mental accounting gives them mental satisfaction when they have sufficient budget in each mental account, which helps them to improve their overall financial satisfaction (Sahi, 2017; Mogilner, 2008)

6.8 Mediation Effect of Perceived Investment Performance and Investment Satisfaction (Objective 5)

6.8.1 Perceived investment performance fully mediates the relationship between overconfidence and financial satisfaction. This indicates that overconfidence has a significant impact on PIP, which in turn has a significant impact on the financial satisfaction levels of individual investors. This may be because overconfident investors are more optimistic and trade more aggressively than rational investors which leads to higher investment performance and higher investment performance implies greater income for investors that increases their overall solvency and helps in satisfying all their life's needs leading to higher financial satisfaction among individual investors of Delhi-NCR. Vera-Toscano et al. (2006) and Seghieri et al. (2006) in their respective studies have established the role of higher income in achieving higher levels of financial satisfaction.

6.8.2 Investment satisfaction fully mediates the relationship between overconfidence and financial satisfaction. According to the researcher, this may be the result of overconfidence having a favorable impact on individual investors' satisfaction with their investments because overconfident investors believe they are better than others at making sound financial decisions, increasing the likelihood of their financial independence (Hu et al., 2021) and, as a result, their overall financial satisfaction.

6.8.3 Investment satisfaction partially mediates the relationship between availability and financial satisfaction. The positive mediating effect of investment satisfaction between availability bias and financial satisfaction can be explained using evolutionary psychology. The availability heuristic is a natural tendency that emerges as a result of humans' limited capacity to access all types of information. As a result, humans act decisively on easily accessible information which contributes to their investment satisfaction which in turn, contributes to their financial satisfaction.

6.8.4 Investment satisfaction partially mediates the relationship between anchoring and financial satisfaction. Again, from the standpoint of evolutionary psychology, anchoring can be seen as innate human characteristics that cause decision-makers to act quickly on the basis of already available anchors learned from previous behaviors, thereby assisting investors in financial markets to have better investment satisfaction and, as a result, better financial satisfaction.

6.8.4 Investment satisfaction partially mediates the relationship between mental accounting and financial satisfaction. According to the researcher, this finding results from mental accounting acting as a self-controlling mechanism, economizing the investor's thinking and assisting them in keeping better track of their investments, thus contributing to investment satisfaction and, ultimately, financial satisfaction of investors.

Thus, perceived investment performance and investment satisfaction serve as mediators between behavioral biases and financial satisfaction among Delhi-NCR investors. These mediators are more than just transmitters of behavioral biases' influence; they are the foundation of the stability of the relationship between behavioral biases and financial satisfaction.

6.9 Moderating effects of the Demographic and Investor Sophistication Variables on Hypothesized Relationships (Objective 6)

6.9.1 Impact of gender on hypothesized relationships

The results of the multi-group analysis suggest that gender has a moderating effect on the relationships between representativeness and PIP, regret and PIP, and mental

accounting and FS. Regret has a positive impact on the PIP of male investors, while it has a negative impact on the PIP of female investors. According to Villanueva-Moya and Expósito (2022), after experiencing regret, women internalize a greater fear of negative evaluation than men, because women's decisions are usually directed by others, whereas men make self-oriented decisions, lowering women's overall well-being. This fact may have had a negative impact on women investors' perceived investment performance. Mental accounting has no significant impact on the FS of male investors, but it has a strong positive impact on the FS of Female investors. This finding has resulted because female investors are more prone to mental accounting than male investors, since males do less mental accounting it has no impact on the levels of their financial satisfaction, and women being more susceptible to mental accounting has a strong impact on the levels of their financial satisfaction.

6.9.2 Impact of marital status on hypothesized relationships

The results revealed that the marital status of the respondents has a significant impact on the relationship between regret and PIP. Regret has a positive impact on the PIP of unmarried investors while it has a negative impact on the PIP of married investors. This finding could be explained by the fact that married investors are typically risk averse; they cannot afford to take on the additional financial risk because they have a family to care for. If they experience regret, married investors may withdraw from risky securities and prefer to invest in low-risk assets, which typically have lower returns than risky assets. Unmarried investors, on the other hand, can take additional risks to earn superior returns, which may have a positive impact on unmarried investors' perceived investment performance.

6.9.3 Impact of age on hypothesized relationships

To identify the moderation effects of age on hypothesized relationships, investors are divided into two age groups below 30 years of age and above 30 years of age. The results of the multi-group analysis show that age does not have a significant impact on hypothesized relationships except for the relationship between regret and PIP. Regret has a positive impact on the PIP for investors who are below 30 years of age, but it has a negative impact on investors who are above 30 years of age. Again, the findings show that young investors are adventurous and risk-takers, so when they experience regret, they do not back down and continue to invest in profitable opportunities, which may

result in regret having a positive impact on the PIP of young investors, whereas mature investors have a low-risk appetite, so when they experience regret, they become more cautious and refrain from investing in risky yet profitable opportunities, which results in a negative impact on the PIP of mature investors.

6.9.4 Impact of income on hypothesized relationships

The results of the multi-group analysis revealed that income does not have moderating effect on any of the hypothesized relationships in the proposed model.

6.9.5 Impact of investment experience on hypothesized relationships

Investment experience moderates the relationship between overconfidence and investment satisfaction. Overconfidence positively affects the IS of more experienced investors, while it has a negative effect on the IS of less experienced investors. This could be because more experienced investors are more overconfident, so they trade more aggressively and feel a sense of accomplishment in their trades, which keeps them satisfied with their investment performance. Less experienced investors, on the other hand, are less overconfident, and as a result, they may not be in a position to take advantage of profitable opportunities in time, resulting in lower-than-expected returns and thus remaining dissatisfied with their investment performance.

6.9.6 Impact of trading frequency on hypothesized relationships

Trading frequency is moderating the relationship between mental accounting and investment satisfaction. Based on trading frequency investors are categorized into active and passive investors. Mental accounting has a stronger impact on the investment satisfaction of passive investors as compared to active investors. This finding is due to the fact that passive investors are more prone to mental accounting because they trade less frequently, are more cautious in their investment decisions, and do a lot of mental accounting, which may have resulted in mental accounting positively influencing investment satisfaction. Active investors, on the other hand, trade so frequently that they do not spend time thinking about their trades and are less prone to mental accounting; thus, the impact of mental accounting on investment satisfaction is weaker for active investors than for passive investors.

6.10 Conclusion

The study provided a thorough and in-depth examination of the behavioral biases of Indian individual investors. An integrated research model developed for the study is used to investigate the factors (socio-demographic and investor sophistication variables) that influence these behavioral biases as well as those that are affected by these behavioral biases in terms of performance and satisfaction variables. Thus, the current study attempted to provide a comprehensive view of the underlying mechanisms of behavioral biases and their consequences in the Indian context.

The changing environment of Indian financial markets, evolving financial market instruments, and the vulnerability of Indian financial consumers all contributed to the need for this research. The study focused on research areas that had been largely ignored by previous research studies in the existing literature, and as a result, it attempted to add to the existing behavioral finance literature in a limited manner. Since India is a country with people from diverse social, cultural, and economical backgrounds the finding of the present study becomes more relevant and applicable. The study analysed data in two phases. First, it measured the impact of different socio-demographics and sophistication variables on behavioral biases and then in the second phase, it analysed the impact of behavioral biases on the financial well-being of individual investors.

The present study captured the current state of behavioral biases of Indian investors. The research examined the presence of behavioral biases using a sample of individual investors in Delhi-NCR. According to the survey findings, Indian investors exhibit a variety of behavioral biases, including overconfidence, representativeness, loss aversion, anchoring, mental accounting, regret, and availability. Therefore, the study's results are consistent with the idea that individual investors do not always make rational decisions. Instead, making financial decisions is influenced by emotions, heuristics, and other biases. It has been observed that behavioral biases are influenced by various demographic and investor sophistication variables. The study's findings show that gender, age, education, occupation, and income are the most important demographic variables influencing individual investors' behavioral biases. In terms of gender, the findings show that males appear to be more overconfident in their stock market knowledge than females, and females are more sensitive to losses than male investors. Moreover, older investors are more likely to exhibit overconfidence,

representativeness, and mental accounting than younger investors. An important finding of the study is that higher education reduces the chances of investors being biased in their decisions, and postgraduate investors are less likely to be overconfident and anchored in their financial decisions. Self-employed persons appear to be more overconfident than salaried-class investors. With regard to the income of the respondents, evidence suggests that higher-income group people are more prone to overconfidence and mental accounting, and lower-income group people are more inclined towards loss aversion. Another interesting observation is that investor sophistication variables such as investment experience, trading frequency, and the number of stocks in the portfolio also influence the degree of behavioral biases exhibited by Indian individual investors. Investment experience contributes to the overconfidence bias, whereas trading frequency increases availability bias among investors and the number of stocks in the portfolio influences the degree of regret aversion displayed by a person. Overall, the evidence confirms that individual investors in India are susceptible to different behavioral biases and demographic and investor sophistication variables are related to these biases.

The present study also extends the current knowledge base about the relationships between behavioral biases, perceived investment performance, investment satisfaction, and financial satisfaction. Overconfidence availability, anchoring, and regret are found to have a positive and significant impact on the perceived investment performance of individual investors. Further, heuristics and mental accounting bias have a significant and positive impact on the investment satisfaction and financial satisfaction of individual investors in Delhi-NCR. Moreover, it is also found that the effect of behavioral biases on financial satisfaction is passing through investment performance and investment satisfaction, i.e. these two variables are playing the role of significant mediators in the relationship between behavioral biases and financial satisfaction which is one of the most important findings of the present research.

Overall the study concludes that psychological biases should not always be considered as risk factors because sometimes they have a flip side that can be beneficial for the financial well-being of individual investors. The current research emphasizes the fact that in real financial settings, investors must act quickly with known probabilities and utilities, multiple goals, and poorly defined problems drive investors to choose satisfying solutions rather than the best ones. In such complex situations, the human

mind turns to heuristics and biases like a handyman's toolbox to help itself choose the best course of action from the many options and enable it to go for the less costly errors, helping to achieve better investment performance and satisficing behavior.

6.11 Contributions and Implications of the study

An extensive and thorough analysis was used to arrive at the findings of the current study. Our research made a modest contribution to the body of knowledge while attempting to bridge the gap in the existing literature on behavioral finance. Although there are certain limits, this study has attempted to draw conclusions that could be highly helpful to those involved in the stock markets. Regardless of these limitations, this study will undoubtedly be informative to readers, individual investors, financial professionals, researchers, and other stakeholders in this field as discussed below:-

Implications for individual investors

- The results of the study indicate that behavioral biases have a significant impact on the perceived investment performance and investment satisfaction of individual investors which ultimately affects their overall financial satisfaction. Individual investors should always try to identify the influence of any potential behavioral biases within their personality and should select appropriate investment tools by recognizing their behavioral biases in order to have the upper hand in all of their financial decisions and to further improve their investment performance and returns.
- The results of the study also validated the impact of heterogeneity in demographic variables and investor sophistication measures on behavioral biases of individual investors and hypothesized relationships among variables. These findings provide valuable insights to individual investors to make investment decisions according to their demographic and sophistication characteristics.
- Although the study suggested that heuristics and biases have a positive impact on individual investors' investment performance and financial satisfaction, investors should remember that heuristics are a double-edged sword and that disregarding them can negatively impact their investment returns and financial satisfaction. In order to make better investment decisions and advance the field of finance, the researcher would like to suggest that investors should not solely

rely on cognitive heuristics and sentiments when making investments. Instead, they should perform a proper analysis of investment opportunities, develop quantitative investment criteria, and establish investment objectives and constraints.

- Understanding the behavioral aspects of human psychology can give individual investors a competitive edge to survive and grow in a dynamic market environment, the research's findings also assist retail investors in justifying their investment decisions and dispelling their doubts about market psychology.

Implications for financial advisors and brokerage firms: The findings are also valuable to various financial advisors and brokerage firms that help investors obtain higher returns.

- A good financial advisor is a mix of a psychologist and an economist. By incorporating the research's findings into their thinking, financial advisors can develop relationships with their clients, which is crucial for being competent advisors.
- Financial advisors can offer their clients specialized services based on their demographic and sophistication characteristics, particularly when they have clients from various racial and ethnic origins. Brokerage firms can also plan awareness campaigns to educate their clients about the importance of taking background factors into account when making investing decisions.
- The results of this study also improve advisers' capacity to develop plans that will help clients meet their financial goals. Additionally, it enables advisors to create behaviorally modified portfolios in accordance with the behavioral biases ingrained in their psychology.
- The current study also enables practitioners and advisors to recognize their own mistakes in addition to those of their clients. It helps them predict individual investor behavior more accurately in light of changing market sentiments, enabling them to suggest better stocks to their clients.

Implications for academics: There are several important implications of this study for academics.

- The study increases our understanding of numerous behavioral biases including overconfidence, mental accounting, and regret by establishing them as second-

order constructs of their antecedents for the first time in the context of Indian research studies in the field of behavioral finance.

- The majority of behavioral finance literature to date has focused on the direct connections between behavioral biases and financial satisfaction or investment performance; however, the current study has successfully established the mediating roles of perceived investment performance and investment satisfaction in the relationship between behavioral biases and financial satisfaction. Consequently, the study brought to light the crucial significance that perceived investment performance and investment satisfaction play in determining an investor's level of financial satisfaction.
- Further, additional behavioral biases can be examined using the integrated model that was established for the study.
- Finally, very few studies have been conducted in India that examines the critical role that behavioral biases play in determining financial satisfaction. As a result, the study broadens the knowledge of Indian researchers and academicians for future research in this field.

6.12 Limitations of the study

- The study was carried out in India's national capital region (NCR), where investor trading activity, per capita income, and education levels are all higher than elsewhere in the nation, limiting the relevance of our findings to this region only.
- The study was done on a sample of just 307 respondents due to time and budget constraints, which reduced the generalizability of results even though it fulfilled the required criteria. Also, the study's scope was limited to the equity investments segment of financial markets.
- The present study collected primary data from respondents regarding their financial behavior. In stressful market environments, respondents may be reluctant to acknowledge their biases and may give socially desirable answers that may differ from their true responses.
- The current study is based on cross-sectional data, which captures the respondents' mental state at a certain point in time. Responses may change in reaction to changing market conditions.

- The study uses pre-defined scales to assess behavioral biases and heuristics. Thus, there is a measurement weakness in our study.

6.13 Scope for Future Research

The current study opens up a wide range of research areas that future research studies can investigate in order to contribute to the field of behavioral finance.

- To increase the generalizability of the findings, the study might be carried out in other regions of the nation. Future studies can be carried out in Mumbai or other major Indian metropolises to better understand the behavior of Indian investors because Mumbai serves as the country's financial capital and is home to the Bombay Stock Exchange (BSE) and the National Stock Exchange, two of the world's largest stock exchanges.
- The study can be extended to include other developing nations' economies so that their circumstances can be compared to those of India. Such comparative analysis can be useful in revealing cross-cultural variations in investor behavior and contribute to the body of knowledge already available on behavioral finance.
- To gain a deeper knowledge of retail investors' investment behavior, a comprehensive study that includes a larger sample size across all financial market categories, such as commodity markets, mutual funds, and derivatives, can be carried out.
- The sample of the present study is composed of students, government and corporate employees, professionals, and entrepreneurs. Future research studies can be conducted to focus only on professional investors to make the study more relevant.
- To solve the problem of measurement weakness present study can be replicated using micro-trading data of individual investors to capture their real behavior in actual market conditions.
- The proposed model in the study investigated the impact of seven important behavioral biases (overconfidence, availability, anchoring, representativeness, mental accounting, loss aversion, and regret) on the investment performance and financial well-being of individual investors. The study can be further extended to find the impact of other behavioral biases on these dependent

variables and interrelationships between different psychological biases can also be analysed.

- In the current study, perceived investment performance and investment satisfaction are two mediating variables used to examine the effect of behavioral biases on investors' financial satisfaction. To gain a comprehensive picture of investor behavior, future studies can add additional mediating variables to the model, such as fundamental and technical anomalies, risk perception, and locus of control.

EXCELLENCE INNOVATIONS
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