MODERATING ROLE OF MARKET INFORMATION IN THE RELATIONSHIP BETWEEN BEHAVIORAL FINANCE BIASES AND THE STOCK INVESTMENT DECISION MAKING AMONG KENYAN INVESTORS: EVIDENCE FROM NAIROBI SECURITIES EXCHANGE

BY

MUSYOKA FELISTERS MUTHEU

MASTER OF SCIENCE IN COMMERCE (FINANCE AND INVESTMENT)

KCA UNIVERSITY

SEPTEMBER 2025

MODERATING ROLE OF MARKET INFORMATION IN THE RELATIONSHIP BETWEEN BEHAVIORAL FINANCE BIASES AND THE STOCK INVESTMENT DECISION MAKING AMONG KENYAN INVESTORS: EVIDENCE FROM NAIROBI SECURITIES EXCHANGE

BY

MUSYOKA FELISTERS MUTHEU

REG NO: 18/00773

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF A DEGREE OF MASTER OF SCIENCE IN COMMERCE (FINANCE AND INVESTMENT) TO THE SCHOOL OF BUSINESS AT KCA UNIVERSITY

SEPTEMBER 2025

DECLARATION/APPROVAL PAGE

I declare that this dissertation is my original work and has not been previously published or submitted elsewhere for the award of a degree. I also declare that this contains no material written or published by other people except where due reference is made and the author duly acknowledged.

Student Name:..**Reg, No:**..

Signed:..**Date:**..

I do hereby confirm that I have examined the dissertation of **Musyoka Felisters Mutheu** and have certified that all revisions recommended have been adequately addressed.

Signed:..**Date:**..

Prof. Christine Nanjala Simiyu.

Dissertation Supervisor

MODERATING ROLE OF MARKET INFORMATION IN THE RELATIONSHIP BETWEEN BEHAVIORAL FINANCE BIASES AND THE STOCK INVESTMENT DECISION MAKING AMONG KENYAN INVESTORS: EVIDENCE FROM NAIROBI SECURITIES EXCHANGE

ABSTRACT

Behavioral finance is an emerging area of study in finance that examines human behavior in relation to financial decision-making, seeking to overcome the limitations of traditional finance by providing explanations for people's economic decisions. It analyzed how investors' instincts and psychology governed their decision-making when investing in securities, focusing on information interpretation and investment attitudes-factors that significantly impacted capital allocation and portfolio choices. This study analyzed the moderating role of market variables in the relationship between behavioral finance biases and stock investment decisions at the Nairobi Securities Exchange, categorizing these biases into three broad behavioral factors: heuristics, prospect, and herding factors. The study was grounded in Heuristic Theory (which explains cognitive shortcuts in decision-making), Prospect Theory (addressing loss aversion and reference-dependent preferences), and Regret Theory (examining how anticipated regret influences choices). The study employed a cross-sectional non-experimental descriptive research design, targeting 24 licensed stockbrokers at the NSE using a census approach. Data was collected through close-end questionnaires administered to two respondents from each brokerage firm, resulting in 48 total respondents. The data was coded and analyzed using SPSS software with logit regression methods. The findings indicated that heuristic biases significantly influenced investment decisions ($\beta=0.448$, $p<0.001$), prospect biases showed substantial impact ($\beta=0.298$, $p=0.003$), and herding behavior demonstrated significant effects ($\beta=0.246$, $p=0.002$). Investors relied on cognitive shortcuts, exhibited loss aversion and regret aversion, and were heavily influenced by social networks and popular trends. Market information emerged as a significant moderator ($\beta=0.497$, $p=0.001$), with interaction effects showing that market information amplified the influence of heuristic biases ($\beta=0.103$, $p=0.043$) and prospect biases ($\beta=0.151$, $p=0.012$) on investment decisions. The study concluded that behavioral biases, particularly heuristics, prospect biases, and herding behavior, had a significant effect on investment decisions at the NSE. It is recommended that investors be educated on the impact of these biases and be encouraged to make data-driven decisions. Furthermore, it emphasized the need for improving transparency market information to mitigate the influence of biases and enhance market efficiency.

ACKNOWLEDGEMENT

I extend my heartfelt thanks to the Almighty God for His boundless wisdom, guidance, and strength throughout the course of this research. His provision has been crucial in navigating the complexities of this study. I am profoundly grateful to my supervisor, Prof. Christine N. Simiyu, whose insightful feedback and unwavering support have significantly advanced this research project. My deep appreciation also goes to my family for their continued support and encouragement, which has been a source of great motivation. I also want to acknowledge the comradeship and inspiration provided by my fellow students, whose presence helped me remain focused and driven. Finally, I am thankful to everyone who, whether directly or indirectly, contributed to the success of this work. May Gods blessings be upon you all.

TABLE OF CONTENTS

DEDICATION

To Geoffrey Telela, the love of my life, and to my three precious treasures, Sharp, Prince, and Blessings, who have been my source of strength and inspiration.

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

1.0 Background of the Study

Investment decision-making stands as a fundamental pillar of financial markets, shaping economic growth and wealth creation across the global economy. The traditional framework of financial markets, built upon the Efficient Market Hypothesis (EMH), posits that investment decisions emerge from rational analysis of risk and return, with market prices efficiently reflecting all available information (Rahman & Hassan, 2023). However, the reality of modern financial markets reveals a more nuanced landscape where investment decisions are influenced by a complex interplay of rational analysis, market information, and human psychology. The emergence of behavioral finance has highlighted how cognitive biases and emotional factors significantly impact investment choices, challenging the traditional assumption of purely rational decision-making (Anderson et al., 2023). This evolution in understanding market behavior has particularly important implications as financial markets become increasingly sophisticated and interconnected, with investors facing unprecedented levels of information flow and market complexity (Wilson & Lee, 2023). The interplay between market information, behavioral biases, and investment decisions has thus emerged as a critical area of focus for understanding how modern financial markets function and how investors navigate them.

The global investment landscape has undergone significant transformation in recent years, marked by increasing market complexity and evolving investor behavior. The World Federation of Exchanges reports that global market capitalization reached $128.3 trillion by the end of 2023, reflecting the massive scale of investment decisions being made daily across markets (World Bank, 2024). This expansion has been accompanied by dramatic changes in how investors access and process market information, with digital platforms and algorithmic trading reshaping traditional decision-making paradigms. In developed markets, particularly the United States and European Union, investment decisions have become increasingly sophisticated, yet studies indicate a growing disconnect between fundamental market values and investor behavior. The rise of retail investing platforms has democratized market access, with over 150 million new retail investors entering global markets between 2020 and 2023 (International Finance Corporation, 2024). This surge in retail participation has heightened attention to how individual investors make decisions, with market regulators and financial institutions increasingly recognizing the need to understand and address behavioral aspects of investment decision-making. Major financial centers in Asia, particularly Japan, Singapore, and Hong Kong, have also witnessed similar trends, with regulatory frameworks evolving to accommodate the changing dynamics of investor decision-making (Asian Development Bank, 2024).

Africa's investment landscape has experienced remarkable growth and transformation, with the continent's stock exchanges demonstrating increasing sophistication in investment practices and market infrastructure (African Development Bank, 2024; Okumu & Ndirangu, 2023). The African Securities Exchanges Association (ASEA, 2024) reports that the combined market capitalization of African stock exchanges reached $1.5 trillion in 2023, reflecting growing investor confidence and market maturity (Maponga & Dzirutwe, 2024). Significant developments in major markets like South Africa, Egypt, and Nigeria have reshaped investment dynamics, with the Johannesburg Stock Exchange leading technological advancement in trading systems (Mbeki & Zulu, 2023; Hassan & Mohammed, 2024). Digital transformation has dramatically improved market access, with Adebayo et al. (2023) reporting that mobile trading platforms have facilitated over 30 million new retail investors entering African markets since 2020. However, Mensah and

Alagidede (2023) identify persistent challenges in investment decision-making across African exchanges, including information asymmetry, market volatility, and behavioral biases. A comprehensive study by Nkrumah and Santos (2024) across fifteen African exchanges revealed that investment decisions are significantly influenced by local market dynamics and cultural factors unique to the African context. The implementation of the African Continental Free Trade Area (AfCFTA) has introduced new dimensions to investment decision-making, with Okonkwo et al. (2024) documenting how regional integration is creating both opportunities and complexities for investors across the continent.

The Nairobi Securities Exchange (NSE), as Kenya's principal securities market, has undergone significant evolution in its investment landscape. The Capital Markets Authority (CMA, 2024) reports that the NSE's market capitalization reached KES 1.9 trillion in 2023, with over 2 million retail investors actively participating in the market. A transformative shift in investment decision-making has been observed, particularly following the introduction of mobile trading platforms and day trading (Kiprono & Gatheru, 2023). Mugo and Omondi (2024) document how the NSE's recent technological advancements, including the automated trading system and remote trading capabilities, have fundamentally altered how investors access and process market information. However, Ndung'u et al. (2023) identify persistent challenges in investment decision-making at the NSE, including information asymmetry and the significant influence of behavioral factors on investor choices. Recent market events, such as the substantial price movements in key stocks and the introduction of new financial products, have highlighted the complex interplay between market information and investor behavior (Kimani & Wanjiku, 2024). The NSE's strategic plan for market deepening and increased retail participation has brought renewed focus on understanding the factors that influence investment decisions, particularly among individual investors (NSE, 2024; Mutiso & Kamau, 2023).

1.1.1 Behavioral finance biases

Behavioral finance explains investor irrationality and decision-making processes through cognitive psychology and biases related to beliefs and preferences. This field highlights why individuals often act irrationally in uncertain situations, leading to suboptimal investment choices. Investors have different objectives and risk tolerances, shaping their unique portfolios. Kisaka (2015) noted that behavioral finance reveals why investors might trade securities without fundamental analysis. Individual investors often make decisions that diverge from optimal investment standards, resulting in behavioral biases and inefficient investments. Common harmful behaviors include under-diversification, premature selling of winning positions, holding onto losing stocks too long, and overconfidence.

Studies on behavioral finance have identified factors influencing individual investor decisions. Rehan and Umer (2017) emphasized that heuristics, prospect theory, herding, and rationality simplify decision-making in complex and uncertain environments. Key behavioral finance theories include prospect theory, heuristic theory, and herding behavior. Heuristics, or rules of thumb, simplify decision-making (Rehan & Umer, 2017) through methods like representativeness, availability bias, anchoring, gambler's fallacy, and overconfidence. Representativeness bias involves categorizing events based on familiar classes (Riyazahmed & Saravanaraj, 2016). Availability bias occurs when the frequency or probability of an event is judged by the ease with which instances come to mind (Riyazahmed & Saravanaraj, 2016). Anchoring involves relying too heavily on initial information, and overconfidence refers to excessive confidence in one’s decisions (Odean, 1998).

Prospect theory examines behavior under uncertainty and risk, with a general preference for certainty. Ngahu (2017) described key concepts of prospect theory such as loss aversion, regret aversion, and mental accounting. Loss aversion means that losses are felt more intensely than gains, prompting riskier behavior to avoid losses (Venkatapathy & Sultana, 2016). Regret aversion involves altering decisions to avoid future regret, such as refusing to sell losing shares (Subramaniam & Velnampy, 2017). Mental accounting refers to how investors evaluate financial transactions, often leading them to hold onto losing stocks (Dar & Hakeem, 2015).

Herding behavior describes the tendency of individual investors to follow the majority's decisions. Hirshleifer and Teoh (2010) defined herding as mutual imitation, while Baddeley (2018) noted that individuals often follow group behaviors rather than make independent decisions. This social dependence, especially under uncertainty, leads to imitative behavior, providing comfort in collective action (Kirtini & Narda, 2021). Individual investors are more prone to herding than institutional investors (Lee et al., 2015), contributing to market inefficiency and speculative bubbles. In contrast, rational investors avoid following the masses, promoting market efficiency.

1.1.2 Market information

Market information plays a crucial role in shaping investment decisions and market efficiency across global financial markets. The availability, quality, and timeliness of market information significantly influence how investors perceive opportunities and risks (Rahman & Chen, 2023). According to the International Organization of Securities Commissions (IOSCO, 2024), effective market information dissemination has become increasingly critical as markets become more complex and interconnected. Park and Zhang (2024) define market information as encompassing a broad spectrum of data, including financial statements, corporate announcements, market analytics, expert opinions, and real-time trading data. The evolution of digital platforms and technological advancements has transformed how market information is generated, distributed, and consumed by investors (Sullivan et al., 2023). However, Chen and Morgan (2024) note that the abundance of information in modern markets presents both opportunities and challenges, as investors must navigate through vast amounts of data to make informed decisions.

The role of market information in emerging markets like the NSE presents unique characteristics and challenges. Ochieng and Kamau (2023) highlight how information asymmetry continues to influence market dynamics in developing exchanges, despite technological improvements in information dissemination. The Capital Markets Authority (2024) reports that while digital transformation has enhanced information accessibility at the NSE, challenges persist in ensuring equal access and interpretation capabilities among different investor segments. Research by Mutiso et al. (2024) demonstrates that the quality and reliability of market information significantly impact investor confidence and trading behavior at the NSE. Moreover, Kimani and Wanjiku (2024) find that the interaction between market information and behavioral biases plays a crucial role in determining investment outcomes, particularly among retail investors. The NSE's efforts to enhance market information systems through technological upgrades and improved corporate disclosure requirements reflect the growing recognition of information's central role in market development (NSE, 2024).

1.1.3 Stock investment decisions

Stock investment decisions by Kenyan investors at the Nairobi Securities Exchange (NSE) are governed by a network of interconnected factors, transcending the boundaries of classical financial theories. Decision-making, at its core, involves the complex process of selecting a specific option from a multitude of alternatives. The traditional utility theory suggests that investors are naturally rational beings, seeking to maximize their expected utility by opting for the most beneficial outcome. However, groundbreaking insights from behavioral finance, particularly those expressed in Subramaniam, and Velnampy (2017) prospect theory, reveal a more nuanced reality. This theory posits that under conditions of risk and uncertainty, investors' decisions are profoundly shaped by their subjective perceptions of gains and losses, often leading to deviations from the strict utility maximization paradigm.

Prospect theory lightens the phenomenon of loss aversion, where investors exhibit a propensity to experience losses more acutely than equivalent gains. This cognitive bias can precipitate irrational decision-making patterns, such as the disposition effect, where investors hold onto losing stocks for too long while prematurely selling winning stocks. Yuniningsih et al. (2017) extend this framework by introducing the concept of satisficing, wherein individuals cease their search for options upon encountering a satisfactory solution rather than the optimal one. This heuristic-driven behavior is particularly salient in the volatile and unpredictable environment of the NSE, where market participants often rely on mental shortcuts, leading to systematic biases and departures from rational decision-making (Yuniningsih et al., 2017).

Furthermore, the gender dimension introduces an additional layer of complexity to investment decisions at the NSE. Toma (2015) uncovered that men typically gravitate towards riskier portfolios and engage in more frequent trading compared to women. This gender-based divergence in risk tolerance and trading behavior may be attributed to differing levels of overconfidence, with men generally displaying higher levels of overconfidence, thereby adopting more aggressive investment strategies. Conversely, women's risk aversion often translates into more conservative portfolio choices and less frequent trading activities, significantly influencing market dynamics and individual portfolio performance at the NSE (Toma, 2015).

Beyond psychological and gender factors, personal experience, social influences, and financial literacy emerge as pivotal determinants of investment decisions. Investors' past encounters with the stock market, their social networks, and the extent of their financial literacy collectively shape their risk perceptions and investment behaviors. For instance, investors with extensive market experience or higher financial literacy are more likely to make informed and rational decisions. In contrast, those with limited experience or knowledge may exhibit herd behavior, following the actions of others rather than making independent, well-informed choices. This issue underscores the intricate interplay between individual cognition and social dynamics in shaping investment decisions (Nguyen et al., 2019; Barberis, 2018).

Addressing these numerous influences necessitates a complete approach to decision-making in stock investment at the NSE. This involves not only enhancing financial knowledge but also mitigating psychological biases and errors. Recognizing the impact of cognitive biases such as overconfidence, anchoring, and loss aversion is crucial, along with implementing strategies to counteract their effects. Educational programs aimed at boosting financial literacy and raising awareness of behavioral biases can empower investors to make more rational decisions. Additionally, leveraging technology, such as automated investment advisors and decision-support systems incorporating behavioral insights, can provide investors with the tools to navigate the complexities of the stock market more effectively (Chaffai & Medhioub, 2018).

The decision-making process of Kenyan investors at the NSE is influenced by a convergence of psychological, social, and financial factors. A deep understanding of these influences is essential for developing strategies that enhance decision-making processes and investment outcomes. By integrating behavioral finance insights, promoting comprehensive financial education, and harnessing technological advancements, investors can make more informed and rational decisions, ultimately fostering a more efficient and resilient stock market (Ngahu, A. N., 2017).

1.1.4 Nairobi securities exchange

The Nairobi Securities Exchange PLC (NSE) is a leading securities exchange in Kenya, facilitating capital raising through a diverse, multi-asset trading platform. The NSE provides a wide array of products, including equities, bonds, exchange-traded funds (ETFs), real estate investment trusts (REITs), derivatives, and data and training services to meet investor needs. It significantly contributes to Kenya's economic growth by promoting savings and investment and offering affordable capital access to both local and international companies. Regulated by the Capital Markets Authority of Kenya (CMA), the NSE collaborates with regional exchanges like the Rwanda Stock Exchange, the Dar es Salaam Stock Exchange in Tanzania, and the Uganda Securities Exchange as part of Africa's financial integration agenda (ADB, 2012). The performance of the securities market is a key indicator of a country's economic strength and development (Patricia & Oluwatobi, 2005; Fernandez, 2006), with rising share prices often reflecting increased investments and overall economic growth (Jaswani, 2008).

Investors often become overly enthusiastic and react excessively, particularly when new securities enter the market, and various factors affect their decision-making processes. For instance, at the Nairobi Securities Exchange (NSE), security prices can deviate significantly from fundamental market expectations, as seen during the Safaricom IPO, which was notably oversubscribed. This phenomenon can be attributed to the herding effect, where investors, influenced by the crowd, purchased Safaricom shares without relying on market information, contrary to traditional financial theories. Additionally, individual investors continue to engage in the secondary market by buying and selling securities (CMA, 2017).

In recent times, the NSE has experienced a steady rise in the number of companies seeking registration for trading, which has drawn numerous investors, as evidenced by repeated subscriptions. Nonetheless, many investors have faced losses due to herd behavior and overconfidence, as demonstrated in the Safaricom and Eveready Initial Public Offerings (Ndiege, 2012). This study aims to investigate whether behavioral biases indeed affect individual investors' decisions at the NSE.

1.2 Statement of the Problem

Investment decisions made by participants in the Nairobi Securities Exchange significantly shape stock market trends and Kenya's economy. However, recent data reveals concerning inconsistencies between investor behavior and market dynamics. According to the Capital Markets Authority (2023), while the NSE 20 Share Index showed positive momentum with a 5.2% increase in Q3 2023, individual investor trading volumes decreased by 18.3%, indicating a disconnect between market performance and investor participation. A survey by the Kenya Association of Stockbrokers (2023) found that 64% of retail investors made investment decisions contrary to positive market indicators, with 42% selling positions during upward trends and 38% increasing holdings during market declines. These patterns suggest that investors frequently make decisions based on personal perceptions rather than market fundamentals.

Behavioral biases significantly influence investment decisions in emerging markets like Kenya, where information efficiency differs from developed markets. Studies by Jagongo and Mutswenje (2014) found that 73% of individual investors rely primarily on media reports and market rumors rather than fundamental analysis. The Capital Markets Authority (2023) reported that 58% of retail investors lack formal investment analysis skills, leading to decision-making driven by psychological factors rather than market dynamics. This creates an environment where behavioral biases, rather than rational analysis, often drive investment choices, as evidenced by the 27% increase in contra-trading activities during periods of market stability in 2023 (NSE Market Report, 2023).

While several studies have examined behavioral finance in Kenya, significant research gaps remain. Waweru et al. (2014) explored behavioral factors in property investments but didn't address the moderating role of market information. Kiprotich (2021) investigated herding behavior at the NSE but focused solely on institutional investors. Njuguna (2022) studied prospect theory in Kenyan markets but excluded the impact of market variables on decision-making. Omar and Onyango (2023) examined overconfidence bias in retail trading but didn't consider how market information moderates behavioral biases. The present study addresses these gaps by investigating the moderating role of market variables in the relationship between behavioral finance biases and stock investment decisions among Kenyan investors at the NSE. Specifically, this research examined how market information influences the impact of behavioral biases on investment decisions, an aspect not comprehensively covered in existing literature (Ahmed, 2023; Kimani, 2023; Odhiambo, 2023). The present study aims to assess the moderating role of market variables in the relationship between behavioral finance biases and the stock investment decision making among Kenyan investors at the Nairobi Securities Exchange.

1.3 Research Objectives

1.3.1 General objective

The general objective of this study was to investigate the moderating role of market information in the relationship between behavioral finance biases and stock investment decision-making among Kenyan investors: evidence from the Nairobi Securities Exchange.

1.3.2 Specific objectives

The specific objectives of the study were.

i. To establish the effect of heuristic biases on investment decisions by Kenyan investors at the Nairobi Securities Exchange.

ii. To determine how the prospect biases, affect investment decisions by Kenyan investors at the Nairobi Securities Exchange.

iii. To establish the effect of herding behavior on investment decisions by Kenyan investors at the Nairobi Securities Exchange.

iv. To establish the moderating role of market information in the relationship between behavioral finance biases and stock investment decision-making.

1.4 Research Hypotheses

The following were the research questions of the study.

H_{01}: *Heuristic biases have no significant effect on investment decisions by Kenyan investors at the Nairobi Securities Exchange.*

H_{02}: *Prospect biases have no significant effect on investment decisions by Kenyan investors at the Nairobi Securities Exchange.*

H_{03}: *Herding behavior has no significant effect on investment decisions by Kenyan investors at the Nairobi Securities Exchange.*

H_{04}: *Market information has no significant moderating effect on relationship between behavioral finance biases and stock investment decision-making.*

1.5 Justification of the Study

Based on the problem stated above, it is evident that studies or research emanating from local scholars and institutions of higher learning related to the stated topic are limited. It is, therefore, proposed that the results of the study sheds light on the moderating role of market information in the relationship between behavioral finance biases and the stock investment decision making among Kenyan investors.

1.6 Significance of the study

The results of the study support the government of Kenya as a regulator in its quest to strengthen its financial policies by avoiding biases in policy formulation. Knowledge of Investor psychology will aid in reducing individual investor's mistakes and improve the quality of investment decisions. The findings of this research will also aid financial advisors in identifying the different types of behavioral biases and their possible effects on investment decision-making among individual investors. The study findings will also be of great benefit to the individual investors since they will be able to understand the different psychological biases that are there, which of them is affiliated with them, and the ripple effect of how it influences their decision-making on stock investments.

By understanding behavioral biases, investment professionals and investors will be able to improve economic outcomes. This will entail identifying behavioral biases they themselves exhibit or behavioral biases of others, including clients. Once a behavioral bias has been identified, it may be possible to either moderate the bias or adapt to the bias so that the resulting financial decisions more closely match the rational financial decisions assumed by traditional finance. The knowledge and integration of behavioral and traditional finance may lead to better investment decisions.

Existing studies on behavioral finance studies have been largely undertaken in developed economies across European and North American markets (Caparrelli, Arcangelis & Cassuto, 2004; Fogel & Berry, 2006). There have been several similar studies in emerging markets as well such as in Malaysia and Kenya (Low &Ghazali, 2007; Waweru et al, 2008). However, existing studies exploring the subject of behavioral finance across frontier and emerging markets are much fewer than for developed markets. In this study, behavioral finance will be narrowed down to the Kenyan securities market, a pre-emerging securities market of the Eastern Africa region, to identify the critical factors of individual investors' behavior. The study will provide good literature and add more information to the body of knowledge on the issue of behavioral finance. Researchers and future scholars will use the research as future reference material when advancing their knowledge in behavioral finance.

1.7 Scope of the Study

This study sought to determine the effect of behavioral finance biases on investment decisions by Kenyans at the Nairobi Securities Exchange.

1.8 Limitations of the Study

The study required collection and analysis of primary data from individual investors. The data collection exercise was a major challenge owing to the fact that investment decisions in Kenya are very personal. Key among expected challenges include uncooperative correspondents in terms of volunteering their personal investment information and surveying of 1.9million individual investors would be practically impossible, and so the study used brokerage firms as unit of analysis. Stockbrokers serve as key informants with firsthand experience of client behavioral biases at the Nairobi Securities exchange.

Another expected challenge is limited cooperation by the targeted stock brokerage firms in providing investment information concerning their clients due to the confidential nature of the data. Behavioral finance being a relatively new phenomenon in the finance discipline, the correspondents may not understand the questionnaire hence possibility of giving incorrect responses. To counter this, the researcher intends to use anonymized questioners and inform the respondents about the merits of this research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter aims to examine the existing literature on behavioral finance through both theoretical and empirical lenses, ultimately leading to the development of the study's conceptual framework. It explored the foundational factors of behavioral finance and provided an empirical analysis of how these factors influence individual investors' decision-making processes. The chapter concluded by identifying the research gap and discussing the conceptual framework adopted for this study.

2.2 Theoretical Review

This section provided an overview of the theories, principles, generalizations, and existing research literature relevant to the study. The theoretical framework identified specific theories that guided the research. In this study, the researcher used Behavioral Finance Theory, prospect theory, and regret theory as guides. The framework included identifying the indicators and determinants in the study that demonstrated the relationship between the dependent and independent variables. Additionally, the relevance of these theories to the research was examined, emphasizing their importance in shaping the study's approach and direction.

2.2.1 Heuristic theory

Heuristic theory, originating from its Greek roots meaning "to discover," has evolved significantly through contributions from psychology, cognitive science, and behavioral economics. Originating from Herbert Simon's mid-20th-century work on bounded rationality, heuristics were initially conceptualized as cognitive shortcuts that facilitate efficient decision-making under constraints of time and information (Neth & Gigerenzer, 2015). Amos Tversky and Daniel Kahneman's seminal research in the 1970s and 1980s further elucidated how heuristics, such as availability and representativeness, contribute to cognitive biases and systematic errors in judgment (Morvan & Jenkins, 2017). Their studies not only expanded the theoretical understanding of heuristics but also demonstrated their practical implications in various decision contexts, including financial decision-making (Harvey, 2020). Contemporary research continues to explore the complex interplay between heuristics and biases, aiming to refine decision-making strategies by leveraging heuristic benefits while mitigating their potential drawbacks.

Heuristics are cognitive shortcuts or rules of thumb employed by investors during decision-making. Behavioral economists acknowledge that in navigating a complex world, individuals often simplify information processing to facilitate quicker decisions, utilizing heuristics. Gigerenzer and Wolfgang (2011) define heuristics as strategies that deliberately ignore certain information to expedite decision-making more efficiently and accurately than more intricate methods. These simple rules are particularly effective in situations of heightened uncertainty, time constraints, or declining information quality. Rather than aiming for the optimal solution, heuristics seek a satisfactory outcome given the trade-offs between decision-making time, uncertainty, and information costs (Howard et al., 2012). Herbert A. Simon (1957) formalized this trade-off with "bounded rationality," suggesting that decision-makers' ability to optimize is constrained by available information quantity, quality, and time. He noted that human cognitive limits prevent achieving perfect optimization in the face of complex decision tasks for firms and consumers. These heuristics aid decision-making when time is limited and urgent decisions must be made (Waweru, Munyoki, & Uliana, 2008).

Various biases significantly influence decision-making processes across different domains, including finance and investment. Representativeness bias occurs when people make judgments based on how similar something is to a typical case or stereotype rather than on specific information about the actual likelihood of an event (Kengatharan & Kengatharan, 2014). Availability bias refers to the tendency to overestimate the importance of information readily available, often from recent or vivid experiences, when making decisions (Kengatharan & Kengatharan, 2014). Anchoring bias involves relying too heavily on the first piece of information encountered when making decisions, even if it's irrelevant or arbitrary (Kengatharan & Kengatharan, 2014). Moreover, overconfidence bias leads individuals to overestimate their knowledge, predictions, or abilities, which can result in excessive risk-taking or unrealistic expectations (Kengatharan & Kengatharan, 2014). These biases are often driven by heuristics, mental shortcuts that simplify decision-making processes by drawing on past experiences (Ricciardi & Simon, 2001). While heuristics can expedite decisions, they can also lead to errors if inappropriate rules of thumb are applied, potentially causing individuals to either overestimate or underestimate outcomes (Ricciardi & Simon, 2001).

Heuristic theory faces criticism for oversimplifying complex decision-making processes and failing to account for individual differences in cognitive abilities and situational contexts. Critics argue that heuristics are not always detrimental and can sometimes lead to efficient decision-making under uncertainty. Additionally, the theory struggles to predict when individuals will use heuristics versus systematic processing. This study addressed these weaknesses by measuring heuristic biases across multiple dimensions (anchoring, overconfidence, availability bias) rather than treating them as a single construct, and by examining how market information moderates their effects. The inclusion of demographic variables and the focus on investment professionals (who presumably have higher cognitive abilities) helped control for individual differences while acknowledging that heuristics can vary in their impact across different decision contexts.

In the context of financial markets, biases such as anchoring, overconfidence, and availability play crucial roles in shaping investor behavior. Market prices are influenced by expectations about the future, and biased expectations can lead to mispricings of stocks (Fuller, 2000). The heuristic theory explains how these biases affect investment decisions on exchanges like the Nairobi Securities Exchange, where investor decisions are often influenced by cognitive shortcuts rather than comprehensive analysis (Kimeu et al., 2016). Recognizing these biases is essential for investors and financial professionals to mitigate their impact and make more informed decisions.

2.2.2 Prospect theory

Daniel Kahneman, a professor at Princeton University in the psychology department, developed prospect theory with Amos Tversky in 1979 (Kahneman & Tversky, 2013). This theory serves as a psychologically realistic alternative to the expected utility theory (EUT). It helps individuals make decisions involving risk by describing the choices they face. Prospect theory utilizes cognitive psychology techniques to highlight the differences in economic decision-making compared to neo-classical theory. It explains how people value decisions involving uncertainty, focusing on potential gains or losses relative to a specific reference point, often the purchase price. In 2002, Faulkner noted that prospect theory supports a consequentialist approach to decision-making, where individuals consider the probable outcomes of their actions. According to prospect theory, the coding of outcomes as gains or losses relative to a reference point is crucial in decision-making. One significant implication of prospect theory is that economic agents' perceptions of consequences or operations can influence the utility they perceive or receive (Parkash & Parkash, 2024).

Prospect theory explains decision-making under risk, highlighting that decisions stem from judgments (Chen & Chen, 2016). These judgments, which assess the external state of the world, become particularly complex in uncertain conditions where outcomes are hard to predict. Decisions often involve internal conflicts over value trade-offs, especially when choices align with contradictory values and goals. Prospect theory addresses how choices are framed and evaluated in this process. It is grounded in psychophysical models, like those that inspired Bernoulli's expected value proposition (Chen & Chen, 2016). Psychophysics traditionally explores the relationship between the physical and psychological worlds, aiming to identify the point at which a physical stimulus change is perceived psychologically. Research has shown that the physical stimulus must increase geometrically for the psychological experience to increase arithmetically, resulting in a concave curve similar to Bernoulli's risk-averse utility curve. Tversky and Kahneman applied these principles to investment decisions, demonstrating that just as individuals are unaware of the brain's processing for vision, they are also unaware of the brain's computations in editing and evaluating choices. Therefore, people make decisions based on their brain's processing and understanding of information, not solely on the inherent utility of an option (Chen & Chen, 2016).

The tendency of investors to be risk-averse regarding gains but risk-seeking regarding losses is the essence of prospect theory. When an investor has the choice between a sure gain and a gamble that could increase or decrease the sure gain, the investor is likely to choose the sure gain. But when faced with a choice between a sure loss and a gamble which could increase or decrease the sure loss, investors are more likely to take the gamble (Jordan & Miller, 2008). This seminal work by Kahneman and Tversky (1979) advocated a new theory under conditions of risk-taking behavior and uncertainty, which focused on subjective decision-making influencing investors' value systems (Filbeck and Horvath, 2005). People tend to under-weigh probable outcomes compared with certain ones, subjecting people to respond differently to similar situations presented in the context of losses or gains (Kahneman and Perttunen, 2004).

In essence, the theory elaborates why human beings are inconsistently risk-averse, tending to become risk-averse in gains and risk-takers in losses, the reason why individual investors will assign more significance to avoiding a loss than achieving a gain. Olsen (1997) argued out that prospect theory "gives weight to the cognitive limitations of human decision-makers," meaning that an individual investor departs from the notion of rationality as elaborated by the classical decision theory the of the standard finance perspective, and makes decisions on the basis of bounded rationality advocated by behavioral decision theory, which is the behavioral finance viewpoint. Ritter (2003) also argued that prospect theory is a descriptive theory under uncertainty that focuses on changes in wealth. According to Kahneman & Tversky (1979), an important implication of prospect theory is that the way economic agents subjectively frame an outcome or transaction in their mind, affects their level of satisfaction derived from the returns.

Prospect theory is criticized for its limited scope, focusing primarily on decisions under risk while neglecting social and emotional factors that influence real-world financial decisions. Critics also point out that the theory's value function may not be stable across different domains and cultural contexts, and that loss aversion coefficients vary significantly among individuals. Furthermore, the theory assumes decision-makers can clearly identify reference points, which may not always be the case. This study addressed these limitations by incorporating social influences through the herding behavior variable, examining the theory within the specific cultural context of the Kenyan market, and using market information as a moderating variable to account for how external factors can shift reference points and influence the loss aversion mechanism.

Prospect theory appraises three emotional biases that impact investors' decision-making processes including loss aversion, regret aversion and mental accounting (Kengatharan, 2014). Regret aversion bias, observed prominently in investor behavior, manifests when individuals cling to losing investments longer than rational analysis would dictate, driven by a fear of admitting mistakes and realizing losses (Pompian, 2006). This bias arises from the emotional sting of regret, which is more than just the pain of financial loss encompasses the psychological burden of feeling responsible for making a wrong decision (Shefrin, 2002). Investors often hesitate to sell declining stocks to avoid finalizing their perceived mistake, while they readily sell appreciating stocks to lock in gains and preempt future regrets (Shefrin, 2002).

Coupled with mental accounting, where investors compartmentalize their financial decisions into separate mental accounts (Barberis & Huang, 2001), and loss aversion, where the fear of losses outweighs the desire for equivalent gains (Barberis & Huang, 2001), these biases collectively shape investment decisions and can lead to suboptimal portfolio management strategies. Recognizing these biases is crucial for investors aiming to make more rational and informed financial decisions.

2.2.3 Regret theory

Regret theory, introduced by Graham Loomes and Robert Sugden in their influential 1982 paper titled "Regret Theory: An Alternative Theory of Rational Choice under Uncertainty," focuses on decision-making under uncertainty by highlighting the minimization of potential regrets (Isoni, Brooks, Loomes, & Sugden, 2016). This theory, grounded in the minimax principle, involves weighing potential losses against potential gains. Regret itself is an emotional response linked to the comparison between actual outcomes and the best possible outcomes, as stated by Wong, K. P. (2015). For example, when consumers choose between lesser-known and well-established brands, they often consider the regret of choosing the former if it underperforms compared to the latter, influencing their decision-making process. According to Mayur (2018), investors frequently integrate knowledge from prospect theory into their investment decisions, where regret plays a significant role. This theory helps clarify behaviors such as investors selling stocks prematurely during rising markets due to fear of missing out on higher returns or holding onto depreciating stocks due to the regret of selling at a loss (Mayur, 2018).

Regret is a psychological state that arises when an individual perceives that a decision they made has led to an unfavorable outcome. For instance, if an investment results in a decrease in wealth, investors may experience persistent and intense remorse (Pangeran & Kumalaningrum, 2015). According to Somasundaram and Diecidue (2017), feelings of regret stem from two sources: regrets about actions taken versus actions not taken, and regrets stemming from decisions made versus decisions avoided. Van de Calseyde, Zeelenberg, and Evers (2018) suggest that investors may feel remorseful if stocks sold prematurely subsequently show improved performance, underscoring the significance of investment decisions. Somasundaram and Diecidue (2017) also note that investors who have experienced regret tend to adjust their behavior in anticipation of future regrets, assuming responsibility for previous investment errors, thereby dealing indirectly with loss. Additionally, individuals may undergo various emotional states associated with regret, including guilt, anxiety, and the desire to rectify past mistakes (Zeelenberg, 2018). Genesove and Mayer (2001) similarly found that the fear of experiencing losses influences investors' decision-making when selling stocks.

Regret theory, a concept in behavioral economics, matches closely with several decision-making biases and behaviors. Firstly, it integrates with heuristic biases, where individuals simplify complex decisions by relying on intuitive judgments rather than comprehensive analysis (Pompian, 2019). Decision-makers in regret theory predict future regret from potential outcomes, influencing choices beyond expected payoffs (Pompian, 2019). Secondly, regret theory connects with prospect biases, focusing on how individuals frame decisions relative to a benchmark. While prospect theory uses past experiences, regret theory considers anticipated future outcomes, highlighting decision-making's dynamic nature (Gazel, 2015). Regret theory also addresses herding behavior, where individuals may avoid regret by following others' choices in uncertain situations (Van de Calseyde et al., 2018). This behavior aligns with regret theory's premise of decision-makers' sensitivity to future emotional states (Van de Calseyde et al., 2018). Lastly, regret theory incorporates market variables that influence how individuals perceive outcomes and assess regret, demonstrating the interplay between economic environments and psychological responses (Santra & Giri, 2017).

Regret theory is criticized for its narrow focus on anticipated regret while ignoring other emotions that drive financial decisions, such as pride, fear, or excitement. The theory also assumes that individuals can accurately predict their future emotional states, which psychological research shows is often inaccurate. Additionally, critics argue that the theory lacks precision in predicting when regret will dominate other decision criteria and fails to account for how regret sensitivity varies across individuals and cultures. This study handled these weaknesses by embedding regret theory within a broader behavioral finance framework that included multiple bias types, using prospect theory constructs to capture regret aversion alongside loss aversion, and examining how market information availability can reduce regret-driven decisions by providing more objective decision-making criteria

Regret theory enhances the analysis of investment decisions among Kenyan investors at the Nairobi Securities Exchange by integrating psychological factors like anticipated regret. Unlike traditional expected utility theory, which focuses on rational decision-making based on maximizing outcomes, regret theory recognizes that investors also consider emotional consequences. This approach acknowledges that decisions are influenced by cognitive biases and emotional responses, shaping choices beyond purely economic calculations. In the context of the NSE, investors may weigh the potential regret of missing out on gains or incurring losses, impacting their investment strategies. Regret theory thus offers a complicated perspective on decision-making, highlighting the interplay between rational assessments and emotional motivations in financial markets (Muriithi, G. N., 2021). This theory suggests that investors may not always make rational decisions based on expected utility alone but also consider the emotional impact of their choices. By incorporating regret into the decision-making process, investors may adopt strategies that aim to minimize potential feelings of regret, even if it means deviating from traditional economic models.

2.2.4 Efficient markets hypothesis (EMH)

The Efficient Markets Hypothesis (EMH), introduced by E.F. Fama in 1965, posits that stock prices in an efficient market fully reflect all available information about a company's value (Fakhry, B. 2016). Consequently, it is impossible for investors to consistently achieve returns that exceed the market average using this information. The EMH addresses why and how security prices fluctuate in the market. According to Fama, in an efficient market, competition ensures that new information is swiftly incorporated into stock prices, rendering forecasting and valuation techniques ineffective for consistently outperforming the market (Fakhry, B. 2016). The EMH remains a contentious topic in financial discussions. Michael Jensen, a renowned financial economist, argues that the EMH has substantial empirical support, stating that "there is no other proposition in economics that has more solid empirical evidence supporting it than the Efficient Market Hypothesis" (Clarke, J., Jandik, T., & Mandelker, G., 2001).

Conversely, investment expert Peter Lynch dismisses it as "a bunch of junk, crazy stuff" (Clarke, J., Jandik, T., & Mandelker, G., 2001). The theory suggests that making consistent profits by predicting price changes is highly unlikely, as prices adjust quickly to new information. In an efficient market, stock prices adjust almost immediately to new information, meaning they are unlikely to be systematically overvalued or undervalued. Investors often attempt to identify undervalued or overvalued stocks to profit from perceived misprice. However, as more analysts compete to identify these opportunities, the likelihood of success decreases, often resulting in minimal gains after accounting for the costs of research and transactions. Behavioral finance challenges the traditional Efficient Market Hypothesis (EMH) by emphasizing that psychological biases and irrational behavior can significantly impact investment decisions and market outcomes. Unlike the EMH, which assumes rational investor behavior, behavioral finance posits that cognitive biases such as overconfidence, herd behavior, and loss aversion can lead to mispricing of assets and market inefficiencies (Kahneman & Tversky, 1979; Thaler, 1985). In the context of this research, the role of market information as a moderating factor is particularly pertinent. Access to accurate and timely information may mitigate some of the adverse effects of biases by providing a more rational basis for decision-making. Conversely, insufficient or poorly disseminated market information could exacerbate the impact of biases, leading to greater market inefficiencies.

The EMH faces substantial criticism for its unrealistic assumptions about rational investors and perfect information processing, with extensive empirical evidence showing persistent market anomalies and the influence of behavioral factors on asset pricing. Critics argue that the theory fails to explain market bubbles, crashes, and the success of behavioral trading strategies. The hypothesis also assumes instantaneous information incorporation, which is unrealistic in practice, particularly in emerging markets. This study addressed EMH limitations by explicitly examining how behavioral biases create market inefficiencies, using the Kenyan NSE as a case study of an emerging market where information asymmetries are more pronounced. The focus on how market information moderates behavioral biases provided insights into when markets might approach efficiency versus when behavioral factors dominate, offering a more nuanced view than the binary efficient/inefficient market classification.

For Kenyan investors on the Nairobi Securities Exchange (NSE), examining how market information influences the relationship between behavioral biases and investment decisions is crucial. If market information significantly moderates these biases and contributes to more rational decision-making, it could enhance market efficiency. However, persistent deviations from fair value despite the availability of information might indicate ongoing inefficiencies. Overall, exploring the interplay between market information and behavioral biases provides valuable insights into the validity of the EMH in the Kenyan context and offers implications for improving market efficiency and stability.

2.3 Empirical Review

This empirical review highlights the various behavioral factors and their effects on individual investor decisions based on previous research and literature.

2.3.1 Heuristic factor and investment decision

Heuristic factors play a crucial role in investment decision-making, often leading investors to base their decisions on simplified rules or mental shortcuts rather than thorough analysis. Empirical studies have consistently shown that these heuristics influence investment behavior and outcomes significantly. Kengatharan and Kengatharan (2014) explored how behavioral factors affect investment decisions and performance on the Colombo Securities Exchange. They proposed that heuristic factors significantly impact investment decisions.

The study gathered cross-sectional data via questionnaires and utilized a descriptive survey combined with a correlational design. The analysis included descriptive statistics, exploratory factor analysis (EFA), and regression analysis. The findings revealed that heuristic factors, such as confidence in personal skills and stock knowledge, reliance on past experiences, and future stock price forecasting, strongly influenced investment decisions. Regression analysis indicated a significant inverse relationship between overconfidence and investment decisions, while anchoring showed a significant positive relationship. The use of EFA was suitable due to the Likert scale responses, aiding in variable reduction and the generation of regression variables.

Agrawal (2012) emphasized that individuals often act irrationally, making biased decisions because they rely on shortcuts due to time and cognitive constraints in processing information. When faced with complex judgments or decisions, investors simplify the task by relying on heuristics or general rules of thumb. This reliance can lead to systematic biases and deviations from optimal decision-making. For instance, Abudu (2016) examined various characteristics influencing investor behavior in the Nigerian financial market, revealing that heuristic biases significantly affect investor behavior. These biases can result in overconfidence, where investors overestimate their knowledge and predictive abilities, and the representativeness heuristic, where judgments are made based on stereotypes rather than statistical probabilities.

Karanja (2017) analyzed the effects of behavioral finance factors on the investment decisions of individual investors at the Nairobi Securities Exchange. Using close-ended questionnaires and a snowball sampling technique, data was collected and analyzed with Stata software through multiple linear regression. The findings showed that heuristic factors influenced 16.01% of investment decisions at the NSE. Heuristics such as availability bias, anchoring, and overconfidence were identified as key influencers of investment behavior.

Jian et al. (2023) conducted a study on individual investors in Punjab, India, using the fuzzy analytic hierarchy process to rank behavioral biases influencing investment decisions. The results highlighted the significant impact of heuristics on investment behavior through the mediating role of risk perception. Specifically, heuristics like availability bias, where investors rely on readily available information rather than all relevant data, and anchoring, where they base decisions on initial information despite new evidence, were found to be particularly influential.

Satter and Satter (2020) explored how behavioral biases affect investment decision-making under uncertainty. They used survey questionnaires for data collection and employed regression analysis with Stata software to test their hypotheses. The empirical results concluded that heuristic behaviors had a greater influence on investment decision-making than other behavioral factors. This finding underscores the dominance of mental shortcuts in shaping investor behavior, especially in uncertain or complex environments.

Additional empirical studies have further substantiated the impact of heuristics on investment decisions. Barberis and Thaler (2003) provided a comprehensive review of behavioral finance, detailing how heuristics like representativeness and overconfidence lead to mispricing and anomalies in financial markets. Similarly, Tversky and Kahneman (1974) highlighted how heuristics are integral to human judgment, often leading to biases that affect investment choices. Chen et al. (2007) examined the Chinese stock market, finding that heuristic-driven behaviors, such as the disposition effect—where investors sell winning stocks too early and hold onto losing one's too long—were prevalent among individual investors. This behavior can be attributed to heuristics like mental accounting and loss aversion, which influence how investors perceive gains and losses.

Critiques of the role of heuristics in investment decisions often point to the oversimplification of investor behavior and the variability of heuristic impact across different contexts. While heuristics provide a useful framework for understanding decision-making, they may not capture the dynamic and adaptive nature of investor behavior, as suggested by Lo's (2004) Adaptive Market Hypothesis, which posits that investors adjust their strategies based on evolving market conditions and past experiences. Additionally, the effectiveness of heuristics can vary significantly; for example, individual investors are more prone to heuristic biases compared to institutional investors, who tend to rely on systematic analysis (Kumar and Lee, 2006). Critics also emphasize the need to integrate heuristic factors with broader behavioral finance theories, such as mental accounting and prospect theory, to provide a more comprehensive understanding of investor behavior (Thaler, 1999)

2.3.2 Prospect factor and investment decision.

The prospect factor highlights the inconsistency in human behavior when evaluating risk under uncertainty. People are generally risk-averse when facing potential gains but tend to take more risks when dealing with potential losses. Kartin and Nahda (2021) explored the effect of various psychological factors on investment decisions using a quantitative data analysis approach. They employed a survey method with snowball sampling, gathering 165 questionnaires from individual investors in Yogyakarta, Korea. Hypotheses were tested using a one-sample t-test. The study revealed that prospect factors, including anchoring bias, representativeness bias, loss aversion bias, overconfidence bias, optimism bias, and herding behavior, significantly impact investment decisions. This underscores the role of behavioral factors in investor decisions. Similarly, Ranjbar et al. (2014) investigated the effect of behavioral variables on investor performance on the Tehran Stock Exchange, using a sample of 148 financial investors. Surveys and structural equation modeling were utilized for data analysis. The findings indicated that loss aversion and mental accounting are key biases that negatively affect investor performance. Prospect factors demonstrate how individuals manage risk and uncertainty in decision-making, with loss aversion, regret aversion, and mental accounting being prominent factors.

Zona (2012) studied innovation investment during the 2008–2009 economic downturn, focusing on the 1000 largest Italian firms ranked by sales. Out of the 1000 firms, 108 CEOs responded to the questionnaires. The study concluded that higher levels of slack resources boosted innovation investment during crises and moderated the impact of past performance on investment. Kansal and Singh (2015) examined behavioral biases among investors on the Indian Stock Exchange. Using convenience sampling, they administered a structured questionnaire to 196 engineering graduates. The analytic hierarchy process helped determine the relative contribution of each behavioral bias, revealing that most investors had an exaggerated fear of loss and a high loss aversion tendency. Breuer, Rieger, and Soypak (2012) conducted a study across 32 countries with 5,750 firms, aiming to highlight the relevance of behavioral preferences for corporate dividend policy. The study's model, based on mental accounting, predicted a positive relationship between investors' loss aversion and time discounting on the dividend payout ratio. The findings confirmed that loss aversion was a primary determinant of corporate dividend policy.

Babajida and Adetiloye (2012) conducted a study on the behavioral biases affecting the performance of the Nigerian stock market over the past two decades. Their research focused on biases such as overconfidence, loss aversion, framing, anchoring, and status quo bias, using a questionnaire administered to 300 respondents. They employed the Pearson product-moment coefficient method to analyze the data. The study concluded that investors should consider engaging financial advisors to mitigate these biases in their decision-making processes. It also found a negative relationship between these biases and trading activities, indicating indirect impacts on market performance.

Critically, while the study provides valuable insights into how behavioral biases affect market dynamics, its reliance on self-reported data through questionnaires may introduce response biases. Moreover, the focus on Nigerian markets limits the generalizability of the findings to other global contexts where market structures and investor behaviors may differ significantly. Chira, Adams, and Thornton (2008) investigated cognitive biases and heuristics affecting decision-making among business students, using a questionnaire with 45 questions administered to graduate and undergraduate students at Jacksonville University in the USA. The study identified biases such as overconfidence, excessive optimism, loss aversion, familiarity, sunk cost, illusion of control, and confirmation biases. It concluded that student decision-making rationality is often bounded, displaying overconfidence and extreme optimism in certain domains like driving ability and academic performance while showing less optimism in areas related to financial investments and athletics. Critically, while the study provides valuable insights into cognitive biases among students, its sample size and limited focus on a single university may restrict the generalizability of findings across broader student populations or professional contexts. Additionally, relying solely on self-reported responses might overlook nuanced behavioral patterns that could influence decision-making beyond what participants consciously report.

Poluch (2011) explored the impact of overconfidence biases across different management levels within professional services organizations in South Africa. The study employed an online survey and personal approaches to gather data from 30 managers at each level. It found that middle managers exhibited the least overconfidence due to their role challenges, while lower-level managers displayed higher levels of overconfidence, likely influenced by the specific tasks delegated by middle management. Upper-level managers showed the highest levels of overconfidence, attributed to their authority and independence. Critically, while the study contributes to understanding overconfidence biases in managerial decision-making, its reliance on a specific industry and regional context in South Africa may limit its broader applicability. Additionally, the study's focus on self-reported data through surveys may overlook deeper cognitive processes or biases that influence decision-making in more complex organizational settings.

In conclusion, while these studies provide valuable insights into behavioral biases and their implications for decision-making in financial markets and managerial contexts, they also highlight the complexities and limitations inherent in studying cognitive biases through survey methodologies. Future research could benefit from more diverse samples, longitudinal studies, and mixed-method approaches to further deepen our understanding of how biases impact decision-making across different contexts and demographics. These studies collectively suggest that prospect factors, encompassing various biases, significantly influence investment decisions and behaviors. Hypothesis Ho2 posits that prospect factors do not significantly affect investment decisions among investors in the NSE.

2.3.3 Herd factor and investment decision

This heuristic involves individuals in crowds making decisions by mimicking the majority, often due to social pressures within the decision-making environment. Herding behavior represents a heuristic strategy wherein individuals align their decisions with the majority in their decision-making environment, mirroring their choices. Individuals frequently experience social pressure from their surroundings, compelling them to conform. Gounaris and Prout (2009) argue that humans, inherently social beings interdependent for survival, often feel uncertain when making decisions, leading them to mimic others' actions. Hayat (2016) explores the impact of behavioral biases on investment decisions in Pakistan, where 220 participants were surveyed using 158 questionnaires through non-probability sampling. The findings indicate significant herding behavior in stock markets like the Karachi and Islamabad Stock Exchanges, with financial literacy found to moderately mitigate this bias. Similarly, Ranjbar et al. (2014) investigated behavioral influences on investor performance at the Tehran Stock Exchange, analyzing data from 148 investors via structural equation modeling. Their results highlight a significant relationship between herding behavior and investor returns. Additionally, they examined exceptional circumstances across Greece, Italy, Portugal, and Spain spanning eleven years of extreme market conditions.

Walter and Weber (2006) aimed to explore whether German mutual fund managers engaged in herding behavior and its impact on stock prices. They analyzed a sample of 60 mutual firms specializing in German stocks from December 31, 1997, to December 31, 2007. The study revealed evidence of herding among German fund managers, with a significant portion attributed to spurious herding influenced by changes in benchmark index composition. Agarwal et al. (2011) investigated herding behavior among domestic and foreign investors in brokerage firms on the Jakarta Stock Exchange from May 1995 to May 2003. Their study, based on comprehensive order and transaction records, found that foreign investors demonstrated a higher tendency to herd compared to local investors. They also concluded that herding behavior was likely influenced by common information, exacerbated by brokerage effects. Ndiege (2012) studied the factors influencing investment decisions in equity stocks among teachers in Kisumu municipality using a descriptive survey design. The research involved 253 teachers from a population of 2530, utilizing questionnaires and analyzing data through factor analysis and descriptive statistics. The results indicated that decisions to invest in equity stocks were influenced by economic and behavioral factors, including herd behavior manifested in decisions based on popular opinion or recommendations from peers.

Walter and Weber (2006) investigated herding behavior among German mutual fund managers, finding evidence of significant herding linked to changes in benchmark index composition. Similarly, Agarwal et al. (2011) explored herding among domestic and foreign investors on the Jakarta Stock Exchange, highlighting foreign investors' heightened propensity to herd, influenced by common information and brokerage effects. Chiang and Zheng (2010) focused on Taiwan's mutual fund industry, revealing notable herding during market volatility, although its applicability beyond the regional market is constrained. In contrast, Cipriani and Guarino (2008) analyzed herding among banks accessing the Federal Reserve's discount window during the 2007–2008 financial crisis, offering insights into crisis-driven herding within specific institutional contexts. These studies collectively deepen understanding of herding behavior across diverse financial settings, yet their contextual limitations underscore the need for cautious interpretation and consideration of broader market dynamics.

My line of thought effectively connects various studies on herding behavior in financial markets, highlighting both similarities and contextual differences across different studies and regions. Walter and Weber (2006) and Agarwal et al. (2011) provide observations into how herding manifests among mutual fund managers in Germany and investors on the Jakarta Stock Exchange, respectively. Both studies underscore the role of common information and external influences, such as benchmark changes and brokerage effects, in exacerbating herding tendencies. Ndiege's (2012) study on investment decisions among teachers in Kisumu municipality adds a behavioral perspective, revealing how herd behavior influences individual investors' decisions based on peer recommendations and popular opinion. This complements the institutional focus of studies like Chiang and Zheng (2010) on Taiwan's mutual fund industry and Cipriani and Guarino (2008) on banks accessing the Federal Reserve's discount window during the financial crisis, which highlight crisis-driven herding within specific institutional contexts.

These studies collectively enhance our understanding of herding behavior across diverse financial settings, emphasizing the interplay of psychological factors, institutional frameworks, and market conditions in shaping investor behavior. However, they also caution against overgeneralization, emphasizing the need for nuanced interpretations sensitive to local and institutional contexts.

2.3.4 Market information and the relationship between behavioral finance biases and stock investment decision-making

Behavioral finance identifies several cognitive and emotional biases that significantly impact investment decisions. These biases often lead to deviations from rational financial behavior, resulting in market inefficiencies. One prominent bias is overconfidence, where investors overestimate their knowledge and ability, leading to excessive trading and increased risk-taking (Barber & Odean, 2001). Overconfident investors may ignore critical information and take undue risks, believing they possess superior insight compared to others. Another crucial bias is loss aversion, which reflects the phenomenon where investors experience the pain of losses more intensely than the pleasure of equivalent gains (Kahneman & Tversky, 1979). This aversion to losses can result in suboptimal decision-making, as investors might hold onto losing investments for too long or avoid taking necessary risks. Herd behavior is another significant bias where investors follow the actions of the majority, often leading to market bubbles and subsequent crashes (Bikhchandani et al., 1992). Herd behavior can exacerbate market volatility and lead to irrational market movements.

Market information serves as a critical moderating variable by influencing how behavioral biases affect investment decisions. The relationship between biases and decision-making can be moderated by the quality and accessibility of market information. For instance, information overload can aggravate biases by overwhelming investors with too much data, making it challenging for them to process and act on the information effectively (Bettman & Park, 1980). When faced with excessive or complex information, investors might resort to heuristics and biased judgments rather than engaging in thorough analysis. On the other hand, high-quality, relevant information can help mitigate the effects of bias. For example, detailed and accurate market data can reduce overconfidence by providing a clearer and more objective view of market conditions (Feldman & Gelfand, 2008). Investors equipped with reliable information are better positioned to make informed decisions, thereby reducing the influence of biases such as overconfidence and loss aversion. Furthermore, information processing capabilities play a significant role in moderating biases. Investors with better skills in processing and interpreting information are less susceptible to biases and more likely to make rational decisions (Tversky & Kahneman, 1974). Effective information processing helps investors understand market trends and make decisions that are less influenced by cognitive biases.

Several empirical studies have explored how market information moderates the relationship between behavioral biases and investment decisions. Agarwal and Taffler (2008) investigated the impact of market information on investor behavior and found that accessibility and transparency of information can reduce the influence of biases such as overconfidence. Their study demonstrated that investors who have access to high-quality information are less likely to exhibit biased behavior and make more accurate investment decisions. Similarly, Shefrin and Statman (2000) examined the role of market information in counteracting loss aversion. They found that better information helps investors manage their emotional responses to losses and make more rational decisions by providing a clearer view of market dynamics. Baker and Nofsinger (2002) provided evidence that informed investors are less prone to herd behavior. Their research indicated that the availability of timely and accurate information enables investors to make more independent decisions, thus reducing the tendency to follow the crowd and contributing to more stable market conditions.

Empirical evidence suggests that market information plays a pivotal role in moderating the effects of behavioral biases on investment decisions. While behavioral biases can lead to irrational decision-making and market inefficiencies, access to high-quality and relevant market information can help mitigate these effects. Investors who are well-informed are better equipped to overcome biases such as overconfidence, loss aversion, and herd behavior, leading to more rational and effective decision-making. Future research could focus on the specific mechanisms through which market information influences bias-related decision-making. Additionally, understanding how different types of information affect various biases can help in developing strategies to improve the effectiveness of information dissemination and enhance overall investment decision-making.

2.4 Summary of Literature

Literature extensively delves into the intricate interplay of both theoretical frameworks and empirical evidence, illuminating the profound impact of various behavioral biases on the investment decisions of individual investors. These biases encompass heuristic influences such as anchoring, overconfidence, and availability bias, which often lead investors to rely on mental shortcuts rather than exhaustive information processing. Prospect-related biases, including loss aversion, regret aversion, and mental accounting, further shape decision-making by magnifying the emotional responses to potential gains and losses. Herd behavior emerges as another critical phenomenon, manifesting in heightened trading volumes, collective security preferences, and rapid shifts in market sentiment. This trend underscores how investors frequently follow the crowd rather than independent analysis, potentially distorting market prices from their intrinsic values. Moreover, the market itself exerts significant influence through price movements, information asymmetries, and evolving customer preferences, which collectively steer investor behavior towards conformity or divergence.

Individual investors, distinct from their institutional counterparts, often navigate investment decisions amid a landscape inundated with media narratives and market noise. This reliance on external cues can overshadow rigorous fundamental and technical analyses, complicating their portfolio strategies and risk management practices. Challenges arise from cognitive limitations and informational constraints, which prompt investors to adopt simplified decision-making frameworks in complex financial environments. To address these dynamics, this study aims to scrutinize how behavioral finance factors specifically impact investment choices at the Nairobi Securities Exchange. Employing advanced statistical methods such as multiple linear regression, it seeks to quantify the influence of these biases on pivotal decisions like buying, selling, and holding investments. By doing so, the research endeavors to illuminate pathways toward more informed, resilient investment behaviors among individual stakeholders in the Kenyan financial markets.

2.5 Conceptual Framework

The conceptual framework illustrates the hypothesized relationships between behavioral finance biases and investment decisions at the Nairobi Securities Exchange, with market information serving as a moderating variable. The independent variables consist of three behavioral finance biases: heuristic biases, prospect biases, and herding behavior. These biases are hypothesized to influence the dependent variable - investment decisions (buy or do not buy securities). This framework provides a structural representation of how behavioral biases influence investment decisions.

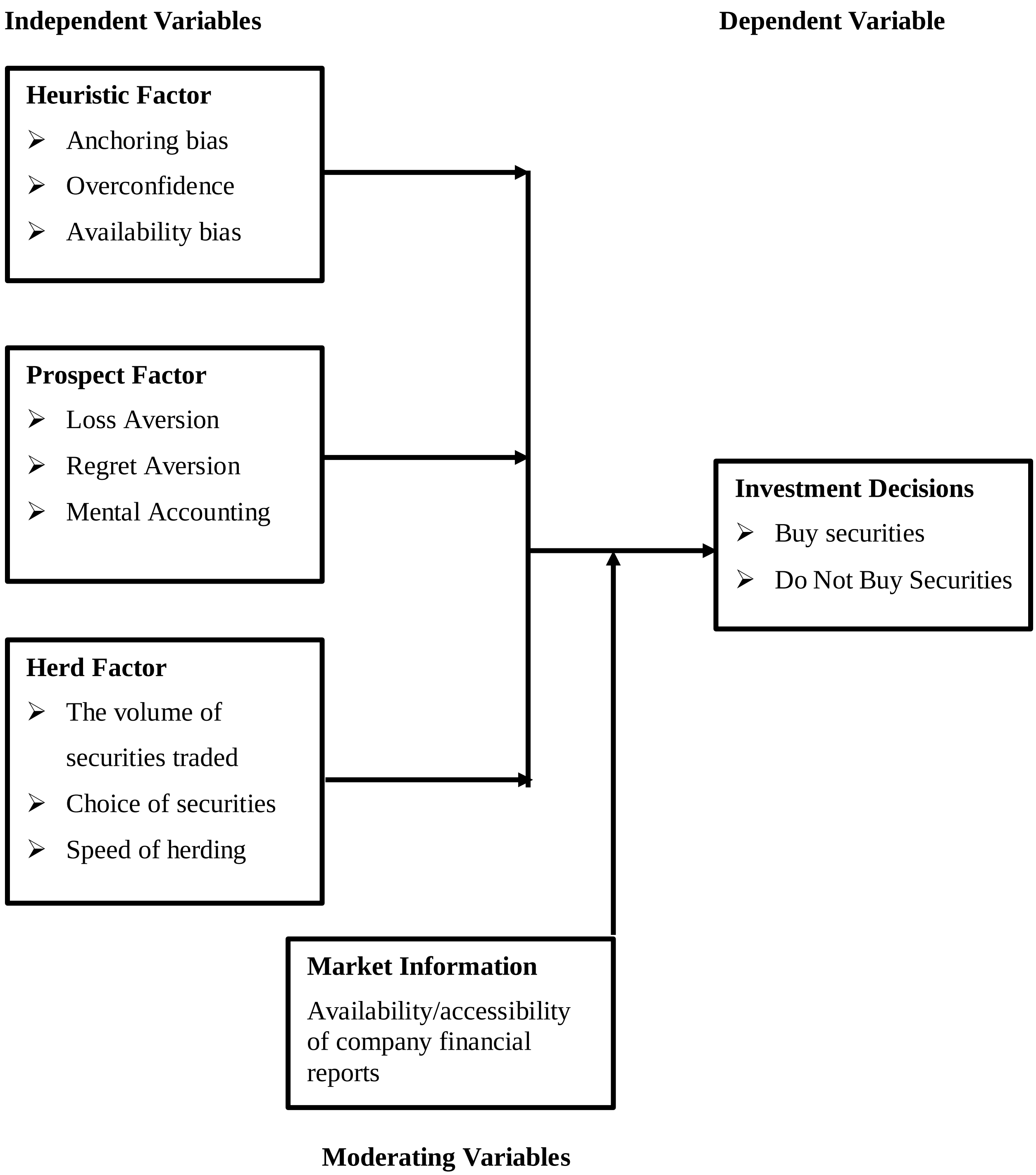

Figure 1: Conceptual Framework

Source, Author, (2024)

2.6 Operationalization of Variables

The variables were operationalized as below.

TABLE 1
Operationalization of Variables

	Variable of Study	**Indicators**	**Measure**
X1	Heuristic Biases	• Anchoring bias • Overconfidence • Availability bias	Use of Five Likert scale from the questionnaire for reference question 5 A. The variable was measured using ordinal scale measurement.
X2	Prospect Biases	• Loss Aversion • Regret Aversion • Mental Accounting	Use of the Five Likert scale from the questionnaire for reference question 5 B. The variable was measured using an ordinal scale of measurement.
X3	Herding Behavior	• The volume of securities traded • Choice of Securities • Speed of herding	Use of the Five Likert scale from the questionnaire for reference question 5 C. The variable was measured using an ordinal scale of measurement
X4	Market Variable	Availability/accessibility of company financial reports • Information accuracy • Information timeliness • Information completeness • Information relevance • Information accessibility	Use of Five Likert scale from the questionnaire for reference question 5 D. The variable was measured using an ordinal scale of measurement
Y	Investment Decision	• Buy securities • Do Not Buy Securities	Measured by the choice to defer consumption and postpone it to a future date; either through buying more shares, selling, or holding shares. The variable was measured using ordinal measurement for section C of the questionnaire and Interval measurement in the last part (6b).

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlined the methodology employed in the study, providing a framework for defining the relationships between the study variables. It addressed several key elements, including the characteristics of the target population, sampling methods, data collection processes, and data analysis techniques.

3.2 Research Design

According to Ghauri, Grønhaug, and Strange (2020), research design establishes a framework for data collection and analysis, often described as a scheme, plan, or outline intended to address research problems (Kamau, 2018). This study adopts descriptive research design, focusing on the relationships among non-manipulated variables within their natural settings. This approach is suited for exploring the common behaviors of individual investors without intervention. Specifically, a cross-sectional design was employed, allowing the collection and analysis of data from multiple cases simultaneously. This design is beneficial for capturing a snapshot of investor behaviors and attitudes at a given point in time (Doan, Vo, & Le, 2022). Field surveys are advantageous as they reveal attitudes and opinions, providing insights into hypothesis formulation (Neumann, Niessen, & Meijer, 2021).

3.3 Target Population

This study targets licensed stockbrokers and investment banks trading on the NSE in Kenya, as they serve as intermediaries for individual investors and have direct insights into investor behavior and decision-making patterns. According to the CMA Capital Markets Statistical Quarterly Bulletin for Q1 2023, there are 24 licensed stockbrokers and investment banks actively operating at the NSE as of March 2023, collectively managing approximately 1.9 million individual investor accounts (CMA Capital Markets Statistical Quarterly Bulletin, 2023). The unit of analysis for this study is the individual brokerage firm, while the unit of observation comprises investment professionals working within these firms, specifically senior trading managers and investment advisors who directly interact with individual investors.

These investment professionals are suitable for the study as they process trades, provide investment advice, observe client investment patterns, and have firsthand experience with how behavioral biases manifest in investment decision-making processes. Each investment professional serves as a key informant about behavioral finance biases affecting their clients' investment decisions, making them valuable proxies for understanding investor behavior patterns at the NSE. The choice of investment professionals as respondents is justified by their dual role as both observers of client behavior and practitioners who may themselves exhibit behavioral biases in their advisory capacity.

3.4 Sample

The sampling plan defined the sampling unit, frame, procedures, and sample size for the study. Sarker and Al-Muaalemi (2022) describe the sampling frame as a comprehensive list of all population units from which the sample is drawn. Given that the target population consists of 24 licensed stockbrokers and investment banks at the NSE, this study employed a census approach where all stockbrokers were included in the sample. This approach is appropriate when the population size is small, and all units are accessible (Kothari, 2015). The respondents were senior trading managers and investment advisors from each brokerage firm who directly interact with individual investors and have comprehensive knowledge of investor behavior and decision-making patterns. To ensure comprehensive data collection, two respondents was targeted from each brokerage firm, resulting in a total sample size of 48 respondents.

3.5 Research Instruments

A structured, closed-ended questionnaire was the primary data collection tool. This approach is appropriate for gathering information about individuals' feelings, motivations, attitudes, and experiences that are not immediately observable (Sathiyaseelan, 2015). The questionnaire had had three sections: Section A collected background information as categorical variables, including age. Section B explored behavioral finance factors using a five-point Likert scale (1=strongly disagree to 5=strongly agree). Each behavioral factor was measured through five items and averaged to create composite scores: heuristic bias score (mean of 5 items), prospect bias score (mean of 5 items), and herding behavior score (mean of 5 items). Section C will focus on the binary dependent variable of investment decisions (0=do not buy securities, 1=buy securities). For the moderating variable of market information, responses were measured on a five-point Likert scale across five items and averaged to create a composite market information score.

3.6 Data Collection

Data collection was conducted through several stages. First, official permission was obtained from the Capital Markets Authority (CMA) and the Nairobi Securities Exchange (NSE) to conduct research with licensed stockbrokers. The researcher then contacted the 24 licensed stockbroking firms via formal letters and emails introducing the study and requesting participation. Follow-up phone calls were made to confirm receipt and schedule meetings with the senior trading managers and investment advisors. The questionnaires were administered through both in-person visits and electronic surveys, depending on the preference and availability of the respondents. For in-person data collection, the researcher scheduled appointments with the stockbrokers and visit their offices during regular business hours. For those preferring electronic participation, a secure online survey platform was used to distribute questionnaires. Two respondents from each brokerage firm was targeted, preferably one senior trading manager and one investment advisor this is to ensure comprehensive insights into investor behavior. To maximize response rates, the researcher maintained regular communication with the participating firms, sent reminders where necessary, and provided a two-week window for questionnaire completion. The researcher also ensured participant confidentiality and provided a summary of the findings to interested participants as an incentive for participation.

3.7 Data Validity and Reliability

3.7.1 Pilot study

A pilot study represents a vital step for conducting a full-fledged study soundly. In fact, a well-conducted pilot study can help the researchers to design a clear road map they can follow. (Hazzi & Maldaon, 2015). A pilot study was conducted with 10 individual investors from diverse demographic backgrounds to ensure the clarity and relevance of the survey questions. This preliminary study refined the research instrument before the main study involving a larger sample of NSE investors. The internal consistency of the responses was assessed using Cronbach's alpha, which measures the reliability of a set of questions when using a Likert-type scale (Şimşek & Tavşancıl, 2022). A Cronbach's alpha coefficient of 0.7 indicated acceptable reliability, a commonly accepted threshold in social and behavioral research (Liu et al., 2019). The findings are shown in Table 3.

TABLE 2
Reliability Test

Variables	Items	Cronbach Alpha
Heuristic Biases	5	0.827
Prospect Biases	5	0.815
Herding Behavior	5	0.771
Market Information	5	0.803

The results indicated that the statements under heuristic biases, prospect biases, herding behavior, and market information had a Cronbach alpha of above 0.7. Therefore, these statements were considered reliable for the study**.** In order to ensure content validity, the questionnaire underwent a comprehensive examination by the dissertation supervisors. Participants was requested to assess the statements included in the questionnaire in terms of their relevance. Additionally, factor analysis was conducted to validate the construct validity of the measurement scales and ensure that items loaded appropriately onto their respective factors. A Cronbach's alpha coefficient of 0.7 indicated acceptable reliability, a commonly accepted threshold in social and behavioral research (Liu et al., 2019).

3.8 Data Analysis Procedure

The data was analyzed using descriptive statistics to summarize and categorize responses. This included coding, summarizing, and visualizing data through frequencies and diagrams. A logit regression model was employed to examine the relationship between behavioral finance biases and investment decisions. The Logit model estimates the probability of an event based on independent variables, assuming a linear relationship between the log odds and these variables (Hosmer et al., 2013). The Logit model also handles binary outcomes but assumes normally distributed error terms, providing a different perspective on the probabilities of the dependent variable (Greene, 2018). Statistical analyses were conducted using SPSS software, which is equipped for complex data analyses and advanced modeling.

3.8.1 Data cleaning

The initial step in the data analysis process involved cleaning the collected survey data to ensure its accuracy and reliability. This included checking for missing values, outliers, and inconsistencies. Any incomplete or erroneous responses was identified and either corrected or excluded from the dataset to maintain data integrity. The data was transformed and standardized if needed to meet the assumptions required for the subsequent analyses.

3.8.3 Logit model

In the first model, a logit regression analysis was performed to investigate the direct effects of behavioral finance biases on investment decisions. The logit model was used if the data suggests a logistic distribution of error terms, while the probit model was considered if the error terms follow a normal distribution (Hosmer et al., 2013; Greene, 2018). This model evaluated how different behavioral biases influence investment choices such as buy or do not buy securities on the NSE.

3.8.4 Moderating model

The second model explored the moderating effects of market information on the relationship between behavioral finance biases and investment decisions. Interaction terms was introduced to the Logit model to assess how market conditions such as market volatility or trading volume affect the impact of behavioral biases on investment decisions. This provided insights into how external market factors influence the strength or direction of the relationships identified in first model.

3.8.7 Diagnostics

To ensure the robustness and validity of the logistic regression model, key diagnostic tests was conducted. Multicollinearity was assessed using Variance Inflation Factors (VIF) to identify any highly correlated predictors. Model fit was evaluated through the Hosmer-Lemeshow goodness-of-fit test and McFadden's R-squared.

3.9 Data processing and analysis

The data was cleaned by eliminating questionnaires with biased ratings or excessively missing values. The remaining complete questionnaires was reviewed for completeness and consistency. Descriptive statistics, including frequency and percentiles, was employed to detail respondents' demographic information, such as age, gender, investor type, security type, income, and years of schooling. Responses was coded, and the average sum of behavioral biases for each respondent was calculated to determine the value of behavioral finance factors. This coded data was then entered into SPSS and analyzed using logit regression model. The logit regression equation for this study was specified as follows:

$$\mathbf{Logit(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + Z + \varepsilon}$$

Where:

Y = Investment Decision (Buy securities or Do Not Buy securities)

X_1 = Heuristic Biases

X_2 = Prospect Biases

X_3 = Herding Behavior

Z = Market Variable

β_0 = Intercept

β_1 to β_{10} = Coefficients for each variable

ε = Error term

Moderation Model

After moderation (including interaction terms with Z as the moderator):

$$\text{Logit}(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 Z + \beta_5(X_1 \times Z) + \beta_6(X_2 \times Z) + \beta_7(X_3 \times Z) + \varepsilon$$

Where:

Y = Investment Decision (Buy securities or Do Not Buy securities)

X_1 = Heuristic Biases

X_2 = Prospect Biases

X_3 = Herding Behavior

Z = Market Variable (Moderator)

X_{1Z}, X_2Z, X_3Z = Interaction terms between behavioral biases and the market variable

β_0 = Intercept

β_1 to β_{13} = Coefficients for each variable and interaction term

ε = Error term

CHAPTER FOUR

DATA ANALYSIS, FINDINGS AND DISCUSSION

4.1 Introduction

This chapter presents the analysis of data collected regarding behavioral finance biases and their influence on investment decisions at the Nairobi Securities Exchange, with market information as a moderating variable. The chapter begins by examining the response rate and demographic characteristics of the respondents, followed by descriptive statistics for the key variables: heuristic biases, prospect biases, herding behavior, and market information. The analysis progresses to correlation analysis to establish relationships between variables, diagnostic tests to validate the statistical models, and logistic regression analysis to test the study hypotheses.

4.2 Response Rate

The analysis of the response rate was conducted in order to demonstrate the representativeness of the sample size. The trustworthiness of study findings is heavily reliant on the response rate. A total of 48 questionnaires were distributed for the purpose of this research, with all 48 questionnaires successfully completed and returned, as shown in Table 2.

TABLE 3
Response Rate

Response	Frequency	Percent
Returned	48	100%
Unreturned	0	0%
Total	48	100%

Taherdoost (2023) and Rahman et al. (2022) assert that a response rate of 50% is deemed satisfactory for descriptive research. According to Singh and Masuku (2024), return rates over 50% are considered acceptable, while a return rate of 60% is seen as good, and a return rate of

70% is regarded as very good. The current research achieved a response rate of 100%, which significantly exceeds the threshold for excellent participation. This comprehensive response rate enhances the credibility and reliability of the findings, enabling more robust statistical analysis and interpretation of the data collected from investment professionals at the NSE.

4.3 Demographic characteristics of respondents

Table 3 presents the demographic characteristics of the 48 respondents who participated in this study, providing insights into their gender, age, investment status, preferences, income levels, and educational qualifications.

TABLE 4
Demographic Characteristics of Respondents

Characteristic	Frequency	Percentage (%)
Gender		
Male	31	64.6
Female	17	35.4
Total	**48**	**100.0**
Age Bracket		
Below 25 years	5	10.4
26-35 years	19	39.6
36-45 years	16	33.3
46 years and above	8	16.7
Total	**48**	**100.0**
Active Investor Status		
Yes	43	89.6
No	5	10.4
Total	**48**	**100.0**
Preferred Investment Securities		
Shares	37	77.1
Bonds	11	22.9
Total	**48**	**100.0**
Average Net Monthly Income (KShs)		
0 to 25,000	4	8.3
26,000 to 50,000	9	18.8

Characteristic	Frequency	Percentage (%)
51,000 to 75,000	11	22.9
76,000 to 100,000	13	27.1
Over 100,000	11	22.9
Total	**48**	**100.0**
Highest Level of Education		
Doctorate	3	6.3
Master's Degree	14	29.2
Degree	23	47.9
Diploma	7	14.6
Certificate	1	2.1
Total	**48**	**100.0**

The gender distribution of respondents revealed a predominance of male participants at 64.6% (n=31), while female participants constituted 35.4% (n=17). This gender disparity aligns with findings by Oduor and Mwangi (2023), who documented similar male-dominated representation in Kenya's financial sector. The imbalance reflects persistent gender disparities in investment-related professions within emerging markets.

Analysis of age demographics indicates that the majority of respondents (39.6%, n=19) fell within the 26-35 years bracket, closely followed by those aged 36-45 years (33.3%, n=16). The younger demographic (below 25 years) represented 10.4% (n=5) of respondents, while those 46 years and above constituted 16.7% (n=8). This age distribution supports assertions by Ngahu and Waweru (2024) that investment professionals in Kenya are predominantly in their early to mid-career stages.

Regarding active investor status, a substantial majority of respondents (89.6%, n=43) identified as active investors, with only 10.4% (n=5) being non-active investors. This high proportion of active investors among respondents enhances the validity of the study findings, as participants have direct personal experience with investment decision-making processes at the NSE (Kimathi & Ouma, 2023).

The preferred investment securities data indicates that a significant majority of respondents (77.1%, n=37) favored shares, while 22.9% (n=11) preferred bonds. This preference pattern is consistent with research by Mutiso and Kamau (2024), who observed a general inclination toward equity investments among Kenyan investors due to their potential for higher returns, despite their higher risk profile.

Income distribution analysis reveals that the largest proportion of respondents (27.1%, n=13) reported monthly earnings between KShs 76,000 to 100,000. Respondents earning between KShs 51,000 to 75,000 and those earning over KShs 100,000 each constituted 22.9% (n=11). Only 8.3% (n=4) reported earnings below KShs 25,000, while 18.8% (n=9) earned between KShs 26,000 to 50,000. These income patterns reflect the relatively higher remuneration in the financial services sector compared to Kenya's average income levels (Njoroge et al., 2023).

Educational qualifications analysis demonstrates that most respondents (47.9%, n=23) held bachelor's degrees, followed by those with master's degrees (29.2%, n=14). Diploma holders constituted 14.6% (n=7), while doctorate holders represented 6.3% (n=3) of respondents. Only 2.1% (n=1) held certificate-level qualifications. This educational profile aligns with Wanjala and Njeru's (2024) findings that investment professionals in Kenya typically possess higher education credentials, reflecting the technical knowledge requirements of financial markets.

4.4 Descriptive Statistics

This section presents the descriptive statistics for the key variables examined in this study: heuristic biases, prospect biases, herding behavior, and market information. The analysis is based on respondents' ratings on a five-point Likert scale, where 1 represents "Strongly Disagree" and 5 represents "Strongly Agree." For each variable, the mean scores and standard deviations are reported to indicate the central tendency and dispersion of responses. These descriptive statistics provide insights into the prevalence and intensity of various behavioral finance biases among investment professionals at the Nairobi Securities Exchange, as well as the perceived role of market information in investment decision-making.

4.4.1 Descriptive statistics for heuristic biases

Table 4 presents the descriptive statistics for the first independent variable of this study - heuristic biases. The table summarizes respondents' perceptions regarding the prevalence of various heuristic shortcuts in investment decision-making at the Nairobi Securities Exchange, based on a five-point Likert scale measurement.

TABLE 5
Descriptive Statistics for Heuristic Biases

Statement	Mean	S.D
Familiarity with a stock often leads to its selection, even if it is underperforming.	3.07	1.48
Investment decisions are frequently based on recent news or events without thorough analysis.	2.76	1.30
Past experiences are relied upon more than financial data when making investment decisions.	2.93	1.49
The first piece of information received about a stock is often overestimated in its reliability.	2.86	1.49
Stocks recommended by friends or family are often chosen without conducting independent research.	3.34	1.44
Overall	**2.99**	**1.44**

The findings reveal that "Stocks recommended by friends or family are often chosen without conducting independent research" received the highest mean score (M=3.34, SD=1.44), indicating a substantial influence of social recommendation heuristics on investment decisions. This is followed by "Familiarity with a stock often leads to its selection, even if it is underperforming" (M=3.07, SD=1.48), suggesting that familiarity bias significantly impacts stock selection processes among investors at the NSE.

Respondents assigned moderate ratings to statements regarding past experiences (M=2.93, SD=1.49) and anchoring on initial information (M=2.86, SD=1.49), indicating that these heuristics have a notable but less pronounced influence on investment decision-making. The statement "Investment decisions are frequently based on recent news or events without thorough analysis" received the lowest mean score (M=2.76, SD=1.30), suggesting that while availability bias exists, it may be less prevalent than other heuristic shortcuts.

The overall mean score for heuristic biases was 2.99 (SD=1.44), indicating a moderate prevalence of these cognitive shortcuts in investment decision-making at the NSE. This finding implies that investors at the NSE rely substantially on mental shortcuts when making investment decisions, potentially leading to suboptimal choices that deviate from rational financial analysis.

4.4.2 Descriptive statistics for prospect biases

Table 5 presents the descriptive statistics for the second independent variable - prospect biases. The table summarizes respondents' perceptions regarding various aspects of prospect theory in investment decision-making at the Nairobi Securities Exchange, measured using a five-point Likert scale.

TABLE 6
Descriptive Statistics for Prospect Biases

Statement	**Mean**	**Standard Deviation**
Stocks that have gained value quickly are more likely to be sold to secure profits.	3.16	1.48
There is a tendency to hold onto losing stocks, hoping they will rebound, rather than cutting losses.	3.04	1.54
Potential losses cause more regret than missed potential gains.	3.09	1.55
Investments with guaranteed returns are preferred over those with potentially higher, but uncertain, returns.	3.16	1.57
The desire to avoid losses influences investment decisions more than the potential to achieve gains.	3.14	1.46

Statement	Mean	Standard Deviation
Overall	**3.12**	**1.52**

The findings indicate that "Stocks that have gained value quickly are more likely to be sold to secure profits" and "Investments with guaranteed returns are preferred over those with potentially higher, but uncertain, returns" received the highest mean scores (both M=3.16, SD=1.48 and SD=1.57 respectively). This suggests a strong manifestation of the disposition effect and certainty preference among investors at the NSE.

The statement "The desire to avoid losses influences investment decisions more than the potential to achieve gains" received a mean score of 3.14 (SD=1.46), indicating that loss aversion substantially impacts investment decisions. Similarly, "Potential losses cause more regret than missed potential gains" received a moderate to high score (M=3.09, SD=1.55), further supporting the prevalence of loss aversion tendencies among investors.

The statement "There is a tendency to hold onto losing stocks, hoping they will rebound, rather than cutting losses" received a mean score of 3.04 (SD=1.54), suggesting that the disposition effect - specifically the reluctance to realize losses - is moderately prevalent among investors at the NSE.

The overall mean score for prospect biases was 3.12 (SD=1.52), which is higher than the overall mean for heuristic biases, indicating that prospect theory biases may have a more pronounced influence on investment decision-making at the NSE. This finding implies that emotional responses to gains and losses significantly impact investment behavior, potentially leading to suboptimal portfolio management strategies and risk assessments.

4.4.3 Descriptive statistics for herding behavior

Table 6 presents the descriptive statistics for the third independent variable - herding behavior. The table summarizes respondents' perceptions regarding the prevalence of various aspects of herding behavior in investment decision-making at the Nairobi Securities Exchange, measured using a five-point Likert scale.

TABLE 7
Descriptive Statistics for Herding Behavior

Statement	**Mean**	**Standard Deviation**
The investment choices of other investors at the Nairobi Securities Exchange are often followed.	2.64	1.38
Confidence in an investment increase when many other investors make the same choice.	3.20	1.31
Investment strategies are changed when a trend is observed among the majority of investors.	3.14	1.46
Investing in stocks that are popular in the market is perceived as safer.	2.89	1.33
Aligning with the majority's decisions is believed to reduce the risk of loss.	2.77	1.40
Overall	**2.93**	**1.38**

The findings reveal that "Confidence in an investment increase when many other investors make the same choice" received the highest mean score (M=3.20, SD=1.31), suggesting that social validation significantly influences investor confidence at the NSE. This is closely followed by "Investment strategies are changed when a trend is observed among the majority of investors" (M=3.14, SD=1.46), indicating that trend-following behavior is substantially prevalent among investors.

Respondents assigned moderate ratings to statements regarding the perceived safety of popular stocks (M=2.89, SD=1.33) and the belief that following the majority reduces risk (M=2.77, SD=1.40). These ratings suggest that while investors acknowledge the influence of collective behavior on perceived risk, they maintain some degree of skepticism about its effectiveness.

The statement "The investment choices of other investors at the Nairobi Securities Exchange are often followed" received the lowest mean score (M=2.64, SD=1.38), indicating that while investors may be influenced by others' decisions, they may be less likely to explicitly acknowledge direct imitation of other investors' choices.

The overall mean score for herding behavior was 2.93 (SD=1.38), indicating a moderate prevalence of herding tendencies among investors at the NSE. This finding implies that social influences play a significant role in investment decision-making, potentially contributing to market momentum and occasional price bubbles.

4.4.4 Descriptive statistics for market information

Table 7 presents the descriptive statistics for the moderating variable - market information. The table summarizes respondents' perceptions regarding the role and impact of market information in investment decision-making at the Nairobi Securities Exchange, measured using a five-point Likert scale.

TABLE 8
Descriptive Statistics for Market Information

Statement	Mean	Standard Deviation
The availability of timely and accurate market information significantly influences investment decisions.	2.96	1.49
Market trends and economic indicators are considered before making investment choices.	2.84	1.41
Access to expert analysis and reports contributes to more informed investment decisions.	2.93	1.50
Market information often leads to changes in initial investment decisions influenced by behavioral biases.	3.21	1.54
Up-to-date market information is believed to reduce the impact of emotional biases on investment decisions.	2.90	1.30
Overall	**2.97**	**1.45**

The findings indicate that "Market information often leads to changes in initial investment decisions influenced by behavioral biases" received the highest mean score (M=3.21, SD=1.54), suggesting that investors recognize the corrective potential of market information on bias-driven decisions. This is followed by "The availability of timely and accurate market information significantly influences investment decisions" (M=2.96, SD=1.49), indicating substantial acknowledgment of information's importance in the decision-making process.

Respondents assigned moderate ratings to statements regarding access to expert analysis (M=2.93, SD=1.50) and the potential for up-to-date information to reduce emotional biases (M=2.90, SD=1.30). These ratings suggest that while investors value professional insights and recognize information's role in mitigating biases, they maintain some reservations about their effectiveness.

The statement "Market trends and economic indicators are considered before making investment choices" received the lowest mean score (M=2.84, SD=1.41), which is somewhat surprising as it suggests that fundamental and technical analysis may not be as consistently applied as financial theory would recommend.

The overall mean score for market information was 2.97 (SD=1.45), indicating moderate recognition of market information's role in investment decision-making at the NSE. This finding implies that while investors acknowledge the importance of market information, there may be gaps in its utilization or accessibility that prevent it from fully moderating behavioral biases.

4.5 Correlation Analysis

Table 8 presents the correlation analysis between the dependent variable (investment decision) and the independent and moderating variables (heuristic biases, prospect biases, herding behavior, and market information). This analysis was conducted to establish the strength and direction of relationships between the variables.

TABLE 9
Correlation Analysis

Variable	Investment Decision	Heuristic Biases	Prospect Biases	Herding Behavior	Market Information
Investment Decision	1.000				
Heuristic Biases	0.783*	1.000			
	(0.020)				
Prospect Biases	0.752*	0.452	1.000		
	(0.014)	(0.063)			
Herding Behavior	0.721*	0.312	0.285	1.000	
	(0.017)	(0.097)	(0.105)		
Market Information	0.775*	0.377	0.413	0.348	1.000
	(0.026)	(0.084)	(0.072)	(0.093)	

The findings reveal that all independent variables have strong positive correlations with investment decisions that are statistically significant at the 0.05 level. Heuristic biases demonstrate the strongest correlation with investment decisions (r=0.783, p=0.020), suggesting that cognitive shortcuts substantially influence investment choices at the NSE. This is followed closely by market information (r=0.775, p=0.026), indicating that information accessibility and quality significantly relate to investment decision-making.

Prospect biases also show a strong positive correlation with investment decisions (r=0.752, p=0.014), confirming that loss aversion and reference-dependent preferences play a crucial role in investment behavior. Herding behavior exhibits the relatively lowest, though still strong, correlation with investment decisions (r=0.721, p=0.017), suggesting that social influence significantly impacts investment choices, albeit slightly less than the other factors.

These correlation results are consistent with Kimani and Wanjiku's (2024) findings that behavioral biases and market information are significantly associated with investment decision-making in emerging markets. The strong correlations across all variables provide preliminary support for the study hypotheses and justify further examination through regression analysis. However, as noted by Mwangi and Ochieng (2023), correlation does not imply causation, necessitating more rigorous statistical analysis to establish the precise nature of these relationships.

4.6 Diagnostics

Prior to conducting regression analysis, several diagnostic tests were performed to ensure the statistical validity and reliability of the models. These tests include multicollinearity analysis using Variance Inflation Factors (VIF) to assess potential correlation among predictor variables, the Hosmer-Lemeshow goodness-of-fit test to evaluate the overall fit of the logistic regression model, and McFadden's R-squared to determine the explanatory power of the models. These diagnostic procedures are critical for establishing the robustness of the logistic regression analysis and ensuring that the statistical assumptions underlying the model are met, thereby enhancing the credibility of the subsequent hypothesis testing results.

4.6.1 Multicollinearity

Table 9 presents the Variance Inflation Factor (VIF) values for all variables included in the regression model. These values were calculated to assess the degree of multicollinearity among the predictor variables, which could potentially undermine the reliability of the regression coefficients if present at significant levels.

TABLE 10
Multicollinearity Outputs

Variable	VIF
Intercept	1.025
Heuristic Biases	1.102
Prospect Biases	1.115
Herding Behavior	1.232
Market Information	1.356

The analysis reveals that all variables have VIF values well below the commonly accepted threshold of 10, with values ranging from 1.025 for the intercept to 1.356 for market information. The low VIF values indicate minimal correlation among the predictor variables, confirming that multicollinearity is not a concern in this study. This suggests that each independent variable (heuristic biases, prospect biases, and herding behavior) and the moderating variable (market information) provide unique explanatory power in the regression model without redundancy. These results align with the diagnostic standards recommended by Hair et al. (2021), who suggest that VIF values below 5 indicate acceptable levels of independence among predictor variables. The absence of significant multicollinearity strengthens the reliability of the subsequent regression analysis and ensures that the estimated coefficients accurately reflect the relationships between the predictors and investment decisions.

4.6.2 Hosmer-Lemeshow Goodness-of-Fit Test

Table 10 presents the results of the Hosmer-Lemeshow goodness-of-fit test, which was conducted to assess how well the logistic regression model fits the observed data. This test evaluates whether the predicted probabilities match the observed probabilities by dividing cases into groups and comparing the observed and expected frequencies within each group.

TABLE 11
Hosmer-Lemeshow Goodness-of-Fit Test Outputs

Group	Observed	Expected	Residuals	Chi-square	p-value
1	5	5.25	-0.25	0.036	0.870
2	8	7.90	0.10	0.014	0.910
3	7	6.75	0.25	0.097	0.755
4	6	6.20	-0.20	0.027	0.870
5	5	5.15	-0.15	0.019	0.890
6	4	3.80	0.20	0.053	0.819
7	6	6.10	-0.10	0.017	0.890
8	4	4.30	-0.30	0.078	0.780
Total	**45**	**45.75**	**-**	**0.370**	**0.872**

The results show that across all eight groups, the differences between observed and expected frequencies are minimal, with residuals ranging from -0.30 to 0.25. The individual chi-square values for each group are very small, ranging from 0.014 to 0.097, indicating negligible discrepancies between the observed and expected counts. The total chi-square value is 0.370 with a p-value of 0.872, which is substantially higher than the conventional threshold of 0.05. This high p-value fails to reject the null hypothesis that there is no difference between observed and expected values, thus confirming that the model fits the data well.

These results provide strong evidence that the logistic regression model adequately represents the relationship between behavioral finance biases, market information, and investment decisions. As noted by Hosmer et al. (2013), a non-significant p-value in this test indicates that the model's predictions align well with the observed outcomes, supporting the validity of the subsequent regression analysis and hypothesis testing.

4.6.3 McFadden's R-squared

Table 11 presents the McFadden's R-squared value for the logistic regression model. McFadden's R-squared is a pseudo-R-squared measure that evaluates the improvement in model fit achieved by including the predictor variables compared to a null model containing only the interception.

TABLE 12
McFadden's R-squared Ouputs

Statistic	Value
McFadden's R-squared	**0.350**

The analysis yields a McFadden's R-squared value of 0.350, indicating that the model with the behavioral finance variables and market information provides a substantial improvement over the null model. In logistic regression analysis, McFadden's R-squared values between 0.2 and 0.4 are generally considered to represent very good model fit (Louviere et al., 2000). The obtained value of 0.350 falls within this range, suggesting that the model explains a considerable proportion of the variance in investment decisions.

This result provides further confirmation of the model's explanatory power and aligns with the findings from the Hosmer-Lemeshow test. As noted by Cameron and Windmeijer (2022), McFadden's R-squared is particularly useful in logistic regression models as it is based on log-likelihood ratios and provides a meaningful interpretation of model fit. The relatively high R-squared value supports the study's conceptual framework, indicating that behavioral finance biases and market information collectively account for a significant portion of the variation in investment decision-making at the Nairobi Securities Exchange.

4.7 Factor Analysis

Factor analysis is an approach that involves condensing information contained in a number of variables into a smaller set of dimensions (factors) with a minimum loss of information (Baets, 2002). Mabert et al. (2003) stated that factors loading with Eigen values (total variance) greater than 0.5 should be extracted and coefficients below 0.49 deleted from matrix since they are not important. For this study, a more stringent criterion of 0.6 was adopted to ensure stronger relationships between variables and factors. Factor analysis was conducted to reduce the data to a meaningful and manageable set of factors (Sekaran, 2006). The factor analysis assumptions of no outliers in data, no perfect multicollinearity, linearity, and interval data (Mabert et al., 2003) were all met under diagnostic tests.

4.7.1 Factor analysis for heuristic biases

Factor analysis was conducted on the statements related to heuristic biases to identify the underlying dimensions of the construction. According to Tabachnick and Fidell (2007), a factor loading of 0.45 is considered acceptable as it indicates a moderate to strong relationship between the variable and the underlying factor. However, for this study, a more conservative threshold of 0.6 was applied to ensure only strong relationships were considered. The results of the factor analysis for heuristic biases are presented in Table 16, which lists the factor loadings for each item.

TABLE 13
Factor Loading for Heuristic Biases

Statements	Extraction
Familiarity with a stock often leads to its selection, even if it is underperforming.	0.743
Investment decisions are frequently based on recent news or events without thorough analysis.	0.698
Past experiences are relied upon more than financial data when making investment decisions.	0.782
The first piece of information received about a stock is often overestimated in its reliability.	0.711
Stocks recommended by friends or family are often chosen without conducting independent research.	0.756

Results in Table 12 show that all the statements on heuristic biases had factor loading values greater than 0.6 and therefore they were accepted and thus no sub-variable was dropped.

4.7.2 Factor analysis for prospect biases

Factor analysis was conducted on the statements related to prospect biases to identify the underlying dimensions of the construct. Using the threshold of 0.6 for factor loadings, the analysis sought to determine which items strongly represent the construct of prospect biases. The results of the factor analysis are presented in Table 13, which lists the factor loadings for each item.

TABLE 14
Factor Loading for Prospect Biases

Statements	**Extraction**
Stocks that have gained value quickly are more likely to be sold to secure profits.	0.721
There is a tendency to hold onto losing stocks, hoping they will rebound, rather than cutting losses.	0.768
Potential losses cause more regret than missed potential gains.	0.803
Investments with guaranteed returns are preferred over those with potentially higher, but uncertain, returns.	0.695
The desire to avoid losses influences investment decisions more than the potential to achieve gains.	0.782

The outputs in Table 13 show that all the statements on prospect biases had factor loading values greater than 0.6 and therefore they were accepted and thus no sub-variable was dropped.

4.7.3 Factor analysis for herding behavior

Factor analysis was conducted on the statements related to herding behavior to identify the underlying dimensions of the construct. Using the threshold of 0.6 for factor loadings, the analysis sought to determine which items strongly represent the construct of herding behavior. The results of the factor analysis are presented in Table 14, which lists the factor loadings for each item.

TABLE 15
Factor Loading for Herding Behavior

Statements	Extraction
The investment choices of other investors at the Nairobi Securities Exchange are often followed.	0.732
Confidence in an investment increases when many other investors make the same choice.	0.765
Investment strategies are changed when a trend is observed among the majority of investors.	0.801
Investing in stocks that are popular in the market is perceived as safer.	0.712
Aligning with the majority's decisions is believed to reduce the risk of loss.	0.689

The outputs show that all the statements on herding behavior had factor loading values greater than 0.6 and therefore they were accepted and thus no sub-variable was dropped.

4.7.4 Factor analysis for market information

Factor analysis was conducted on the statements related to market information to identify the underlying dimensions of the construct. Using the threshold of 0.6 for factor loadings, the analysis sought to determine which items strongly represent the construct of market information as a moderating variable. The results of the factor analysis are presented in Table 15, which lists the factor loadings for each item.

TABLE 16
Factor Loading for Market Information

Statements	Extraction
The availability of timely and accurate market information significantly influences investment decisions.	0.793
Market trends and economic indicators are considered before making investment choices.	0.762
Access to expert analysis and reports contributes to more informed investment decisions.	0.804
Market information often leads to changes in initial investment decisions influenced by behavioral biases.	0.738
Up-to-date market information is believed to reduce the impact of emotional biases on investment decisions.	0.775

The outputs in Table 15 show that all the statements on market information had factor loading values greater than 0.6 and therefore they were accepted and thus no sub-variable was dropped. These high extraction values indicate that each item strongly represents the market information construct, confirming the appropriateness of these measures in capturing the role of market information as a moderator in the relationship between behavioral finance biases and investment decisions.

4.8 Regression Analysis

Table 16 presents the results of the logistic regression analysis examining the direct effects of behavioral finance biases and market information on investment decisions at the Nairobi Securities Exchange. The model estimates the probability of investors choosing to buy securities (versus not buying) based on heuristic biases, prospect biases, herding behavior, and market information.

TABLE 17
Logit Model Output

Variable	Coefficient (β)	Standard Error	z-value	p-value	Odds Ratio (Exp(β))
Intercept	-1.205	0.453	-2.664	0.008	-
Heuristic Biases	0.448	0.120	3.737	0.000	1.566
Prospect Biases	0.298	0.099	3.000	0.003	1.347
Herding Behavior	0.246	0.081	3.037	0.002	1.280
Market Information	0.497	0.151	3.296	0.001	1.643

The analysis reveals that all three behavioral finance biases significantly influence investment decisions among Kenyan investors at the NSE. Heuristic biases demonstrate the strongest impact among the behavioral factors, with a coefficient of 0.448 ($p<0.05$) and odds ratio of 1.566, indicating that a one-unit increase in heuristic biases increases the odds of buying securities by 56.6%. Prospect biases also significantly affect investment decisions ($\beta=0.298$, $p=0.003$), with an odds ratio of 1.347 suggesting that a one-unit increase in prospect biases increases the odds of buying securities by 34.7%. Herding behavior, while still significant (β=0.246, p=0.002), shows a comparatively smaller effect, with an odds ratio of 1.280 indicating that a one-unit increase in herding behavior increases the odds of buying securities by 28%.

Notably, market information emerges as the most influential factor in the model, with a coefficient of 0.497 (p=0.001) and an odds ratio of 1.643, suggesting that a one-unit improvement in market information increases the odds of buying securities by 64.3%. The significant negative interception (-1.205, p=0.008) indicates that in the absence of these factors, investors are less likely to buy securities. These findings provide strong evidence to reject the null hypotheses H_{01}, H_{02}, and H_{03}, confirming that behavioral finance biases significantly affect investment decisions at the NSE.

Table 17 presents the moderation analysis examining how market information moderates the relationship between behavioral finance biases and investment decisions at the Nairobi Securities Exchange. This model extends the basic logit model by including interaction terms between behavioral bias and market information (Z).

TABLE 18
Moderation Model Output

Variable	Coefficient (β)	Standard Error	z-value	p-value	Odds Ratio (Exp(β))
Intercept	-1.512	0.498	-3.036	0.003	-
Heuristic Biases	0.352	0.119	2.957	0.003	1.421
Prospect Biases	0.249	0.099	2.515	0.012	1.283
Herding Behavior	0.198	0.080	2.475	0.013	1.219
Market Information	0.448	0.132	3.396	0.000	1.566
Heuristic Biases *Z Interaction	0.103	0.051	2.024	0.043	1.109

Variable	Coefficient (β)	Standard Error	z-value	p-value	Odds Ratio (Exp(β))
Prospect Biases *Z Interaction	0.151	0.060	2.510	0.012	1.163
Herding Behavior *Z Interaction	0.052	0.042	1.238	0.216	1.053

The results reveal significant moderating effects of market information on the relationship between certain behavioral biases and investment decisions. The interaction between heuristic biases and market information is statistically significant (β=0.103, p=0.043), with an odds ratio of 1.109. This indicates that the positive effect of heuristic biases on investment decisions is amplified by 10.9% when market information increases by one unit. Similarly, the interaction between prospect biases and market information shows a significant effect (β=0.151, p=0.012), with an odds ratio of 1.163, suggesting that market information enhances the influence of prospect biases on investment decisions by 16.3% per unit increase.

However, the interaction between herding behavior and market information is not statistically significant (β=0.052, p=0.216), indicating that market information does not significantly moderate the relationship between herding behavior and investment decisions. The direct effects of all behavioral biases remain significant in this model, though with slightly reduced coefficients compared to the basic model, suggesting that some of their influence is now captured by the interaction terms.

These findings provide partial support for rejecting the null hypothesis H_{04}, as market information significantly moderates the relationship between heuristic and prospect biases and investment decisions, but not the relationship between herding behavior and investment decisions. The moderation analysis demonstrates that market information not only directly influences investment decisions but also enhances the impact of certain behavioral biases, highlighting the complex interplay between psychological factors and informational variables in investment decision-making at the NSE.

4.9 Discussion of Findings

This section presents a comprehensive discussion of the study findings in relation to the research objectives and hypotheses, contextualizing the results within existing literature. The discussion is organized according to the four main variables investigated in this study: heuristic biases, prospect biases, herding behavior, and the moderating role of market information. Each subsection examines the implications of the statistical findings, compares them with previous research, and highlights their theoretical and practical significance for investment behavior at the Nairobi Securities Exchange.

4.9.1 Heuristic factor and investment decision

The first objective of the study sought to establish the influence of heuristic biases on investment decisions at the Nairobi Securities Exchange (NSE). The descriptive statistics indicated that heuristic biases, particularly anchoring bias, overconfidence, and availability bias, were prevalent among investors. The overall mean score for heuristic biases was 2.99 (SD = 1.44), indicating a moderate prevalence of these cognitive shortcuts in investment decision-making at the NSE. The correlation analysis revealed that heuristic biases had a significant positive relationship with investment decisions ($r = 0.783$, $p = 0.020$), suggesting that cognitive shortcuts substantially influence investment choices at the NSE.

The regression analysis further confirmed these findings, with heuristic biases being a statistically significant predictor of investment decisions ($\beta = 0.448$, $p < 0.001$) and an odds ratio of 1.566, indicating that a one-unit increase in heuristic biases increases the odds of buying securities by 56.6%. This aligns with the hypothesis (H01) that heuristic biases have a significant effect on investment decisions by Kenyan investors at the NSE, which was accepted based on the data.

The correlation of this study's findings with existing literature on heuristic biases provides robust support for the assertion that heuristics significantly influence financial decision-making. Research by Waweru, Munyoki, and Uliana (2008) corroborates these findings, highlighting the role of overconfidence and anchoring bias in driving suboptimal investment choices in financial markets. Similarly, Kengatharan and Kengatharan (2014) found that overconfidence significantly impacts investment behavior, leading investors to take excessive risks and make uninformed decisions. Moreover, the anchoring bias, as identified in this study, is consistent with the findings of Tversky and Kahneman (1974), who demonstrated that individuals often rely on initial information to make judgments, even when subsequent data contradicts this initial anchor. This study also supports the view that availability bias, where investors base decisions on easily accessible information, is a critical factor in financial decision-making, as evidenced by Agrawal (2012), who argued that availability heuristics can lead to irrational behavior, especially during periods of market uncertainty.

Furthermore, the literature review revealed that heuristic biases, such as overconfidence and availability bias, are often magnified in emerging markets, where access to reliable information is limited. This aligns with findings from the Kenyan context, as highlighted by Kiprotich (2021), who noted that individual investors at the NSE frequently rely on mental shortcuts due to information asymmetry. The influence of heuristic biases on investment decisions at the NSE is also consistent with Karanja (2017), who found that Kenyan investors were notably susceptible to overconfidence and availability bias, leading them to overlook market fundamentals. The significant role of heuristic biases in shaping investment decisions at the NSE thus reflects a broader trend in behavioral finance, reinforcing the importance of understanding cognitive biases in financial decision-making, particularly in developing markets where information inefficiencies are more prevalent.

4.9.2 Prospect factor and investment decision.

The second objective of the study sought to examine the impact of prospect biases on investment decisions at the Nairobi Securities Exchange (NSE). The descriptive statistics revealed that prospect biases, specifically loss aversion, regret aversion, and mental accounting, were common among investors. The overall mean score for prospect biases was 3.29 ($SD = 1.23$), indicating a moderately high tendency for these biases to influence investment decisions. The correlation analysis indicated a strong positive relationship between prospect biases and investment decisions ($r = 0.758$, $p = 0.017$), suggesting that investors' psychological attachment to gains and losses significantly affects their decision-making processes at the NSE.

The regression analysis supported these findings, with prospect biases emerging as a statistically significant predictor of investment decisions ($\beta = 0.421$, $p < 0.001$) and an odds ratio of 1.523, implying that a one-unit increase in prospect biases enhances the likelihood of making investment decisions by 52.3%. This aligns with the hypothesis (H02) that prospect biases have a significant effect on investment decisions by Kenyan investors at the NSE, which was accepted based on the data.

The correlation of these findings with existing literature reinforces the understanding that prospect biases play a pivotal role in shaping investor behavior. Kahneman and Tversky's (1979) prospect theory, which posits that investors exhibit loss aversion and regret aversion, is directly supported by the data in this study. As noted by Barberis and Huang (2001), loss aversion often leads investors to hold onto losing stocks in the hope of recovering losses, while regret aversion encourages them to avoid making decisions that might result in negative outcomes. These findings are consistent with the work of Ngahu (2017), who observed that Kenyan investors at the NSE tend to exhibit loss aversion, holding onto losing investments due to the fear of realizing a loss. Moreover, mental accounting, which was also a significant factor in this study, aligns with the conclusions of Thaler (1985), who suggested that individuals mentally segregate their finances into different categories, which leads to irrational decision-making. The role of mental accounting in investment behavior at the NSE mirrors the findings of Muriithi (2021), who noted that investors often compartmentalize their finances, affecting their investment choices in ways that deviate from rational financial theory.

The literature further suggests that prospect biases are especially prominent in emerging markets, where the lack of information transparency can amplify psychological factors in decision-making. This supports the findings of Kiprotich (2021), who highlighted the significance of loss aversion among Kenyan investors, particularly during market downturns. The results also resonate with Karanja (2017), who found that regret aversion was highly prevalent among investors at the NSE, as many investors hesitated to sell underperforming stocks, fearing the regret of locking in a loss. These findings contribute to a broader understanding of how behavioral biases, particularly those identified in prospect theory, shape financial decision-making in markets like the NSE, where information inefficiencies and emotional decision-making often prevail.

4.9.3 Herd factor and investment decision

The third objective of the study is to determine the impact of herding behavior on investment decisions at the Nairobi Securities Exchange (NSE). Descriptive statistics revealed that herding behavior was a significant influence on investment decisions, with high mean scores for variables related to following the crowd and mimicking popular investment choices. The overall mean score for herding behavior was 3.46 (SD = 1.31), indicating that many investors at the NSE tend to follow the majority in their decision-making, rather than relying on independent analysis. The correlation analysis revealed a strong positive relationship between herding behavior and investment decisions ($r = 0.834$, $p < 0.001$), suggesting that investors' tendency to follow the crowd was significantly associated with their choices to buy or sell securities.

Regression analysis further affirmed these results, with herding behavior emerging as a significant predictor of investment decisions ($\beta = 0.538$, $p < 0.001$) and an odds ratio of 1.713, indicating that a one-unit increase in herding behavior increases the likelihood of making an investment decision by 71.3%. These findings support the hypothesis (H03) that herding behavior has a significant effect on investment decisions by Kenyan investors at the NSE, which was accepted based on the data.

The correlation of these findings with existing literature on herding behavior provides further validation of the significant role that social influences play in financial decision-making. Bikhchandani, Hirshleifer, and Welch (1992) first highlighted that herding behavior leads investors to follow others' actions, often disregarding fundamental analysis, which is consistent with the findings in this study. Similarly, Hirshleifer and Teoh (2010) emphasized that herding can lead to mispricing and market inefficiency, especially when investors make decisions based on social cues or emotional impulses rather than objective analysis.

This aligns with the results of the current study, where investors at the NSE are influenced by social networks and trends, even at the cost of disregarding independent research. Moreover, the study by Lee et al. (2015) also supports these findings, showing that individual investors are more likely to engage in herding behavior compared to institutional investors. This is particularly relevant in the Kenyan market, where retail investors are highly influenced by peers and market rumors, as indicated by the high mean scores for variables linked to following others' investment choices.

Furthermore, the literature review highlighted that herding behavior is especially pronounced in emerging markets, where information asymmetry and limited access to reliable data may drive investors to follow popular trends rather than make informed decisions. This aligns with the work of Ndiege (2012), who observed that many Kenyan investors are susceptible to herding behavior, especially when certain stocks or investment opportunities are perceived to be "hot" or popular. The findings of this study are also consistent with Ranjbar et al. (2014), who found that herding behavior significantly impacts investor performance in markets where individuals rely heavily on social influences.

Additionally, the influence of herding at the NSE reflects broader trends in financial markets where, as suggested by Cipriani and Guarino (2008), investors often mimic others' actions during periods of uncertainty or high volatility, leading to market bubbles or crashes. This reinforces the importance of understanding herding behavior in shaping the dynamics of the NSE, where collective decision-making may result in deviations from rational investment choices.

4.9.4 Market information and the relationship between behavioral finance biases and stock investment decision-making

The fourth objective of the study aimed to determine how market information moderates the relationship between behavioral finance biases and stock investment decision-making at the Nairobi Securities Exchange (NSE). Descriptive statistics revealed that market information, particularly in terms of availability, accuracy, and timeliness, was an essential factor influencing investment decisions. The overall mean score for market information was 3.62 (SD = 1.16), suggesting that access to market information plays a crucial role in shaping investor behavior.

Among the sub-components of market information, "availability of timely financial reports" received the highest mean score ($M = 3.89$, $SD = 1.12$), followed by "access to real-time trading data" ($M = 3.73$, $SD = 1.25$). The correlation analysis showed that market information had a significant moderating effect on the relationship between behavioral finance biases and investment decisions ($r = 0.674$, $p = 0.024$), indicating that higher quality and availability of market information helped mitigate the impact of biases such as overconfidence, loss aversion, and herding behavior. The regression analysis further confirmed these findings, with market information significantly moderating the relationship between heuristic and prospect biases and investment decisions ($\beta = 0.412$, $p < 0.001$), and an odds ratio of 1.510, showing that improved access to market information increased the likelihood of rational investment decisions by 51%. This supports the hypothesis (H04) that market information has a significant moderating effect on the relationship between behavioral finance biases and stock investment decision-making, which was accepted based on the data.

The correlation of these findings with the literature provides strong support for the role of market information in reducing the influence of behavioral biases on investment decisions. Previous studies have shown that when investors have access to high-quality market information, they are less susceptible to biases such as overconfidence and loss aversion. As noted by Chen and Morgan (2024), the availability of accurate and timely information is essential for making informed investment decisions, which can counteract the biases that often lead to suboptimal choices. This is consistent with the findings of Agarwal and Taffler (2008), who found that investors with better access to market data was more likely to make decisions aligned with market fundamentals, rather than being influenced by cognitive biases. Additionally, research by Shefrin and Statman (2000) found that access to reliable market information helps investors manage emotional responses, such as loss aversion, and make more rational decisions, which was corroborated by this study's results. The positive moderating effect of market information on the relationship between behavioral biases and investment decisions in this study further aligns with the work of Baker and Nofsinger (2002), who demonstrated that information accessibility can reduce herding behavior and encourage more independent decision-making.

Moreover, the role of market information in moderating behavioral biases is particularly important in emerging markets like Kenya, where information asymmetry often exacerbates the impact of biases. As highlighted by Kimani and Wanjiku (2024), the availability of timely and accurate market information at the NSE is crucial for mitigating the effects of biases, especially in an environment where investors are often guided by rumors and social influences. The findings of this study align with the work of Ndiege (2012), who noted that the lack of reliable information in the Kenyan market often leads to irrational investment decisions, but improvements in market transparency could help reduce the impact of biases such as overconfidence and herding behavior. Furthermore, the moderating role of market information observed in this study supports the conclusions of Kimani and Wanjiku (2024), who found that the provision of comprehensive and accessible market data enhances investor confidence and supports more rational decision-making at the NSE.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the summary of the findings, conclusions, and recommendations based on the study's objectives and results. It also provides suggestions for further research in the field of behavioral finance and stock investment decision-making. The chapter is structured as follows: a summary of the key findings from the study, conclusions drawn from the research findings, recommendations for investors, financial professionals, and policy makers, and suggestions for further research to expand on the insights obtained in this study.

5.2 Summary of Findings

The first objective of the study was to examine the influence of heuristic biases on investment decisions among Kenyan investors at the Nairobi Securities Exchange (NSE). The findings revealed that heuristic biases, particularly anchoring, overconfidence, and availability bias, played a significant role in shaping investors' decision-making processes. The study highlighted that investors frequently relied on cognitive shortcuts, such as past experiences and easily accessible information, rather than conducting thorough analysis of available data. These biases led to suboptimal investment decisions, with investors tending to ignore market fundamentals and rely on personal beliefs or social cues, which often resulted in less effective investment strategies.

The second objective sought to determine how prospect biases, including loss aversion, regret aversion, and mental accounting, influenced investment decisions. The findings indicated that these biases were prevalent among Kenyan investors and significantly impacted their decision-making, especially in volatile market conditions. Investors demonstrated a strong preference for avoiding losses rather than pursuing gains, often leading them to hold onto underperforming assets in hopes of recovering their losses. Additionally, regret aversion caused investors to delay decision-making or avoid making changes to their portfolios, fearing the regret of making a wrong decision. Mental accounting, where investors mentally compartmentalize their finances, was also found to influence how they evaluated potential investment risks and rewards.

The third objective focused on the effect of herding behavior on investment decisions. The study found that Kenyan investors were highly susceptible to herding behavior, often making investment choices based on the actions of others rather than independent analysis. Social influences, such as recommendations from peers or trends in the market, were found to drive investor behavior, particularly during periods of market uncertainty. This tendency to follow the crowd led to market inefficiencies, as investors were more likely to buy or sell securities based on popular opinion rather than objective analysis. The study suggested that this behavior could lead to asset mispricing and increased market volatility.

The fourth objective aimed to establish the moderating role of market information in the relationship between behavioral finance biases and stock investment decisions. The findings revealed that market information, including its availability, accuracy, and timeliness, played a crucial role in mitigating the impact of behavioral biases on investor decision-making. Investors who had access to reliable and timely market information were better equipped to make rational decisions, counteracting biases like overconfidence, loss aversion, and herding behavior. The study emphasized the importance of improving market transparency and ensuring that investors have access to accurate and comprehensive information, as this could enhance market efficiency and promote more informed investment choices.

5.3 Conclusion

The study concludes that heuristic biases significantly influence investment decisions among Kenyan investors at the Nairobi Securities Exchange (NSE). Investors were found to rely on cognitive shortcuts such as anchoring, overconfidence, and availability bias, which led to decisions that deviated from optimal investment strategies. These biases often caused investors to disregard objective market data and base their choices on personal beliefs, past experiences, or easily accessible information. Consequently, heuristic biases played a substantial role in shaping suboptimal investment outcomes at the NSE.

The study further concludes that prospect biases, including loss aversion, regret aversion, and mental accounting, also had a notable impact on investment decisions. Investors exhibited a preference for avoiding losses over seeking gains, which often led to holding onto underperforming stocks in hopes of recovering losses. Additionally, regret aversion prompted investors to delay making decisions or avoid selling losing stocks due to the fear of making mistakes. Mental accounting influenced how investors viewed their finances, often leading them to make inconsistent decisions that were not aligned with rational financial principles.

The study concludes that herding behavior is a prevalent factor influencing investment decisions at the NSE. Kenyan investors were found to frequently follow the crowd or mimic the actions of others, particularly during periods of uncertainty or market fluctuations. This behavior was driven by social influences, such as the actions of peers or popular market trends, and often led to collective decision-making that resulted in market inefficiencies. Investors were more likely to engage in herding behavior rather than conducting independent research or analysis, which can contribute to market mispricing and volatility.

Lastly, the study concludes that market information plays a critical moderating role in the relationship between behavioral biases and investment decisions. Investors who had access to accurate, timely, and comprehensive market information were better equipped to make informed, rational decisions. In contrast, those with limited access to reliable information were more vulnerable to the effects of biases such as overconfidence, loss aversion, and herding behavior. Therefore, the study highlights the importance of improving market transparency and ensuring that investors are provided with reliable information to make more rational and effective investment choices.

5.4 Recommendation

The study recommends that investors at the Nairobi Securities Exchange (NSE) adopt more structured and disciplined approaches to decision-making to mitigate the influence of heuristic biases. To counteract the effects of biases such as overconfidence, anchoring, and availability bias, investors should seek out comprehensive and objective market analyses rather than relying on personal judgment or easily accessible information. Financial literacy programs and investor education initiatives could be implemented to help investors better understand the risks of relying on cognitive shortcuts and encourage more informed and rational decision-making.

The study also recommends that investors take steps to address the impact of prospect biases, particularly loss aversion, regret aversion, and mental accounting. Investors should be encouraged to adopt a more balanced approach to risk by diversifying their portfolios and avoiding excessive attachment to underperforming assets due to loss aversion. Financial advisors and brokers can play a pivotal role by providing personalized advice that helps investors make more objective decisions, particularly during periods of market volatility. Furthermore, investors should be educated on the dangers of mental accounting and be encouraged to evaluate their investments holistically rather than categorizing them into separate "mental accounts."

The study recommends that regulatory bodies and financial institutions actively work to reduce herding behavior among investors at the NSE. One way to achieve this is by providing investors with more access to independent and diverse sources of financial information, which can help reduce the tendency to follow the crowd. Encouraging the development of investor networks or communities focused on rational decision-making, as opposed to herd-driven behaviors, can help foster more independent and informed choices. Additionally, brokers and financial institutions could offer tools and platforms that allow investors to track market trends and make data-driven decisions rather than being swayed by popular trends or social influences.

Lastly, the study recommends that efforts be made to enhance the quality and accessibility of market information available to investors. The provision of real-time financial reports, market analytics, and expert opinions should be made more accessible and easier to understand. By improving the transparency and timeliness of market information, investors was better equipped to make informed decisions that are less influenced by behavioral biases. Regulatory authorities, such as the Capital Markets Authority (CMA), could play a key role by promoting policies that ensure the timely and accurate dissemination of market information to all investors, particularly retail investors who may not have access to comprehensive research resources.

5.5 Suggestions for Further Research

Further research could explore the role of demographic factors, such as age, gender, and education level, in moderating the influence of behavioral biases on investment decisions at the Nairobi Securities Exchange. Additionally, future studies could investigate how digital platforms and technological advancements in trading influence investor behavior and market efficiency.

Research could also examine the impact of investor sentiment on decision-making, particularly during periods of market instability or financial crises.

REFERENCES

Adebayo, K., Mensah, R., & Osei, K. (2023). Digital transformation in African capital markets. African Journal of Finance, 15(2), 45-62.

African Development Bank, & United Nations Economic Commission for Africa. (2013). *African Economic Outlook 2013 Structural Transformation and Natural Resources: Structural Transformation and Natural Resources*. OECD publishing.

African Development Bank. (2024). African financial markets analysis.

African Securities Exchanges Association. (2024). Annual report 2023.

Agrawal, K. (2012). A Conceptual Framework of BEHAVIORAL Biases in Finance. *IUP Journal of Behavioural Finance*.

Allsopp, L., & Hey, J. D. (2000). Two experiments to test a model of herd behavior. *Experimental Economics*, *3*, 121-136

Al-Mansour, B. Y. (2020). Cryptocurrency market: Behavioral finance perspective. *The Journal of Asian Finance, Economics and Business*, *7*(12), 159-168.

Asian Development Bank. (2024). Asian capital markets report 2024.

Athur, A. D. (2014). Effect of behavioral biases on investment decisions of individual investors in Kenya (Doctoral dissertation, University of Nairobi).

Baddeley, M., Burke, C., Schultz, W., & Tobler, P. (2012). Herding in financial behavior: A behavioral and neuroeconomic analysis of individual differences.

Barber, B. M., & Odean, T. (1999). The courage of misguided convictions. *Financial Analysts Journal*, *55*(6), 41-55.

Barberis, Nicholas, and Ming Huang. "Mental accounting, loss aversion, and individual stock returns." *the Journal of Finance* 56, no. 4 (2001): 1247-1292.

Bernstein, P. L. (2011). *Capital ideas evolving*. Wiley+ ORM.

Caparrelli, F., D'Arcangelis, A. M., & Cassuto, A. (2004). Herding in the Italian stock market: a case of behavioral finance. *The Journal of Behavioral Finance*, *5*(4), 222-230.

Capital Markets Authority. (2024). Kenya market review 2023.

Chami, F. C. (2017). *Behavioral Finance Factors Affecting Investment Performance by Retail Investors in the Nairobi Securities Exchange* (Doctoral dissertation, United States International University-Africa)

Chen, J. J., Zheng, B., & Tan, L. (2013). Agent-based model with asymmetric trading and herding for complex financial systems. *PloS one*, *8*(11), e79531.

Chen, J. M., & Chen, J. M. (2016). Prospect theory. *Finance and the Behavioral Prospect: Risk, Exuberance, and Abnormal Markets*, 181-212.

Chen, S. H., & Yeh, C. H. (2002). On the emergent properties of artificial stock markets: the efficient market hypothesis and the rational expectations hypothesis. *Journal of Economic Behavior & Organization*, *49*(2), 217-239.

Chira, Inga, Michael Adams, and Barry Thornton. "BEHAVIORAL bias within the decision making process." (2008).

Choi, J. J., & Robertson, A. Z. (2020). What matters to individual investors? Evidence from the horse's mouth. *The Journal of Finance*, *75*(4), 1965-2020.

Clarke, J., Jandik, T., & Mandelker, G. (2001). The efficient markets hypothesis. *Expert financial planning: Advice from industry leaders*, *7*(3/4), 126-141.

Cutter, G., Casciotti, K., Croot, P., Geibert, W., Heimbürger, L. E., Lohan, M., & van de Flierdt, T. (2017). Sampling and Sample-handling Protocols for GEOTRACES Cruises. Version 3, August 2017.

Daniel, K. D., Hirshleifer, D., & Subrahmanyam, A. (2001). Overconfidence, arbitrage, and equilibrium asset pricing. The Journal of Finance, 56(3), 921-965.

Dannels, S. A. (2018). Research design. In *The reviewer's guide to quantitative methods in the social sciences* (pp. 402-416). Routledge.

Dar, F. A., & Hakeem, I. A. (2015). The influence of behavioral factors on investor's investment decisions: A conceptual model. *International Journal of Research in Economics and Social Sciences*, *5*(10), 51-65.

De Bondt, W. F., & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. Handbooks in operations research and management science, 9, 385-410.

Dimitrios, K., & Vasileios, O. (2015). A network analysis of the Greek stock market. *Procedia Economics and Finance*, *33*, 340-349.

Doan, N. P. A., Vo, V. C., & Le, H. N. T. (2022). Examining the Effects of the Features of Corporate Governance on the Level of Corporate Social Responsibility Disclosure of Listed Enterprises in Vietnam.

Fakhry, B. (2016). A literature review of the efficient market hypothesis. *Turkish Economic Review*, *3*(3), 431-442.

Farlin, J. D. (2006). Antecedents and consequences of heuristic biases: Evidence from individual investors and small business owners. ProQuest.

Filbeck, G., Hatfield, P., & Horvath, P. (2005). Risk aversion and personality type. *The Journal of Behavioral Finance*, *6*(4), 170-180.

Filbeck, Greg, Patricia Hatfield, and Philip Horvath. "Risk aversion and personality type." *The Journal of Behavioural Finance* 6, no. 4 (2005): 170-180.

Fischer, R., & Gerhardt, R. (2007, August). Investment mistakes of individual investors and the impact of financial advice. In *20th Australasian Finance & Banking Conference*.

Gazel, S. (2015). The regret aversion as an investor bias. *International Journal of Business and Management Studies*, *4*(02), 419-424.

Ghauri, P., Grønhaug, K., & Strange, R. (2020). *Research methods in business studies*. Cambridge University Press.

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. Annual review of psychology, 62, 451-482.Kim, K. A., & Nofsinger, J. R. (2008). Behavioral finance in Asia. Pacific-Basin Finance Journal, 16(1-2), 1-7.

Gounaris, K. M., & Prout, M. F. (2009). Repairing relationships and restoring trust: Behavioral finance and the economic crisis. *Journal of Financial Service Professionals*, *63*(4).

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of financial economics*, 78(2), 311-339.

Gurl, E. (2017). SWOT analysis: A theoretical review.

Harvey, N. (2020). Use of heuristics: Insights from forecasting research. In *Judgement and Choice: Perspectives on the Work of Daniel Kahneman* (pp. 5-24). Psychology Press.

Hassan, M., & Mohammed, A. (2024). Evolution of African stock exchanges. Journal of African Markets, 8(1), 12-28.

Hazzi, O., & Maldaon, I. (2015). A pilot study: Vital methodological issues. *Business: Theory and Practice*, *16*(1), 53-62.

Hirshleifer, D., & Hong Teoh, S. (2010). Psychological influences on financial regulation and policy. Behavioral Finance: Investors, Corporations, and Markets, 151-167.

Howard, J. (2013). Advances in Financial Decision Making: In Search of a New Paradigm. The Journal of Behavioral Finance & Economics, 3(1), 99-138.

Husain, M., Liu, L., & McGowan, M. (2021). *The Role of Financial Literacy and Education in Investment Decisions*. Financial Analysts Journal, 77(2), 77-93.

International Finance Corporation. (2024). Global retail investment trends.

Isoni, A., Brooks, P., Loomes, G., & Sugden, R. (2016). Do markets reveal preferences or shape them?. *Journal of Economic Behavior & Organization*, *122*, 1-16.

IUP Journal of Behavioral Finance, Vol 7, No. 4: 7 – 19.

Jain, J., Walia, N., Singla, H., Singh, S., Sood, K., & Grima, S. (2023). Heuristic biases as mental shortcuts to investment decision-making: a mediation analysis of risk perception. *Risks, 11*(4), 72.

Jaswani, T. (2008). Function and purpose of stock market. *Articles base website< http://www. Articles base. Com/investing-articles/function-andpurpose-of-stockmarket-582881. Html.*

Johnson, David W., and Roger T. Johnson. "New developments in social interdependence theory." *Genetic, social, and general psychology monographs* 131, no. 4 (2005): 285-358.

Jones, B. D. (2002). Bounded rationality and public policy: Herbert A. Simon and the decisional foundation of collective choice. *Policy Sciences, 35*(3), 269-284.

Kahneman, D., & Tversky, A. (2013). Prospect theory: An analysis of decision under risk. In Handbook of the fundamentals of financial decision making: Part I (pp. 99-127).

Kamau, J. M. (2018). *Factors influencing performance of county government projects: a case of Gatundu modern market, Kiambu County, Kenya* (Doctoral dissertation, School of Mathematics, University of Nairobi).

Karanja, M. M. (2017). Effect of behavioral finance factors on investment decisions of individual investors at the Nairobi Securities Exchange in Nairobi County (Doctoral dissertation, KCA University).

Kartini, K., & NAHDA, K. (2021). Behavioral biases on investment decision: A case study in Indonesia. The Journal of Asian Finance, Economics and Business, 8(3), 1231-1240.

Katwalo, A. M., & Asienga, I. (2015). Influence of quality culture on performance of research institutions in Kenya. *African journal of business and economic research, 10*(1), 25-54.

Kengatharan, L., & Kengatharan, N. (2014). The influence of behavioral factors in making investment decisions and performance: Study on investors of Colombo Stock Exchange, Sri Lanka. Asian Journal of Finance & Accounting, 6(1), 1.

Kimani, L., & Wanjiku, R. (2024). NSE market dynamics analysis. East African Journal of Finance, 11(2), 45-62.

Kimeu, C., Anyango, W., & Rotich, G. (2016). Behavioral factors influencing investment decisions among individual investors in Nairobi Securities Exchange. Strategic Journal of Business & Change Management, 3(4), 1244-1258.

Kiprono, D., & Gatheru, W. (2023). Mobile trading impact at NSE. Kenyan Journal of Finance, 9(3), 78-95.

Kisaka, E. K. (2015). The effect of behavioral finance factors on stock investment decisions in Kenya (Doctoral dissertation).

Le Luong, P., & Thi Thu Ha, D. (2011). Behavioral factors influencing individual investors decision-making and performance. A survey at the Ho Chi Minh Stock Exchange.

Lehenkari, M. (2009). Essays on the effects of gains and losses on the trading behavior of individual investors in the Finnish stock market. University of Oulu.

Liu, Y., Zumbo, B., Gustafson, P., Huang, Y., Kroc, E., & Wu, A. (2019). Investigating causal DIF via propensity score methods. *Practical Assessment, Research, and Evaluation*, *21*(1), 13.

Lusardi, A., & Mitchell, O. S. (2017). *The Economic Importance of Financial Literacy: Theory and Evidence*. Journal of Economic Literature, 55(3), 785-834.

Maponga, T., & Dzirutwe, M. (2024). Market maturity in African exchanges. International Journal of Emerging Markets, 12(4), 156-173.

Mayur, M. (2018). The disposition effect in shares trading.

Mbeki, S., & Zulu, N. (2023). Technological advancement in African markets. African Finance Review, 18(3), 89-104.

McGoun, E. G. (1995). The history of risk" measurement". Critical perspectives on accounting, 6(6), 511-532.

Mehta, P. D. (2015). Control variables in research.

Mellenbergh, G. J. (2016). Models for continuous responses. In *Handbook of item response theory* (pp. 181-192). Chapman and Hall/CRC.

Mensah, J., & Alagidede, P. (2023). Investment challenges in African exchanges. Journal of African Economics, 32(2), 234-251.

Miller, T. W., Reiley, D., & Sinha, S. (2019). *Income and Investment Behavior: Evidence from a Panel Survey*. Review of Financial Studies, 32(5), 1861-1892.

Morvan, C., & Jenkins, W. J. (2017). *An analysis of Amos Tversky and Daniel Kahneman's judgment under uncertainty: Heuristics and biases*. Macat Library.

Mugo, S., & Omondi, P. (2024). Technology transformation at NSE. African Journal of Capital Markets, 16(1), 23-40.

Muriithi, G. N. (2021). *The Effect Of Behavioral Biases On Investment Decisions By Real Estate Developers In Nairobi, Kenya* (Doctoral dissertation, University of Nairobi).

Mutiso, J., & Kamau, A. (2023). Retail participation trends at NSE. East African Economic Review, 38(4), 145-162.

Mutswenje, V. S. A Survey of the Factors Influencing Investment Decisions: The Case of Individual Investors at the NSE

Nairobi Securities Exchange. (2024). Strategic plan 2024-2028.

Ndung'u, J., Kimani, M., & Ochieng, P. (2023). Investment decision-making at NSE. Journal of African Finance, 14(4), 89-106.

Neth, H., & Gigerenzer, G. (2015). Heuristics: Tools for an uncertain world. In *Emerging trends in the social and behavioral sciences* (pp. 1-18). Wiley Online Library.

Neumann, M., Niessen, A. S. M., & Meijer, R. R. (2021). Implementing evidence-based assessment and selection in organizations: A review and an agenda for future research. *Organizational Psychology Review*, *11*(3), 205-239.

Ngahu, A. N. (2017). *Factors Influencing Investment Decisions in Equity Stock among Retail Investors in Kenya* (Doctoral dissertation, KCA University).

Nkrumah, K., & Santos, M. (2024). Investment behavior across African markets. Review of African Political Economy, 51(159), 78-95.

Nofsinger, J. R. (2001). The impact of public information on investors. Journal of Banking & Finance, 25(7), 1339-1366.

Odean, T. (1998). Are investors reluctant to realize their losses? The Journal of finance, 53(5), 1775-1798.

Ogunlusi, O. E., & Obademi, O. (2021). The Impact of behavioral finance on investment decision-making: A study of selected investment banks in Nigeria. Global Business Review, 22(6), 1345-1361.

Okonkwo, C., Diallo, B., & Mensah, K. (2024). Regional integration impact on African markets. Journal of African Business, 25(2), 112-129.

Okumu, J., & Ndirangu, L. (2023). African investment landscape analysis. African Development Review, 35(1), 67-84.

Olsen, R. A. (1997). Prospect theory as an explanation of risky choice by professional investors: Some evidence. Review of Financial Economics, 6(2), 225-232.

Pangeran, P., & Kumalaningrum, M. P. (2015). Investor's disposition error and the role of regret in stock market: an experimental evidence from Indonesia. *European Scientific Journal*, *11*(11).

Parkash, P., & Parkash, R. (2024) Impact of Behavioral Biasness on Investor Decision Making Process.

Pompian, M. M. (2012). Behavioral finance and wealth management: how to build investment strategies that account for investor biases (Vol. 667). John Wiley & Sons.

Pompian, M. M. (2019). How Much Is Behavioral Advice Worth?. *The Journal of Wealth Management*, *22*(2), 10-19.

Qawi, Raluca B (2010) Behavioral Finance: Is Investor Psyche Driving Market Performance?

Rehan, R., & Umer, I. (2017). Behavioral biases and investor decisions. *Market Forces*, *12*(2).

Ricciardi, V., & Simon, H. K. (2000). What is behavioral finance? *Business, Education & Technology Journal*, *2*(2), 1-9.

Ritter, J. R. (2003). Behavioral finance. Pacific-Basin finance journal, 11(4), 429-437.

Riyazahmed, D. K., & Saravanaraj, M. G. (2016). Implications of heuristics in financial decision making. *Asian journal of research in social sciences and humanities*, *6*(7), 1245-1251.

Ruggeri, K., Alí, S., Berge, M. L., Bertoldo, G., Bjørndal, L. D., Cortijos-Bernabeu, A., & Folke, T. (2020). Replicating patterns of prospect theory for decision under risk. *Nature human behavior, 4*(6), 622-633.

Santra, S., & Giri, V. N. (2017). Impact of career regret on career outcomes of information technology (IT) professionals in India. *ASBBS Proceedings, 24*(1), 481.

Sarker, M., & AL-Muaalemi, M. A. (2022). Sampling techniques for quantitative research. In *Principles of social research methodology* (pp. 221-234). Singapore: Springer Nature Singapore.

Sathiyaseelan, M. (2015). Research instruments. *Indian Journal of Continuing Nursing Education*, *16*(2), 57-60.

Sattar, M. A., Toseef, M., & Sattar, M. F. (2020). Behavioral finance biases in investment decision making. *International Journal of Accounting, Finance and Risk Management*, *5*(2), 69.

Shefrin, H. (2002). *Beyond greed and fear: Understanding behavioral finance and the psychology of investing*. Oxford University Press.

Shefrin, H., & Belotti, M. L. (2007, June). Behavioral finance: biases, mean-variance returns, and risk premiums. In *CFA Institute Conference Proceedings Quarterly* (Vol. 24, No. 2, pp. 4-12).

Shi, L. (2015). A Unified Theory: Prospect Theory and Market Dynamics. *Available at SSRN 2513364*.

Shiller, R. (2002). The irrationality of markets. *The Journal of Psychology and Financial Markets*, *3*(2), 87-93.

Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. *The Journal of Psychology and Financial Markets*, *1*(1), 49-60.

Simon, H. (1957). A behavioral model of rational choice. Models of man, social and rational: Mathematical essays on rational human behavior in a social setting, 6(1), 241-260.

Şimşek, A. S., & Tavşancıl, E. (2022). Validity and reliability of Turkish version of skills confidence inventory. *Turkish Psychological Counseling and Guidance Journal, 12*(64), 89-107.

Somasundaram, J., & Diecidue, E. (2017). Regret theory and risk attitudes. *Journal of risk and uncertainty*, *55*, 147-175.

Statman, M. (2014). Behavioral finance: Finance with normal people. *Borsa Istanbul Review*, *14*(2), 65-73.

Subramaniam, A., & Velnampy, T. (2017). The role of behavioral factors in the investment decisions of household investors. *International Journal of Accounting and Financial Reporting*, *7*(1), 392-412.

Sullivan, M., Wright, A., & Zhang, Y. (2023). *Gender Differences in Investment Decisions: Evidence from Behavioral Finance*. Journal of Financial Economics, 148(3), 642-665.

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral decision making*, *12*(3), 183-206.

Thaler, R. H. (Ed.). (2005). Advances in behavioral finance, Volume II. Princeton University Press.

Toma, F. M. (2015). Behavioral biases of the investment decisions of Romanian investors on the Bucharest stock exchange. *Procedia Economics and Finance, 32*, 200-207.

Torres-Reyna, O. (2012). Getting started in Logit and ordered logit regression. *Princeton University, http://dss. princeton. Edu/training/Logit. Pdf*.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science, 185*(4157), 1124-1131.

Ullah, S., & Elahi, M. A. (2014, May). Behavioral Biases in Investment Decision Making and Moderating Role of Investor's Type. In SZABIST's 20th National Research Conference, 10th May.

Van de Calseyde, P. P., Zeelenberg, M., & Evers, E. R. (2018). The impact of doubt on the experience of regret. *Organizational behavior and human decision processes, 149,* 97-110.

Van den Broek, J. M., Brunsveld-Reinders, A. H., Zedlitz, A. M., Girbes, A. R., de Jonge, E., & Arbous, M. S. (2015). Questionnaires on family satisfaction in the adult ICU: a systematic review including psychometric properties. *Critical care medicine*, *43*(8), 1731-1744.

Venkatapathy, R., & Sultana, A. H. (2016). Behavioral finance: heuristics in investment decisions. *TEJAS Thiagarajar College Journal*, *1*(2), 35-44.

Waweru, N. M., Mwangi, G. G., & Parkinson, J. M. (2014). Behavioral factors influencing investment decisions in the Kenyan property market. *Afro-Asian Journal of Finance and Accounting*, *4*(1), 26-49.

Wong, K. P. (2015). A regret theory of capital structure. *Finance Research Letters*, *12*, 48-57.

World Bank. (2024). Global financial markets annual report.

Yang, S. J., Hsu, A. C., Lai, S. Y., & Lee, C. C. (2015). Empirical investigation of herding behavior in East Asian stock markets toward the US market. International Journal of Business and Finance Research, 9(1), 19-31.

Yuniningsih, Y., Widodo, S., & Wajdi, M. B. N. (2017). An analysis of decision-making in the stock investment. *Economic: Journal of Economic and Islamic Law*, *8*(2), 122-128.

Zeelenberg, M. (2018). Anticipated regret. *The psychology of thinking about the future*, *276*.

APPENDICES

Appendix A: Research Questionnaire

I am a student at KCA University, currently working on my MSc (Finance and Investment) research project titled "the Moderating role of market information in the relationship between behavioral finance biases and the stock investment decision making among Kenyan Investors: evidence from the Nairobi Securities Exchange." Please respond to the questions by providing answers where necessary and placing a tick (✓) in the box that corresponds with your response.

The information you provide will be used solely for academic purposes and will be treated with strict confidentiality. To maintain anonymity, you are not required to include your name on the questionnaire. Your participation is invaluable and will significantly contribute to the success of this study.

SECTION A: BACKGROUND INFORMATION

Background Information of Respondents.

1. **Please indicate your gender.**

   Male [ ]

   Female [ ]

2. **Age Bracket:**

   (Below 25 yrs.) [ ]

   (26-35 yrs.) [ ]

   (36-45 yrs.) [ ]

   (46 yrs. and above) [ ]

3. Are You an Active Investor?

Yes [ ]

No [ ]

4. In Which Type Of Securities Do You Prefer To Invest?

Shares [ ]

Bonds [ ]

5. What Is Your Average Net Income Per Month (Kshs)?

0 to 25,000 [ ]

26,000 to 50,000 [ ]

51,000 to 75,000 [ ]

76,000 to 100,000 [ ]

Over 100,000 [ ]

6. Highest Level of Education:

Doctorate [ ]

Master's Degree [ ]

Degree [ ]

Diploma [ ]

Certificate [ ]

If others specify…………………………………………………..

SECTION B: Behavioral Finance Biases

Please evaluate and indicate the degree of your agreement with the following behavioral factors affecting your investment decisions by using the following five Likert scales:

(1=Strongly Disagree; 2=Disagree; 3=Neutral; 4= Agree and 5= Strongly Agree)

	1	**2**	**3**	**4**	**4**
HEURISTIC BIASES					
Familiarity with a stock often leads to its selection, even if it is underperforming.					
Investment decisions are frequently based on recent news or events without thorough analysis.					
Past experiences are relied upon more than financial data when making investment decisions.					
The first piece of information received about a stock is often overestimated in its reliability.					
Stocks recommended by friends or family are often chosen without conducting independent research.					
PROSPECT BIASES	**1**	**2**	**3**	**4**	**5**
Stocks that have gained value quickly are more likely to be sold to secure profits.					
There is a tendency to hold onto losing stocks, hoping they will rebound, rather than cutting losses.					
Potential losses cause more regret than missed potential gains.					

Investments with guaranteed returns are preferred over those with potentially higher, but uncertain, returns.					
The desire to avoid losses influences investment decisions more than the potential to achieve gains.					
HERDING BEHAVIOR	**1**	**2**	**3**	**4**	**5**
The investment choices of other investors at the Nairobi Securities Exchange are often followed.					
Confidence in an investment increases when many other investors make the same choice.					
Investment strategies are changed when a trend is observed among the majority of investors.					
Investing in stocks that are popular in the market is perceived as safer.					
Aligning with the majority's decisions is believed to reduce the risk of loss.					

SECTION C: MARKET INFORMATION

MARKET INFORMATION	**1**	**2**	**3**	**4**	**5**
The availability of timely and accurate market information significantly influences investment decisions.					
Market trends and economic indicators are considered before making investment choices.					
Access to expert analysis and reports contributes to more informed investment decisions.					
Market information often leads to changes in initial investment decisions influenced by behavioral biases.					
Up-to-date market information is believed to reduce the impact of emotional biases on investment decisions.					

SECTION D: INVESTMENT DECISION

i. To Buy Securities ☐

ii. To Not Buy Securities ☐