BEHAVIORAL BIASES AND CRYPTO TRADING DECISIONS AMONG NAIROBI RETAIL TRADERS: MODERATING ROLE OF FINANCIAL KNOWLEDGE.

BY

MULINGE DANSON MITAU

094515

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STUDENT'S DECLARATION

I declare that this thesis has not previously been authorized for a degree by this or any other university. The thesis does not include any previously published or written information unless explicitly stated.

Name: Danson Mulinge Mitau

Admission Number: 094515

Date: 28th of May 2026

Signature: 

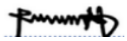
Supervisor's Approval

The thesis of Danson Mulinge Mitau was reviewed and approved by the following:

Name of Supervisor: Dr. Erastus Mbithi

Faculty Affiliation: Strathmore University Business School (SBS)

Institution: Strathmore University

Signature: 

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LIST OF ABBREVIATIONS

CBK-Central Bank of Kenya

CMA-Capital Market Authority

ETM-The Economic Times Market

FOMO-Fear of Missing Out

FSD-Financial Sector Deepening

NACOSTI-National Commission for Science, Technology, and Innovation

NSE-Nairobi Stock Exchange

SEC-Securities and Exchange Commission

SPSS-Statistical Package for Social Sciences

SU-ISERC-Strathmore University Institutional Scientific and Ethical Review Committee

ABSTRACT

The rapid rise in cryptocurrency adoption in emerging markets such as Nairobi, Kenya, created a volatile trading environment in which retail traders were highly vulnerable to behavioural distortions. The purpose of this study was to examine the influence of key behavioural biases, traders' overconfidence, risk aversion, anchoring, and the disposition effect on crypto trading decisions among retail traders, and to assess the moderating effect of financial knowledge on these relationships. Drawing on theoretical foundations such as Behavioral Finance Theory, Heuristic Theory, and Adaptive Market Efficiency Theory, the study achieved its objectives. The study adopted a positivist research philosophy to examine the impact of behavioral biases on crypto trading decisions among retail traders in Nairobi County. The study carried out between March and April 2026 employed an explanatory research design to examine the relationship, targeting 733,300 active cryptocurrency users in Nairobi County. 400 selected respondents completed a structured questionnaire as part of a quantitative research strategy. The suggested hypotheses were tested using inferential and ordinal regression analysis. The study established that overconfidence, anchoring bias, and disposition effect significantly increased the likelihood of cryptocurrency trading decisions among retail traders in Nairobi County. Risk aversion revealed a negative influence. The Financial knowledge revealed a moderating role between the behavioral biases and cryptocurrency trading decisions. The results explained the relationship between behavioral biases and cryptocurrency trading decision-making and offered empirical evidence on the predominant behavioral determinants influencing cryptocurrency trading decisions in the Kenyan setting. The findings provided empirical evidence on the main behavioral factors impacting cryptocurrency trading decisions in the Kenyan context and clarified the connection between behavioral biases and cryptocurrency trading decision-making. By guiding the creation of focused financial education initiatives and investor-protection measures to encourage logical, stable, and knowledgeable participation in the cryptocurrency market, the findings had practical implications for retail traders, financial advisors, legislators, and regulators. Additionally, by applying theory to the new field of virtual assets in developing economies, the study added to the body of literature on behavioral finance.

CHAPTER ONE

INTRODUCTION

1.1 Background to the study

Cryptocurrency markets have experienced remarkable and sustained growth over the past decade, evolving from a niche technological innovation into a globally recognized financial asset class. According to the Global Crypto Adoption Index (2023),Through chain lysis, cryptocurrency adoption has increased significantly across both developed and emerging economies, driven by factors such as financial inclusion, speculative investment opportunities, and advancements in blockchain technology.

Over 560 million people worldwide owned cryptocurrencies as of 2024, accounting for over 6.8% of the world's population (Cryptocurrency Ownership Data,2024). Compared to less than 100 million users in 2020, this is a significant increase with an average yearly growth rate of more than 40%. Market capitalization has also increased, with the total value of cryptocurrencies reaching over USD 3 trillion in 2021 before leveling out at about USD 1-2 trillion in 2024. This indicates both the market's quick growth and extreme volatility.

Geographically, the use of cryptocurrencies varies significantly between nations. According to the Cryptocurrency Ownership Data (2024)The top countries in the world for ownership and trading involvement are the United Arab Emirates (25.3%), Singapore (24.4%), Turkey (19.3%), and Argentina (18.9%). These high adoption rates are frequently linked to macroeconomic factors like inflation, unstable currencies, and favourable legislative frameworks that push people to look for alternative value storage and payment methods.

Within Africa, some nations have adopted cryptocurrencies at remarkably high rates. For example, Nigeria was rated second in the world for grassroots acceptance of cryptocurrencies, indicating that people use them extensively for daily transactions and savings. Similarly, Kenya has continuously been among the top five nations in the world for peer-to-peer (P2P) cryptocurrency trading volume. This is mostly due to the country's strong mobile money penetration and tech-savvy populace. Due to rising digital literacy and emerging fintech ecosystems, other nations like Ghana and South Africa are also exhibiting rising engagement in cryptocurrency markets (Global Crypto Adoption Index, 2023) .

The rapid rise of cryptocurrencies in Africa can be explained by several structural factors. First, with 57% of individuals in Sub-Saharan Africa without access to formal banking services, financial exclusion is still a major problem (Financial Sector Stability Report ,2022). By allowing users to store value, move money, and access financial services without depending on conventional institutions, cryptocurrencies provide an alternate approach to financial inclusion. Second, people are looking for more reliable stores of wealth, like Bitcoin and stablecoins, due to the high rates of inflation and currency instability in many African nations. Third, because of their cheaper costs and quicker processing times, cryptocurrencies have become a popular choice for cross-border payments due to the high cost of remittances in Africa, which averages between 6 and 8% each transaction (World Bank, 2022).

Additionally, the adoption of cryptocurrencies has also been greatly aided by Africa's young population and rising internet coverage. Digital financial solutions are becoming increasingly popular among young people who are more receptive to technological innovation, as over 60% of the population is under 25, and smartphone usage is on the rise (Chainalysis,2023). Accessibility has been further improved by the integration of cryptocurrencies with mobile money platforms, especially in nations like Kenya, where mobile payment systems are already ingrained in daily business operations (Kenya Financial Sector Stability Report, 2022).

Cryptocurrency markets are still quite erratic and mostly speculative despite this growth. Significant price swings occur; Bitcoin, for instance, went from under USD 5,000 in 2020 to over USD 60,000 in 2021 before experiencing severe corrections. Investors, particularly individual retail players, are exposed to significant financial risk due to such volatility (Chainalysis,2023).Consequently, the rapid growth in cryptocurrency participation has raised important questions regarding investor behaviour, financial literacy, and risk management. Individual investors, who constitute a large proportion of market participants, are often influenced by behavioral biases, social media trends, and limited regulatory protection. Understanding how these factors affect investment decisions is critical, particularly in developing economies where financial systems are still evolving (World Bank ,2022).

In Kenya, cryptocurrency adoption has grown markedly over the past several years. The number of active crypto users in the country increased from just 10,400 in 2017 to an estimated 733,300 in 2025, reflecting strong and sustained growth in public interest and participation in digital assets (Business Daily, 2025). Importantly, Kenya now ranks fifth in the world by cryptocurrency transaction volumes, trailing only major markets such as Ukraine, the United

States, Nigeria, and Vietnam, largely due to high peer-to-peer (P2P) activity, stablecoin usage, cross-border remittances, and everyday financial transfers (Global Crypto Adoption Index, 2023). Cryptocurrencies pegged to traditional currencies like the US dollar have become especially prominent in Kenya's crypto ecosystem. In the year to June 2024, Kenyans conducted approximately Kes 426.4 billion (about USD 3.3 billion) in stablecoin transactions, making the country one of Africa's largest markets for these assets (Daily Nation, 2023).

The adoption of cryptocurrency as an investment vehicle has gained considerable momentum in Kenya (Global Crypto Adoption Index, 2023), particularly in Nairobi County, which is home to a vibrant urban population with increasing access to digital platforms (NSE,2022). Although the cryptocurrency nature of easy accessibility offers promising financial opportunities to traders, they have lost money in the name of cryptocurrency trading (Business Daily, 2025).Over 364,800 Kenyan retail traders lost nearly Ksh 30 billion from cryptocurrency trading after a promise of a huge monthly return (Business Daily, 2025).Report from CMA, 2023 revealed that Many people jump into crypto trading because they see others making money. They buy late, when prices are already inflated, and then get stuck when the market corrects. Furthermore, crypto investors don't really understand what they're buying. There are thousands of coins, and not all have real value. Many are hype-driven or even scams.

Trading decisions involve choosing when to buy or sell investment products(Reilly et al., 2016).Traders in the stock market differ according to their trading horizons and strategies. Day traders execute trades within a single trading day, while swing traders hold positions for several days or weeks to exploit short-term price movements. Scalpers seek to profit from small price changes through frequent transactions. These trading types contribute to market liquidity and price discovery (Barber et al., 2014).

In contrast, investment decisions are long-term in nature and focus on wealth creation through capital appreciation and income generation. These decisions are largely informed by fundamental analysis, which involves evaluating financial statements, economic conditions, industry prospects, and firm-specific characteristics to estimate an asset's intrinsic value. Investment decisions emphasize risk reduction through diversification and are less sensitive to short-term price fluctuations, resulting in lower transaction costs and more stable returns over time (Suriadi et al., 2023).

In the cryptocurrency market context, trading decisions involve the decision of when to buy, sell, or hold digital assets, often under conditions of high volatility and uncertainty (Baur et al., 2018). Unlike long-term investment decisions, trading decisions are short-term and driven by factors such as market signals, price fluctuations, and trader sentiment (Statman, 2014). According to Baur and Smales (2022)Trading decisions can lead to mis-timed entries or suboptimal portfolio outcomes.

Traditional finance theory assumes that trading choices are made rationally, based on technical and fundamental analysis, as well as the use of the efficient market hypothesis (Madaan & Singh, 2019). Furthermore, the theory reveals that traders progressively seek to minimize risk and maximize reward. However, behavioral finance theory suggests that psychological factors, such as cognitive biases and heuristics, steadily influence trading decisions, thereby leading to deviations from traders' rationality (Statman, 2014).

Traders are considered rational actors whose goal is to maximize the expected utility based on predictions of short-term price movements (Leonard, 1995). Additionally, traders make decisions by weighing the trade-offs between immediate and postponed consumptions (Kamps & Kleinberg, 2018). Previous scholars also suggest that risk preference, cognitive bias, and heuristics significantly predict the trading behaviour in the short term (Hirshleifer et al., 2018). According to Petrovic and Karanovic (2023)Trading decisions require patience, foresight, and a high level of discipline in decision-making.

Behavioral biases are defined as systematic departures from the investor's rationality that affect how traders assess and analyse investment information, risks, and make sound financial decisions (Callista et al., 2023). These biases contradict the traditional finance theories, such as the Efficient Market Hypothesis (EMH). According to Tversky & Kahneman (1974), The prospect theory explains that investors experience losses more intensely than the equivalent gains because they rely more on heuristics in making trading decisions that distort the investor's rationality.

Previous literature work outlines various behavioural biases influencing trading decisions, which were adopted in this study to provide evidence-based analysis (Shukla, 2020). According to the study done by Jadeja and Nalwaya (2025),These behavioural biases include, but are not limited to, herding bias, disposition bias, risk aversion, representativeness bias, anchoring bias, and traders' overconfidence. The influence of each of these behavioural biases, both separately and collectively, on trading decisions has been thoroughly investigated.

According to Deweaver and Shannon (2010),Herding bias is the practice of traders acknowledging investment advice from others. (Rasool & Ullah, 2020) said that the herding effect is a phenomenon in which investors' propensity to mimic the actions of others enables them to avoid feeling bad about the choices they make. According to Feng and Seasholes (2004); Gavrilakis and Floros (2022), and Goyal et al (2023),Herding bias has a direct relationship with trading decisions.

Disposition bias happens when an investor regrets disposing of a profitable investment portfolio in a short period of time and keeps on holding the losing portfolio for a long period of time (Pangeran, 2015). According to Alhusri (2021), A study carried out on Portuguese investors showed that investors are likely to hold losing stocks in the market and sell the appreciating stocks. Investors are naturally risk-averse. They give more weight to losses than they do (Tversky & Kahneman, 1974). Their decisions are normally informed by rationality.

The traders will choose the less hazardous stocks among the various options (Rasool & Ullah, 2020). Busenitz and Barney (1997) explain representativeness bias as a phenomenon that results from a few observations, generally from small and non-random samples. Daniel et al (1998), Bashir and Mehta (2025), and Khan et al (2021), shown that it has a major positive impact on trading decision-making and market overreaction.

Anchoring bias is when people base their judgment on the first piece of information received (Mahmood et al., 2024). The anchoring effect persists after a theoretical understanding of financial behaviour (Wegrzyn & Kuta, 2024). According to Bhandari and Deaves (2006), Overconfidence is the tendency for people to overestimate their knowledge, abilities, and the veracity of their facts. The increased trading is also explained by overconfidence. Overconfident traders may find it more difficult to make decisions and execute. Nonetheless, risk perception and financial literacy can help traders make better trading decisions (Ahmad et al., 2021).

Recent academic literature confirms the relationship between behavioural bias and trading decisions (Gunasena et al, 2024);(Jain et al., 2019);(Parveen et al., 2023);(Waweru et al., 2008). For instance, the findings from Waweru et al (2008) showed that representativeness biases, anchoring, and herding play a significant role in Kenyan retail traders' decisions.

Similarly, Prasad et al (2021) alluded that behavioural biases have a significant influence on trading decision-making, where investors are driven by emotional factors, leading to irrational

decision-making. Parveen et al (2023) mentioned that behavioural factors, such as traders' overconfidence and disposition effect, are more universal and noticeable in emerging markets with a comparatively low level of financial knowledge, leading to an increasing impact on the trading outcomes.

The crypto market is often remarkably attention-driven, where prices react to social media storylines and search volume. Most research indicates that different reactions and emotions from social media platforms such as Twitter and Telegram App may predict returns, liquidity, and volatility of Bitcoin and other cryptocurrency commodities (Kraaijeveld & De Smedt, 2020; Maître et al., 2025; Zhang et al., 2024).

Behavioral biases tend to spread through a person's attention and mood. Individual traders tend to accommodate eminent influences, very interesting news, or current price volatility, and online networks that favor confirmation bias. When these pressures, like 24-hour markets, derivatives, and debt, are combined, they might create a feedback loop that amplifies boom-bust cycles, separating prices from fundamentals.

Kenya and Sub-Saharan Africa have been confirmed as the hub of grassroots cryptocurrency adoption. Nairobi has been ranked among the top countries for retail and peer-to-peer cryptocurrency usage by the Chainalysis Global Cryptocurrency Adoption Index (Global Crypto Adoption Index, 2023). Major catalysts were remittance needs, hedging strategies, and the high penetration of mobile money applications (The Global Crypto Adoption Index, 2023). Nairobi, the financial and technological Centre of Kenya, offers a significant opportunity to study traders' behavioral biases because it is regarded as the home of the fintech sector.

Financial knowledge plays a moderating role in the connection between behavioural bias and trading decisions by giving traders the information and ability to assess financial data critically, leading to sound trading decision-making (Kadoya & Khan, 2018). According to Lusardi & Mitchell (2014) Financially literate traders are more likely to examine the fundamental and technical analysis, therefore reducing vulnerability to short-term biases.

Traders are exposed to cognitive biases and heuristics when there is limited financial knowledge (Kadoya & Khan, 2018). Literature review by Awais et al (2016) suggested that limited financial knowledge for the traders intensifies vulnerability to behavioural biases, where traders make trading decisions based on their moods and attention, particularly in the short term and in an unpredictable market like crypto. Furthermore, Gunasena et al (2024) and

Mbarak (2022) found that there is no significant influence of financial education on behavioural biases and trading decisions. According to the Kenya Financial Sector Stability Report (2022), Kenya has low financial literacy.

Empirically, studies have been done on behavioural biases in cryptocurrency trading decisions. However, these studies have not provided a solid conclusion on what the most common behavioural biases are in cryptocurrency trading decisions. According to Feng and Seasholes (2004), Gavrilakis and Floros (2022), and Goyal et al (2023)Behavioral bias has a positive relationship with trading decisions. Ahmad et al (2021) reported a negative relationship between behavioral bias and trading decisions.

The controversy arises from a clear academic imbalance, where behavioral finance literature predominantly emphasizes long-term investment behaviour in traditional markets, while short-term trading decisions remain comparatively understudied. Existing scholarship highlights how behavioral biases shape long-horizon portfolio choices, asset allocation, and retirement planning, yet offers limited evidence on how the same biases influence rapid buy-sell decisions in volatile environments such as cryptocurrency trading.

For example, research frequently demonstrates that investors rely on fundamental analysis, macroeconomic trends, and broad market indicators when making long-term commitments, implicitly overlooking the role of heuristics, emotions, and real-time judgment required in short-term trading contexts. The academic imbalance presents a need to explore how behavioral bias distorts real-time trading outcomes in speculative digital markets like cryptocurrency (Gunasena et al, 2024).

The contextual difference arises because of studies focusing on behavioral biases in different investment markets in terms of liquidity, size, structure, and volatility. For instance, Jain et al (2019) concluded that there is a positive relationship between investor overconfidence and investment decision-making of individual equity investors in Punjab, India. In contrast Ahmad et al (2021) reported a negative relationship between behavioral bias and trading decisions. This contextual gap poses a contradiction, and further research needs to be done on the relationship between behavioral biases and trading decisions in emerging markets like crypto.

The controversy arises from the differences in cultural contexts and market liquidity, methodology, and the sample size, which directly affected the results. Additionally, most of the scholars focused on developed economies and failed to account for technological and socio-

cultural factors that are key to the emerging markets (Gunasena et al.,2024). The model identified these biases in the traditional stock markets, leaving a knowledge gap about how the biases influence emerging markets, such as the crypto market (Youssef, 2022).

Previous studies demonstrate that both behavioural biases and financial knowledge significantly influence traders' behaviour. Financial education has not been seen by scholars as a moderating factor between investors' behavioural biases and trading decisions, nor has the relationship between these two factors, which play a big part in trading decisions, been well examined (Ranaweera & Kawshala, 2022; Sezer & Demir, 2015) and (Gunasena et al., 2024).

The strength or shape of the relationship between the dependent variable and its predictor variable can be altered by a moderator variable(Sezer & Demir, 2015). We thus acknowledge that previous research investigations should have considered the potential importance of moderating factors or failed to conduct a thorough examination, based on our evaluation of the literature. Therefore, the current study aims to address the above controversies by including a moderating factor of financial knowledge to test the level of impact between behavioural biases and trading decisions. Given these variations, this study aims to assess the effect of behavioral biases on crypto trading decisions among Nairobi retail traders and the moderating role of financial knowledge.

1.1.1 Cryptocurrency Retail Traders in Nairobi County

Nairobi County provides a uniquely dynamic institutional environment for examining retail traders' decision-making, particularly in emerging digital assets such as cryptocurrency. As Kenya’s political, financial, and technological capital, Nairobi hosts major financial regulators, including the Capital Markets Authority (CMA), the Central Bank of Kenya (CBK), and the Nairobi Securities Exchange (NSE), as well as most licensed investment intermediaries (NSE 2022; CMA, 2023).

This concentration of regulatory infrastructure, brokerage firms, fintech companies, and digital-finance ecosystems makes Nairobi distinct from other Kenyan counties and positions it as the central hub through which most retail trading activities occur. Retail traders in Nairobi County are non-professional individuals who trade financial assets such as equities, government securities, and cryptocurrencies through traditional and digital platforms.

According to CMA classifications, these traders typically possess moderate to low levels of financial sophistication and lower capital bases compared to institutional investors, alongside

limited access to expert analysis (CMA, 2023). Internationally, retail traders are similarly defined as individuals making trading decisions for personal benefit rather than on behalf of an institution, often with lower financial literacy and risk tolerance (OECD/INFE 2020).

Nairobi's suitability for studying retail traders' behaviour stems from its highly advanced fintech and digital-trading ecosystem. The county leads in national adoption of mobile-based investment tools, including M-Akiba, NSE Smart, and mobile money-linked government securities platforms designed to promote financial inclusion (Demirgüç-Kunt et al., 2021). As a fintech hub hosting innovators such as M-Pesa, online exchanges, digital wallets, and blockchain start-ups, Nairobi offers retail investors unprecedented ease of access to a range of financial instruments.

Nairobi has also witnessed significant growth in cryptocurrency activity. Kenya consistently ranks among Africa's top crypto-trading countries, with Nairobi accounting for a large share due to its concentration of blockchain hubs and tech-savvy youth populations (Kamau et al., 2025). Innovation spaces such as iHub and Nairobi Garage further support the development of blockchain applications and crypto-related start-ups. Although the CBK has maintained a cautious regulatory stance toward crypto assets, Nairobi's informal crypto ecosystem, including peer-to-peer (P2P) markets and online trading communities, continues to expand (FSD,2021).

Compared to institutional investors, who rely on structured portfolio management and professional research teams, retail traders in Nairobi frequently depend on heuristics, peer influences, online sentiment, and personal experience. Prior research shows that retail traders exhibit behavioural biases such as overconfidence, herd behaviour, and loss aversion due to limited expertise and information asymmetry (Lusardi & Mitchell, 2014). These behavioural tendencies become even more pronounced in volatile and speculative markets such as cryptocurrency.

Individual traders have a great impact on the financial markets by generating income and improving the performance of the markets (CMA, 2023). Their trading actions are influenced by behavioural characteristics such as cognitive biases and heuristics, limited access to financial knowledge, different social-cultural contexts, economic background, and regulatory framework (Wahome et al., 2014). Nairobi County has a fast-advancing financial environment, distinguished by high fintech adoption and digital platform penetration. It is essential to

evaluate the impact of behavioural biases on crypto trading to raise awareness and safeguard the public from fraudulent financial scams.

1.2 Statement of the Problem

The adoption of cryptocurrency as an investment vehicle has gained considerable momentum in Kenya (Global Crypto Adoption Index, 2023), particularly in Nairobi County, which is home to a vibrant urban population with increasing access to digital platforms (NSE,2022). Although the cryptocurrency nature of easy accessibility offers promising financial opportunities to traders, they have lost money in the name of cryptocurrency trading (Business Daily, 2025).Over 364,800 Kenyan retail traders lost nearly Ksh 30 billion from cryptocurrency trading after a promise of a huge monthly return (Business Daily, 2025).Report from CMA, 2023 revealed that Many people jump into crypto trading because they see others making money. They buy late, when prices are already inflated, and then get stuck when the market corrects. Furthermore, crypto investors don't really understand what they're buying. There are thousands of coins, and not all have real value. Many are hype-driven or even scams.

Empirical studies show that cryptocurrency markets are highly sentiment-driven, with trading decisions influenced by attention dynamics and psychological triggers (Ahmad & Shah, 2022). Research has linked emotions and online activity on platforms such as Twitter, Telegram, and TikTok to price fluctuations, liquidity, and volatility. Findings also suggest that retail traders are especially vulnerable due to fear of missing out, limited financial knowledge, and exposure to manipulative online schemes. However, existing evidence remains inconsistent: For instance Jain et al (2019); Mahmood et al (2024), Ahmad et al (2021); Hasnain and Subhan (2022) report a positive association between behavioural biases and crypto trading decisions, while others Mahmood et al (2024), Al-Mansour (2024), Gurdgiev and O'Loughlin (2020) and Corbet et al (2024) report negative effects.

The controversy arises from the differences in cultural contexts and market liquidity, methodology, conceptual gap, and the simple size, which directly affected the results (Lusardi & Mitchell, 2014). Most of the scholars focused on developed economies, leaving out the emerging and developing markets (Gunasena et al., 2024).Additionally, the moderating role of financial knowledge on the relationship between behavioral biases and crypto trading decisions has been underserved by most scholars (Mahmood et al., 2024).

Previous scholars focused on these biases in the traditional stock markets, leaving a knowledge gap about how the biases influence emerging markets, such as the crypto market (Youssef,

2022). Additionally, there is limited empirical evidence connecting behavioural biases to Kenyan traders' vulnerability to cryptocurrency fraudulent schemes. Despite the growth of academic research on behavioural biases in financial and trading decisions, there is still a significant knowledge gap on how these psychological and behavioural concepts appear in Kenyan contexts, especially in Nairobi County.

Scholars have addressed the relationship between behavioral biases and crypto trading decisions, leaving out financial knowledge as a moderating variable. This study contributes by applying behavioural theories and the moderating role of financial knowledge specifically to the cryptocurrency domain, bridging traditional behavioural finance with modern, decentralised trading platforms. Additionally, the study will employ primary data collection techniques such as a structured questionnaire to present firsthand experimental evidence about crypto trading decisions in Nairobi County.

The study investigated the most common behavioural biases demonstrated by crypto traders and how these result in poor trading decision-making. Stakeholders such as traders, Policymakers, educators, and regulators benefited from the practical insights from the study, enhancing awareness and safeguarding the public from quick financial decision-making in a highly volatile and uncertain environment like crypto. Therefore, the research aimed to establish the influence of behavioural biases in crypto trading decisions among retail traders in Nairobi County and the moderating role of financial knowledge.

1.3 Research Objectives

1.3.1 General Objective

To determine the effect of behavioural biases on crypto trading decisions among retail traders in Nairobi, Kenya, and the Moderating role of financial knowledge.

1.3.2 Specific Objectives

i. To establish the effect of traders' overconfidence in crypto trading decisions among retail traders in Nairobi, Kenya.
ii. To determine the effect of risk aversion on crypto trading decisions among retail traders in Nairobi, Kenya.
iii. To establish the effect of anchoring bias on crypto trading decisions among retail traders in Nairobi, Kenya.
iv. To determine the effect of disposition bias on crypto trading decisions among retail traders in Nairobi, Kenya.

v. To determine the moderating effect of financial knowledge on behavioral bias and crypto trading decisions among retail traders in Nairobi, Kenya.

1.4 Research questions

i. How does a trader's overconfidence affect crypto trading decisions among retail traders in Nairobi, Kenya?
ii. What is the effect of risk aversion on crypto trading decisions among retail traders in Nairobi, Kenya?
iii. What is the effect of anchoring bias on crypto trading decisions among retail traders in Nairobi, Kenya?
iv. How does the disposition bias affect crypto trading decisions among retail traders in Nairobi, Kenya?
v. Is there a moderating effect of financial knowledge on behavioral bias and crypto trading decisions among retail traders in Nairobi, Kenya?

1.5 Scope of the study

The study aimed to assess how behavioural biases affect crypto trading decisions among retail traders in Nairobi County and the moderating role of financial knowledge. By identifying which behavioural factors are most prevalent and how they relate to vulnerability to fraud and scams, the study intends to offer practical insights to retail traders, educators, policymakers, and regulators seeking to enhance awareness and safeguard the public from digital financial fraud and scams. The geographical scope of the study was confined to Nairobi County, which serves as the economic centre of Kenya and houses a significant number of retail traders engaged in financial markets and various trading platforms.

The conceptual scope of the study was grounded on three main constructs: behavioural biases (independent variable), crypto trading decisions (dependent variable), and financial knowledge (moderating variable). It examined how behavioural biases influence trading decisions among retail crypto traders and how financial knowledge alters or strengthens this relationship. The study further conceptualised trading decisions in terms of rationality, risk-taking behaviour, and vulnerability to fraudulent schemes in digital financial markets.

The population targeted was persons trading in Kenyan cryptocurrency,18 years and above. This research focused exclusively on retail traders (individuals, not institutions) and did not include institutional investors like banks or pension funds. The study employed primary data collection methods. A structured questionnaire was used to gather firsthand information about

crypto traders in Nairobi County. Additionally, both qualitative and quantitative techniques were implemented through conducting a questionnaire on behavioural biases, including, but not limited to, investor overconfidence, risk aversion, anchoring, and disposition effect, as well as trading decisions.

To ensure relevance to current market conditions and cryptocurrency trading trends, data was collected in April 2026. This study aimed to provide a detailed examination of the relationship between behavioral biases and sound crypto trading decisions in the Kenyan emerging market, focusing on Nairobi County and retail traders.

1.6 Significance of the study

The study's findings were to provide practical insights into how behavioral biases influence crypto trading decisions among retail traders in Nairobi County and the moderating role of financial knowledge. The cryptocurrency market is rapidly growing and becoming a potential investment and trading scheme. Therefore, gaining insight into how the behavioural biases affect trading choices is critical to both individual and institutional investors.

1.6.1 Retail traders

The study's findings can benefit retail traders by enhancing awareness of behavioural factors, including but not limited to risk aversion, investor overconfidence, anchoring bias, and the disposition effect, that may undermine traders' rational and practical decision-making. The awareness can help them to consider more objectively, fundamental and technical, which are data-driven strategies when trading cryptocurrencies.

1.6.2 Investment firms and financial advisors

The findings enable investment firms and financial advisers to understand the cognitive biases of their clients better. This knowledge can contribute to the development of investor/trader training programs and customised advisory services that identify cognitive and trait pitfalls in trading cryptocurrency.

1.6.3 Regulators and policymakers

The study can benefit regulators and policymakers by helping them understand traders' behavioural biases, which can contribute to the creation of policies and investor/trader protection frameworks to address unregulated fraudulent schemes and mitigate risks related to speculative trading in digital currency. Finally, by providing empirical data from Nairobi

County, an emerging market environment often overlooked in behavioural finance research, this study will contribute to the existing body of academic knowledge.

1.7 Chapter Summary

This chapter discussed the background of behavioural biases and crypto trading decisions and the moderating role of knowledge. The chapter also discussed a detailed study on the problem statement. It defined the research variables, including a moderating variable, which is financial knowledge, study objectives, research questions, scope of the research, and significance of the research, pointing out the stakeholders who are likely to benefit from the findings of the study, which includes, financial institutions, trading platforms, investment firms, policy maker and individual traders on how behavioural biases influences crypto trading decision-making.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter examines the body of knowledge on the subject, which mostly consists of secondary sources and recent and earlier research that has been empirically examined for every variable. A theoretical framework to direct the study is also presented. A review summary follows the identification of the gaps in the literature.

2.2 Theoretical framework

The theoretical framework examines the existing body of literature and establishes the link between behavioural biases and trading decisions. Based on a review of earlier research, the theories supporting this study were emphasised, along with their advantages and disadvantages. This study used multiple theories, including but not limited to behavioural finance theory, Heuristic theory, and the Adaptive Market Efficiency theory, to establish a connection between behavioural biases and trading decisions.

The selection of many theories provided a thorough framework for examining the research variables from various perspectives. Each theory added insight and shed light, which increased the validity of the theories' findings if they came to comparable conclusions. Applying a single theory to a study might give it a narrow viewpoint and increase the likelihood of bias when the researcher chooses evidence that interests them.

2.2.1 Behavioural finance theory

The idea of behavioural finance, which was created by Kahneman and Tversky in 1974, has gained appeal among investors in recent years. According to behavioural finance, social and emotional influences, frame dependency, and biases and errors generated by heuristics can all contribute to the difference between market pricing and underlying value. Judgment may be weakened by cognitive bias and heuristics-driven biases, including but not limited to traders' overconfidence, risk aversion, anchoring bias, and disposition effect, a version of ambiguity and innumeracy. These biases challenge the principle of the efficient market hypothesis (EMH) by demonstrating that markets can be deformed by irrational behaviours.

One major strength of behavioural finance theory is that it provides a realistic explanation of investor behaviour by incorporating psychological and emotional factors, unlike traditional finance models that assume full rationality. It effectively explains market anomalies such as

bubbles, crashes, and excessive volatility, which classical models struggle to justify. Additionally, it improves understanding of individual investor behaviour, particularly in retail-dominated markets such as cryptocurrency trading (Thaler, 1999).

Despite its advantages, the theory has several drawbacks. First, because behavioral biases are hard to measure and apply to different groups, it is frequently criticized for having poor predictive accuracy. Second, it is regarded as descriptive rather than completely prescriptive, which means that while it describes behaviour, it does not necessarily offer precise predictive models. Third, detractors like Fama (1998) contend that behavioral finance-explained market inefficiencies could only last temporarily since markets eventually self-correct through arbitrage.

Bikas et al. (2013) outlined the impact of psychological elements on financial investing activities. They clarified that behavioural finance is based on the understanding that emotional factors significantly influence changes in financial markets. It also highlights the limitations of human reasoning. Madaan & Singh (2019) explained how behavioural finance expands the scope of finance beyond market efficiency, asset pricing, and portfolios. By examining desires, mistakes, preferences, and behaviour through surveys, tests, and field studies, it assesses the actions of managers and investors both directly and indirectly.

Nair & Antony (2013) revealed that traders demonstrate irrational behaviours in the financial markets, and this irrationality is a result of psychological factors and cognitive bias, which play a significant role in stock trading decision-making. (Khare & Kapoor, 2024) suggested that psychological factors and heuristic factors translate to irrationality of a trader, leading to suboptimal decision-making. From the highlights of these irrational patterns, Behavioural Finance Theory still argues the need for a more overarching understanding of practical financial decisions.

In the context of cryptocurrency trading, this theory provides a clear and effective framework for understanding why retail traders in Nairobi often behave inconsistently and speculate with their short-term investments. Kenya’s crypto markets have led most of the traders to be prone to behavioral biases such as traders' overconfidence, risk aversion, representativeness Bias, anchoring bias, and disposition effect due to its volatility (Waweru et al., 2008) Furthermore, behavioral biases influence how the traders interpret information, risk assessment, and make trading choices (Wahome et al., 2014).

In Nairobi, young traders have shown overconfidence biases by believing in predicting crypto price movements with limited information from social media trends. This bias is aligned with the behavioral finance theory, as the model suggests that most traders overestimate their knowledge to monitor and control the uncertainty, resulting in higher risk exposure and excessive trading (Barber et al., 2014). Risk aversion is another bias that is grounded in behavioral finance theory. Traders are naturally risk-averse; they give more weight to losses than gains (Tversky and Kahneman, 1974). Their decisions are normally informed by rationality. Under the premise of behavioral finance theory, the investor will choose the less hazardous short-term investment among the various options (Barber et al., 2014).

Anchoring bias is when people base their judgment on the first piece of information received (Mahmood et al., 2024). The anchoring effect persists after a theoretical understanding of financial behaviour (Wegrzyn & Kuta, 2024). Disposition bias happens when traders regret disposing of a profitable stock in a short period of time and keep on holding the losing portfolio for a long period of time (Pangeran, 2015).This bias is evidenced among the retail crypto users in Nairobi County. Behavioral finance theory explains this bias as one of the prevalent biases that leads to suboptimal trading decision making, asserting that most traders tend to hold on to depreciating assets and dispose of the appreciating assets due to the investor's fear of losing (Waweru et al., 2008).

Financial knowledge plays a critical role in moderating the relationship between behavioral biases and trading decisions. It informs the extent to which behavioral biases affect trading decisions. Behavioral finance theory posits that investors are influenced by cognitive biases and heuristics, mental shortcuts that simplify decisions but can distort judgment, such as overconfidence, loss aversion, and herding (Kadoya & Khan, 2018). These biases are amplified when traders have limited financial knowledge, as they lack the skills to critically evaluate investment opportunities. For example, overconfident traders may overtrade without considering diversification, loss-averse investors may avoid rebalancing losing portfolios, and inexperienced traders may follow market trends without assessing fundamentals (M. Kim, 2021). Financial literacy moderates these effects by enabling investors to recognize biases, apply analytical frameworks, and implement strategies that reduce emotional decision-making, such as rules-based trading or predetermined stop-loss orders (Zhang et al., 2024). Thus, while financial knowledge cannot eliminate behavioral biases, it significantly mitigates their influence on trading decisions by promoting rational, evidence-based reasoning (Kadoya & Khan, 2018).

According to the report from the Central Bank of Kenya (Kenya Financial Sector Stability Report 2022),Financial knowledge among Kenyans remains relatively low, especially for complex investment products such as digital assets. Many traders enter the market due to the fear of missing out (FOMO) and influence from peers, without the risk or technology knowledge (Nyikuli,2021). However, traders with high financial knowledge tend to show rational behaviours. They can analyse the market both technically and fundamentally, understanding the risk-return trade-offs, leading to making a sound trading decision. Financial knowledge, therefore, plays a crucial role in weakening the application of behavioral biases on cryptocurrency trading decisions (Lusardi & Mitchell, 2014)

Behavioral finance theory provides practical insights that can guide both policymakers and traders. The theory suggests that awareness of the psychological factors can aid in developing strategies to reduce suboptimal irrational decision-making. Additionally, regulators and institutional investors can benefit from developing an informed risk management process and policies that assist in stabilizing financial markets. Generally, behavioral finance theory not only explains the behavioral biases influencing investor rationality but also suggests an actionable framework to boost traders' quality decision-making and market efficiency.

2.2.2 Heuristic Theory

Heuristic theory originates from research in cognitive psychology that seeks to explain how people make judgments and decisions in environments of uncertainty and complexity. In the context of decision sciences, a heuristic refers to a mental shortcut or simplified rule that individuals apply to reduce cognitive effort and arrive at decisions more rapidly than through exhaustive analysis (Tversky & Kahneman, 1974)While heuristics can increase efficiency, they also introduce systematic errors known as cognitive biases. These biases are particularly influential in financial markets where traders must make rapid decisions under conditions of incomplete information, ambiguity, and risk (Lockton, 2012)

Goyal et al (2023)introduced the concept of bounded rationality, which underpins heuristic theory by recognizing that individuals do not have unlimited cognitive resources or perfect information. Instead, traders satisfice; they seek a “good enough” solution rather than an objectively optimal one(Goyal et al., 2023). This approach reflects real-world decision-making in financial markets, especially for retail traders who often lack advanced analytical tools, face time constraints, and are exposed to emotionally charged market dynamics. The heuristic

perspective assumes that decisions are shaped as much by psychological factors as by rational calculation (Barber et al., 2014).

In financial decision environments such as cryptocurrency trading, three classes of heuristics are particularly relevant: availability heuristics, representativeness heuristics, and anchoring heuristics. Each plays a role in shaping traders' perceptions of risk and expected returns, and consequently, their trading behaviour (Babu, 2020).

The availability heuristic occurs when traders evaluate the likelihood of events based on how easily examples come to mind (Tversky & Kahneman, 1974).In the context of crypto markets, recent high returns or widely publicized price surges can disproportionately influence traders' expectations because these events are more cognitively salient. This can lead to overestimation of the probability of continued gains and underestimation of the likelihood of declines (Said et al., 2022). For Nairobi retail traders consuming social media narratives, news headlines, and peer success stories, the ease of recalling dramatic price rallies might drive optimistic bias and push traders toward riskier positions (Sachitra & Rajapaksha, 2023). The availability heuristic may therefore contribute to herding behaviour, where retail traders collectively chase trending cryptocurrencies based on anecdotal information rather than fundamental analysis (Sachitra & Rajapaksha, 2023).

Closely related is the representativeness heuristic, where individuals classify events according to how similar they are to existing stereotypes or past experiences, even when those experiences are statistically unrepresentative (Tversky & Kahneman, 1974).In crypto trading, a trader might assume that past price patterns, for example, a rapid rise followed by stabilization, will repeat in the future merely because current market conditions seem similar to previous patterns (Lusardi & Mitchell, 2014). Such pattern matching can lead to overconfidence in predictive ability, underestimation of volatility, and mispriced risk. When a trader believes that a coin exhibiting bullish behaviour "looks like" another that experienced strong gains, they may invest heavily without considering structural differences in technology, adoption, or market liquidity. Representativeness, therefore, not only influences expectation formation but also contributes to erroneous risk assessments (Lockton, 2012).

The anchoring heuristic reflects the tendency to rely on an initial piece of information as a reference point when making subsequent decisions (Goyal et al., 2023).In trading, initial price levels, early forecasts, or first impressions of market sentiment can serve as anchors that disproportionately shape future judgments (Lusardi & Mitchell, 2014). For instance, if a

Nairobi retail trader first encountered Bitcoin when it was trading at a high value, that price may become an “anchor” influencing their perception of what constitutes a fair price. Even in the face of new information, traders may insufficiently adjust away from that anchor, leading to biases such as holding losing positions too long or failing to realize gains promptly (Said et al., 2022)

Collectively, these heuristics demonstrate how cognitive simplifications can have measurable impacts on investment decisions. In experimental and empirical studies, heuristic-driven biases have been linked to speculative bubbles, excessive trading, and suboptimal portfolio choices (R. Wijaya et al., 2023). For retail crypto traders, who operate in highly volatile markets characterized by frequent price swings and limited historical data compared to traditional assets, reliance on heuristics can amplify biases and lead to heightened risk exposure (Gunasena et al., 2024).

However, heuristic theory also suggests that traders are not uniformly biased; the magnitude of heuristic influence depends on individual factors such as experience, cognitive style, and, importantly, financial knowledge (Khan et al., 2021). Financial knowledge refers to the understanding of financial concepts, products, and market mechanisms that enable individuals to process and evaluate financial information more effectively (Lusardi & Mitchell, 2014) .Traders with higher levels of financial knowledge are more likely to recognize when heuristic shortcuts are misleading and can engage in more deliberative, analytical processing. This capacity enables them to evaluate alternative scenarios, seek relevant data, and question anecdotal narratives rather than rely on readily available information (Sangeetha et al., 2025).

Several studies indicate that financial literacy attenuates the adverse effects of heuristics by promoting more reflective and less impulsive decisions (Ahmad et al., 2021;Gavrilakis & Floros, 2022). For example, financially knowledgeable traders are better equipped to interpret order books, understand liquidity risks, and appreciate fundamental drivers of asset prices. This deeper understanding allows them to counteract simple heuristics and reduce the likelihood of overtrading or panic selling in response to short-term market movements (Kadoya & Khan, 2018).

In Kenya, heuristic theory offers a robust framework for understanding the cognitive processes that shape Nairobi retail traders’ decisions in cryptocurrency markets (Musau et al., 2022) . The reliance on mental shortcuts such as availability, representativeness, and anchoring heuristics can lead to systematic biases that influence risk perception, timing decisions, and portfolio

adjustments (Kuria, 2024). Yet, the theory also highlights the moderating role of financial knowledge, suggesting that traders who are better educated about financial concepts can mitigate heuristic biases and make more informed, rational decisions (Nyamache,2024). Understanding these dynamics is crucial for interpreting how retail traders navigate the complexities of crypto trading and for designing interventions such as financial education programs that improve trading outcomes.

2.2.3 Adaptive Market Efficiency Theory

The Adaptive Market Efficiency (AME) theory represents a significant refinement of traditional views on market behaviour. Introduced by Lo (2004),This theory seeks to reconcile the long-standing divide between the Efficient Market Hypothesis (EMH) and findings from behavioral finance Lo, 2004). While EMH asserts that financial markets efficiently and instantaneously reflect all available information, behavioral finance highlights systematic deviations from rationality due to cognitive biases (Das et al., 2024).AME theory integrates these seemingly contrasting perspectives by proposing that market efficiency is not a fixed condition but a dynamic outcome of adaptation and evolution among market participants(Tversky & Kahneman, 1974).

At the core of AME theory is the idea that markets behave similarly to biological ecosystems, where participants adapt, learn, and evolve (Zhou & Lee, 2013). This perspective shifts away from the assumption of fully rational economic agents, recognizing instead that traders' decisions are influenced by limited information processing, emotions, and social dynamics, especially in fast-changing and speculative markets such as cryptocurrencies (Gautam & Kumar, 2023).According to the theory, the degree of market efficiency depends on the interaction between environmental conditions, the number and diversity of market participants, and the degree of competition and learning among traders (N. C. Barberis, 2013).In stable conditions with many experienced participants, markets may appear highly efficient. In turbulent periods or emerging markets, adaptive behaviours and biases become more influential, producing patterns of mispricing and volatility that traditional EMH cannot easily explain (Lo, 2004).

In the context of crypto trading, AME theory is particularly relevant. Cryptocurrencies emerged as a novel asset class less than two decades ago, characterized by rapid price swings, limited regulation, and a large share of retail investors with diverse levels of financial literacy (Quaicoe & Eleke-Aboagye, 2021). In such markets, cognitive and emotional biases, including

overconfidence, herding, and loss aversion, are frequently observed as driving factors in traders' decisions (Tversky & Kahneman, 1974).AME theory posits that these biases are not simply irrational errors but reflections of adaptation to environmental uncertainty. For example, traders may initially overreact to price trends or news events due to limited experience or social influence (N. C. Barberis, 2013). Over time, however, exposure to market outcomes and repeated feedback can lead to learning, causing traders to adjust strategies and potentially reducing the impact of biases on decision-making (Lusardi & Mitchell, 2014).

By emphasizing adaptation and learning, AME theory also highlights the role of financial knowledge as a key moderating factor in trading behaviour. Financial knowledge enables traders to interpret information more accurately, recognize irrational patterns, and refine strategies based on experience. In markets where participants possess higher financial literacy, adaptive processes become more efficient, reducing the persistence of behavioral biases and moving prices closer to their fundamental values (Callista et al., 2023). Conversely, in markets with lower levels of financial knowledge, such as among some retail traders in Nairobi, biases may have stronger effects, and market inefficiencies may persist longer (Statman, 2014). Thus, AME theory suggests that financial knowledge does not eliminate biases but improves traders' ability to adapt to market conditions (G. Kim et al., 2022).

Another important feature of the Adaptive Market Efficiency framework is its treatment of risk and uncertainty. Traditional EMH assumes that risk preferences are stable and that investors respond predictably to changes in information (N. C. Barberis, 2013). In contrast, AME theory recognizes that risk preferences themselves may evolve, influenced by emotional responses and recent outcomes. For instance, after a period of losses, traders may become more risk-averse, leading to panic selling or conservative positions that diverge from what EMH would predict (Lo, 2004) .Over time, as traders learn from these outcomes, they may recalibrate their risk tolerance and decision heuristics, demonstrating an adaptive process rather than rigid rationality. This adaptive view closely resembles concepts in behavioral learning theories, where individuals adjust beliefs based on feedback, but extends it to market-wide phenomena, acknowledging that the aggregate of individual adaptations shapes overall market efficiency (N. C. Barberis, 2013).

Authors such as Malkiel (2003), (G. Kim et al. (2022) have argued that, despite short-term anomalies, markets tend toward efficiency in the long run. AME theory builds on this idea but adds nuance by framing market efficiency as a state dependent on evolutionary processes rather

than an absolute condition (N. C. Barberis, 2013). In cryptocurrency markets, where historical data is limited and structural characteristics evolve rapidly (such as changes in regulation, technology, and trading platforms), AME theory provides a more realistic explanation for observed price dynamics than traditional EMH alone (Liao et al., 2013). AME's evolutionary framework supports the notion that periods of inefficiency driven by behavioral biases are natural outcomes of adaptation, with market efficiency emerging only as traders acquire experience, information processing skills, and financial knowledge (Lo, 2004).

In Kenya, the cryptocurrency market is relatively young and largely driven by retail investors, particularly in urban areas such as Nairobi. Studies indicate that financial literacy levels vary widely among Kenyan crypto traders, which affects their ability to make informed decisions (Mundia,2021). Many traders rely on social media platforms and peer recommendations rather than formal market analysis, which can amplify herding behaviour and speculative trading (Nyamache, 2015).

The Kenyan regulatory environment also influences trading behaviour. Although cryptocurrencies are not illegal, the Central Bank of Kenya has issued warnings about the risks, and there is limited formal infrastructure for crypto investment (Kenya Financial Sector Stability Report 2022,). This uncertainty, coupled with high volatility, creates an environment where behavioral biases are prominent and market efficiency is adaptive rather than constant. Retail traders in Nairobi often exhibit panic selling during market dips or overinvesting during bullish trends, reflecting a learning curve consistent with AME theory (Musau et al., 2022).

The Adaptive Market Efficiency theory offers an important lens for understanding how behavioral biases interact with cognitive processes, environmental conditions, and financial knowledge to shape trading decisions and market outcomes (Lo, 2004). By acknowledging that market efficiency is adaptive and context-dependent, this theory allows researchers to analyse why retail crypto traders may behave irrationally in certain periods but gradually improve decision-making as they learn and gain expertise (Zhou & Lee, 2013). For this study, AME theory provides a theoretical foundation for examining how financial knowledge moderates the influence of behavioral biases on crypto trading decisions among Nairobi retail traders, suggesting that increased financial literacy can enhance adaptive learning and, over time, contribute to more efficient trading behaviour.

2.3 Empirical literature review

This section includes a methodical review of earlier empirical research on the variables under investigation. This section aims to clarify the present study's scope and interest by reviewing the literature and identifying any knowledge gaps regarding the variables under study. This section reviews empirical research internationally, regionally, and locally to show how behavioural biases influence cryptocurrency trading decisions.

2.3.1 Traders' confidence bias on cryptocurrency trading decisions

Ranaweera and Kawshala (2022) carried out research about the influence of behavioural biases on investment decision-making and the moderating role of financial knowledge. Data collected from 110 individual traders actively trading on the Colombo Stock Exchange. The study concludes that overconfidence positively influences trading decision-making and that financial knowledge moderates behavioural biases. However, the focus was limited to a limited number of behavioural biases, hence leaving a conceptual gap. This gap presents a need for expansion of the conceptual framework to include more behavioural biases, to consider a large and more diverse population across the cryptocurrency markets.

Similarly, Jain et al (2019) concluded that there is a positive relationship between traders' overconfidence and investment decision-making of individual equity investors in Punjab, India. This highlights a contextual gap: the Indian market differs from the Kenyan market in liquidity, size, structure, and volatility. Therefore, the finding might not be directly the same due to the Kenyan context, with an emerging market. The current study will assess the effect of overconfidence bias on cryptocurrency trading decisions among retail traders in the Kenyan emerging market.

Wamae (2013) revealed that traders' overconfidence has the strongest influence on investment decisions among investment banks in Kenya. The study surveyed 17 investment banks, collecting data through questionnaires. The study used a small sample size, and it focused on only institutional investors, highlighting a gap in the lack of comparison with retail traders and cross markets. The current study will broaden the scope of the study to include individual investors, use a large sample size, and assess the influence of behavioural biases on cryptocurrency trading behaviour.

Syarkani and Tristanto (2022) empirically reviewed the relationship between overconfidence bias and crypto trading decisions among Indonesian students. The study tested whether the attitude towards crypto moderates the relationship and direct effect of overconfidence on

trading decisions. They conclude that traders' overconfidence has a direct effect on cryptocurrency trading decisions, and the trader's attitude moderates this relationship. The study highlighted a sampling and external validity gap, as it focuses solely on students, thereby limiting its representativeness. The results may not directly generalize to cryptocurrency traders across different age brackets or other contexts. The empirical work of the current study aims to consider behavioural measures, use experimental designs, and expand the sample size to include diverse demographic and experience levels, which contribute to non-theoretical insights

According to Gunasena et al (2024) traders' confidence shows no significant influence on cryptocurrency trading decisions among 158 retail investors in Sri Lanka. Additionally, the study used financial knowledge as a moderator of the relationship, but the findings show no moderating effect. The study employed a small sample size, which impacted the accuracy of the findings. The current study aims to fill this gap by increasing the sample size of individual traders in Nairobi, which will, in turn, assist in testing whether there is a correlation between investors' overconfidence and their cryptocurrency trading behaviour.

While Hasnain and Subhan (2022) revealed a direct effect of traders' overconfidence on cryptocurrency trading decisions among Pakistani retail investors, various research gaps are highlighted. Firstly, the use of judgmental sampling techniques restricts the generalizability of the study findings beyond the Pakistan context. Secondly, the absence of a moderating variable limits the level of explanation of the model. Lastly, relying on surveys without actual cryptocurrency transactions leaves an explanatory gap and an open question of whether the overconfidence bias consistently translates into real-world cryptocurrency investment behaviours. These gaps present a further need for empirical work, including more comprehensive models and a diverse dataset to gather more insights about the behavioral biases of cryptocurrency trading behaviour.

Kristoufek (2015) revealed that bitcoin prices are influenced by overconfidence biases and other online activities. The study used Bitcoin market data from users to interpret the results. Data was collected from Google Trends, Wikipedia searches, and the market prices, which, to some extent, might have failed to provide non-theoretical insights. A conceptual gap is revealed where there was no conceptual grounding in behavioural finance theory, such as mental accounting and heuristic theory. The current study aims to fill the highlighted gap by reviewing the behavioural finance literature and its specific impact on cryptocurrency trading decision-

making, which remains underexplored. Therefore, this study aims to contribute by applying the behavioural finance model to the crypto market.

Sachitra and Rajapaksha (2023) carried out research work about the antecedents of the adoption of cryptocurrency trading in an emerging market, and the role of behavioural biases. He concludes that there is a strong correlation between overconfidence bias and cryptocurrency trading decisions. The study highlights a contextual gap where the Sri Lankan market is different from the Kenyan market in terms of liquidity, size, structure, and volatility. Therefore, the finding might not be generalized due to the Kenyan context, which is an emerging market. The current study aims to assess the effect of overconfidence bias on cryptocurrency trading decisions among retail investors in the Kenyan emerging market.

Although Suriadi et al (2023) revealed that there is a direct effect of traders' overconfidence on cryptocurrency trading decisions among South Asian retail investors. The findings show that overconfidence has a strong relationship, but financial literacy does not significantly moderate the relationship between the two variables. Despite the insights, the study is constrained by a contextual gap. The study focused on young and less experienced retail traders in Southeast Asia, limiting the generalizability. Therefore, the current study aimed to fill the gap by employing experimental designs and actual cryptocurrency trading data to assess the comprehensiveness of the behavioural biases on the crypto market.

The cryptocurrency market in Kenya is still in its infancy, but it is expanding quickly, as seen by the growing number of retail traders and the lack of legal certainty. Investors are exposed to a great deal of uncertainty and are vulnerable to behavioral biases in this setting. Nevertheless, there is still a dearth of empirical data about how overconfidence affects Kenyan retail traders' bitcoin trading choices. Overall, the reviewed literature establishes traders' overconfidence as a key psychological influence on cryptocurrency trading behaviour, though findings vary across contexts and methodologies. Evidence gaps remain regarding emerging African markets, particularly retail traders' behaviour in Nairobi. The present study, therefore, investigated the effect of traders' overconfidence on cryptocurrency trading decisions among Nairobi retail traders, while examining the moderating role of financial knowledge to deepen understanding of behavioural dynamics in the crypto market.

2.3.2 Risk aversion effect on cryptocurrency trading decisions

Crypto markets are distinguished by unique characteristics such as high volatility, liquidity, and strong retail participation (Abdeldayem & Aldulaimi, 2024). Risk aversion bias is central to

elaborate on the type of traders entering the crypto market, the allocation of the funds, and how to counter the shocks (Corbet et al., 2024). Most empirical work addresses the risk aversion bias in relation to market-level analysis and risk tolerance level rather than focusing on individual traders' behaviour in emerging markets.

Sood et al (2023) revealed a strong relationship between risk aversion and cryptocurrency trading decision-making among retail traders in India. However, the study highlighted some gaps that require exploration. Firstly, the study is limited to India with a specific socio-economic and socio-cultural factor. The finding might not generalize to other developing countries such as Kenya. Secondly, the sample size selected was biased since the study focused on active cryptocurrency traders. This research aims to address these gaps by including less active, more risk-averse, and less informed retail investors in Kenya to increase the generalizability of the findings.

Hayashi and Routh (2025) Empirical work on financial literacy, risk aversion, and cryptocurrency ownership revealed that high risk appetite increases the chance of owning cryptocurrency, and high financial knowledge diminishes the probability of ownership. The study focused on the US market only, thus reducing generalizability. The current study aims to carry out the same empirical work in an emerging market like the Kenyan context to provide more insight into how risk aversion biases affect cryptocurrency trading decisions.

Correspondingly, Platanakis et al (2018) revealed that the degree of investor risk aversion greatly influences the best allocation. The study used secondary data for Bitcoin, Litecoin, and Ripple, which could not provide concrete non-theoretical insights. The limitation of this study is that risk aversion bias was considered static, limited to a few cryptocurrencies trading, and failure to consider the time-varying aspects of cryptocurrency investment decisions among retail investors. This limitation presents a need for more empirical work on risk aversion bias on various sets of cryptos to understand the impact level on crypto trading decision-making.

Corbet et al (2024) carried out empirical research about the time-varying risk aversion and its connectedness, evidence from cryptocurrency. The study population was 11 major cryptocurrencies trading on the cryptocurrency market. The study concluded that risk aversion has a strong connection across the 11 major cryptocurrencies. He further alluded that risk aversion bias in the crypto market is highly time varying. The study highlighted a gap in little research on token class heterogeneity; investor-level behaviour is poorly linked.

Risk aversion is a significant behavioral element impacting bitcoin trading decisions, according to the examined research. However, most of the current research focuses on market-level behaviour rather than individual-level behaviour, is restricted in sample size, or is centred on developed or Asian markets. There is not enough empirical data on how risk aversion influences retail trading decisions in Kenya, where the use of cryptocurrencies is expanding despite significant market volatility and unclear regulations.

By investigating the impact of risk aversion on cryptocurrency trading decisions among retail traders in Nairobi, Kenya, and providing context-specific data from a developing African market, this study aims to close these gaps.

2.3.3 Anchoring bias on cryptocurrency trading decisions

An empirical review done by Jain et al (2019) reported a significant and positive effect. The generalizability of this study was limited to the geographical focus, retail traders in Punjab, India. Furthermore, the study used self-reported data from the investor, representing a methodological gap where traders may provide different behavioural information than they actually have. Additionally, the study focused on ranking the behavioural biases rather than examining the causal effect on the trading outcomes. The current study aims to fill the above gaps by assessing and ranking the same bias in an African context. Also, the study aims to use surveys and a structured questionnaire to provide practical insights to traders, policymakers, and financial advisors about the most prevalent behavioural biases affecting cryptocurrency trading decisions.

Quaicoe and Eleke-Aboagye (2021) found that anchoring bias has a significant influence on investment decisions among retail traders in Ghana. This study failed to consider the qualitative exploration of Ghanaian traders' psychological factors. There is an incomplete understanding of how the behavioural bias of Ghanaian investors varies across demographics and how it shapes decisions in high-volatility markets such as cryptocurrency trading. There is a need to present this gap by including the qualitative aspect to deepen the understanding of how behavioural biases influence the cryptocurrency trading behaviour among Nairobi retail traders.

Sheikh (2025) carried out research about the role of financial literacy in the connection between the anchoring bias and investment decision-making among SMEs in Nairobi County. The study used a survey technique to examine how the SMEs have been making investment decisions based on price movement, market trends, and expert opinions. The study revealed that traders

with financial knowledge were less likely to be affected by the anchoring bias as they followed fundamental and technical analysis. This research highlights the significance of financial knowledge in reducing cognitive biases in investing choices, suggesting that educational initiatives might help enhance the rationality of cryptocurrency trading decisions among Nairobi retail traders.

Similarly, Njeru (2023) researched the effect of behavioural biases on investment decisions in real estate in Nairobi County. According to research published in the International Academic Journal of Economics and Finance, anchoring bias significantly influences judgments about property value and acquisition. Investors did not conduct independent market assessments; instead, they utilized the original listing prices as reference points for setting price expectations. According to the study's findings, anchoring can distort value judgments across different asset classes and may likewise influence cryptocurrency traders who rely heavily on past price levels, such as all-time highs or previous support levels, when making trading decisions.

Kasoga (2021) examined heuristic biases in the Tanzanian stock market, including anchoring. Surveys were used in the study that was published in the Journal of Money and Business to examine how heuristic biases in risk tolerance and financial knowledge impact investing choices. Due to their reliance on historical price points rather than fundamental research, traders who exhibited both low risk tolerance and inadequate financial literacy were more likely to succumb to anchoring when choosing equities. The study's conclusions are consistent with observations made at the NSE on how retail traders usually base their trading decisions.

Evbayiro-Osagie and Chijuka (2021) examined the psychological elements that influence capital market investment choices in Nigeria, paying particular attention to anchoring bias. Researchers found that Nigerian investors' expectations are shaped by previous market booms or crises, leading to either over-optimism or over-prudence. The study suggests that NSE investors may exhibit anchoring behaviour, particularly during historical market downturns.

Owusu and Laryea (2023) provided verifiable proof of anchoring bias in Ghanaian investors' investing decisions in their Review of Behavioural Finance article. The researchers discovered evidence that even when fresh information suggests alternative values, investors still base their purchase and sell decisions on historical stock prices. The study suggested behavioural finance training to assist investors in controlling this bias, which is equally relevant for cryptocurrency traders facing rapid and continuous market information flows.

Liao et al (2013) acknowledged the anchoring impact on the momentum behaviour of international institutional investors in the Taiwanese stock market. Their past ownership served as the foundation for their investment choices, and the effect grows with the level of prior ownership. However, momentum profitability is not enhanced by the anchoring effect. Occasionally, this consequence results in a decline in momentum profitability. The study suggests that when using a momentum approach, overseas investors should solely consider a stock's historical performance rather than the amount they have previously purchased. Chang et al (2014) confirmed the informational and anchoring role played by the reference price of the first issued share from a firm cross-listing its share in a segmented market.

Kaustia et al (2008) examined the disparity in expectations for long-term stock returns between 300 financial industry experts from Scandinavia and 213 college students. Anchoring bias was present in both groups, even though students experienced prejudice more severely than professionals. Verousis & ap Gwilym (2014) investigated the London Stock Exchange's upstairs market, which is predicated on a hypothetical minimum price increase. Liquidity providers routinely purchase just below the implied minimum price increment and sell just above it, which they concluded was like the anchoring-and-adjustment effect. Previous research has demonstrated that the anchoring effect is true in the stock market, and it is anticipated that it will also be present in the bitcoin market.

Koskinen (2013) also researched the anchoring effect for his master's thesis and concluded that it exists in the UK equities market. Even seasoned analysts based their future projections on the industry median projected earnings per share. Liao et al (2013) investigated how individual and institutional investors behaved on Bursa Malaysia during periods of market turbulence. Their findings show a notable behavioural difference between the two groups. In particular, institutional investors' price anchoring impact differed considerably from that of individual investors in both bull and negative market conditions. Chang et al (2014) likewise reached a similar conclusion in their findings from the 18th Literature Review. It was discovered that in a down market, anchoring had a far greater impact on institutional investors than in a bull market.

Anchoring bias is a consistent behavioral element impacting investment decisions in both established and emerging economies, according to the reviewed research. However, most studies pay little attention to retail cryptocurrency traders, particularly in African contexts, and instead concentrate on stock markets, institutional investors, or non-cryptocurrency assets.

There is still little empirical data on anchoring bias in Kenya, where cryptocurrency trading is expanding quickly despite significant market volatility and a lack of regulatory direction. By investigating the impact of anchoring bias on cryptocurrency trading decisions among retail traders in Nairobi, Kenya, this study aims to close these gaps and provide context-specific insights into how behavioral biases affect decision-making in developing digital asset markets.

2.3.4 Disposition bias on cryptocurrency trading decisions

The heuristic theory, which remains a solid foundation in behavioural finance, was developed over 30 years after its initial publication. It was created based on Kahneman and Tversky's 1979 experimental investigation into how agents behave when making decisions involving gains and losses in risky situations. The study's results indicate that individuals tend to react negatively in situations where gains and losses are definite (Barberis, 2013) People hate to lose, and when they do, their grief is often greater than the joy they would have if they had made the same amount of money (Kahneman Tversky,1979).

While recent research has made progress in identifying the presence of disposition bias, significant gaps remain concerning its determinants, boundary conditions, and implications. Li & Yang (2013) shown that people's incapacity to identify consistent points of reference has a detrimental impact on investment profit and raises the likelihood of the disposition effect appearing. The researchers saw the disposition effect manifested as a relationship between belief in positive and negative outcomes.

The definition of reference points is one of the elements that seems to strongly influence the disposition effect. According to Alhusri (2021)A study carried out on Portuguese investors showed that traders are likely to hold losing stocks in the market and sell the appreciating stocks. Kumar & Goyal (2016) and Adil et al (2022) From the study about behavioural biases and financial decisions, they found that disposition bias has a significant effect on financial decisions. An empirical study from Delhi, India, by Adil et al (2022) concluded that disposition bias has a significant effect on trading decision-making.

Bodnaruk & Simonov (2015) investigated the presence of disposition impact among mutual fund managers; there was no indication of disposition among German institutional traders. Additionally, Toma (2015) discovered that while making short-term investment decisions, traders are prone to disposition effects. Li et al (2022) revealed that the influence of disposition bias varies with market volatility. For instance, the disposition bias is strong in a bull market

and weak during a market downturn. Additionally, he concluded that institutional and experienced show a weak disposition effect.

The study leaves various significant knowledge gaps that need to be addressed. One of the gaps highlighted is the inability of the study to differentiate between individual and institutional investors, which limits the generalizability of the findings. Furthermore, the study focused on one cryptocurrency asset, excluding other assets, which might show the level of variance of the disposition bias across different asset volatility, liquidity, and demographics.

Barber et al (2024) found that cryptocurrency traders show a strong disposition bias among retail investors in the Taiwan Stock Exchange. The concluded investors are more likely to sell an appreciating stock, holding the losing stock. However, the study highlighted some academic gaps that needed to be addressed in the current study. The study is positioned in the Taiwan Market, limiting generalizability. It remains unclear since markets have different populations, regulation frameworks, and cultural norms. Given the extreme volatility, decentralization, and round-the-clock trading environment of the bitcoin market, these restrictions are especially crucial. Retail traders may make more emotional decisions and exhibit disposition bias because of these characteristics. Nevertheless, empirical data is still scarce, particularly in developing African countries like Kenya, where investor behaviour is still little understood despite bitcoin usage rising.

To close these gaps, this study looks at how disposition bias affects crypto trading decisions made by retail traders in Nairobi, Kenya. Additionally, it seeks to investigate how traders react to market gains and losses across various cryptocurrency assets, adding context-specific data to the expanding body of research on behavioral biases in online financial markets.

2.3.5 The moderating effect of financial knowledge on cryptocurrency trading decisions

Research by Fernandes et al (2014) revealed that financial literacy and behavioural psychologists have encountered many behavioural biases related to investors. Kumar & Goyal (2016) revealed a relationship between financial literacy and the financial behaviors of an investor. Gunasena et al (2024) carried out research on the impact of behavioural biases on cryptocurrency investment decisions with a moderating financial literacy among 158 Sri Lankan investors. He revealed that there is a significant influence of behavioral biases on cryptocurrency among Sri Lankan investors. Additionally, financial literacy did not show any significance as a moderating variable. The study highlighted a gap in the limited sample size as well as the contextual gap. The current study addresses this gap by increasing the sample

size to examine how behavioural bias drives cryptocurrency trading decisions and test the correlation between the two variables with a moderating financial knowledge in an emerging market like Kenya.

Contrarily, Ranaweera & Kawshala (2022) examined the influence of behavioural biases on investment decisions with a moderating financial literacy and risk attitude among 110 individual investors in the Colombo Stock Exchange (CSE). They concluded a positive relationship between investors' overconfidence bias and investment decisions, influenced by a moderating factor. However, the study presented a conceptual framework work on the limited use of behavioural biases and a small sample size. The current study expands the conceptual framework to consider more behavioural biases. Additionally, a moderating financial knowledge will be included to assess the level of the relationship between the two variables.

Empirically, behavioural biases and financial knowledge significantly influence the traders decision-making (Hassan Al-Tamimi & Anood Bin Kalli, 2009);(Coşkun et al., 2016) and (Adil et al., 2022). Coşkun et al (2016) revealed that understanding individual investing choices requires knowledge of the different behavioural biases that affect judgment. Therefore, it may be said that understanding investors' behaviour requires financial knowledge, while empirical data is still equivocal. Additionally, the findings reported a negative effect on behavioural biases and trading decisions.

Financial knowledge is not a mediator variable between behavioural biases and trading decisions in the empirical research currently available. Adil et al (2022) declared that the modifiable moderator variable would affect the strength or form of the relationship between the dependent and independent variables. The literature review emphasized the conflicting findings and ambiguous connection between different behavioural biases and the trader's decision-making process. Therefore, this study aims to assess the influence of behavioural bias on cryptocurrency trading t decisions with a moderating effect of financial knowledge.

Callista et al (2023) examine the impact of behavioural bias on cryptocurrency investment decisions among investors in Indonesia. They revealed that financial knowledge reduces behavioural biases in investment decisions. The study highlighted some gaps underexplored. Firstly, the study did not explore the relationship between behavioural biases and other variables; it was limited to online communities, therefore reducing the generalizability of the results. Secondly, the study presented a contextual gap by focusing solely on Indonesian markets. The current study aims to fill these by examining how behavioural biases drive

cryptocurrency traders in an emerging market like Kenya, informing investors, policymakers, and regulators.

According to Sezer & Demir (2015) There is no relationship between behavioural biases and their level of financial literacy. According to Adil et al (2022),Investors who have less financial knowledge and poor cognitive abilities develop biases and make poor investing choices. Sevim et al (2012), revealed that investors with greater financial knowledge are more likely to utilize their credit cards sensibly and refrain from acting in an excessive way while borrowing. Takeda et al (2013) suggested that while investors with high investment literacy are less overconfident, those with low investment literacy are more likely to be overconfident.

As previously said, understanding investor behaviour requires analysing behavioural biases and financial knowledge. Researchers studying behavioural finance are becoming more interested in examining how financial knowledge affects the investment habits of individuals (Coşkun et al., 2016).Numerous studies demonstrate that traders' behaviour is significantly influenced by both behavioural biases and financial knowledge. Financial literacy has not been seen by scholars as a moderating factor between investors' behavioural biases and trading decisions, nor has the relationship between these two factors, which play a big part in investment decisions, been well examined (Ranaweera & Kawshala, 2022);(Coşkun et al., 2016);(Sezer & Demir, 2015) and (Gunasena et al., 2024).

The strength or shape of the relationship between the dependent variable and its predictor variable can be altered by a moderator variable (Sezer & Demir, 2015). We thus acknowledge that previous research investigations should have considered the potential importance of moderating factors or failed to conduct a thorough examination, based on our evaluation of the literature. Therefore, the current study aims to address the above controversies by including a moderating factor of financial knowledge to test the level of impact between behavioural biases and cryptocurrency trading decisions.

Yusuf Hendri Gunawan & Khresna Bayu Sangka (2025) investigated how digital and financial knowledge impact cryptocurrency investment choices in quantitative research employing a poll of 366 members of the Indonesian Nakama DAO community, with FOMO serving as a moderating variable. They concluded that financial and digital literacy significantly influence cryptocurrency trading decisions among retail traders in Indonesia. The study focused solely on online communities in Indonesia, thus limiting the generalizability of the findings. To provide a more thorough understanding of traders' behaviour in digital asset markets, this study

aims to address the gap by extending to diverse populations and expanding the conceptual framework to include more behavioural biases.

When making financial decisions, particularly when it comes to trading in digital currencies, financial literacy is essential. According to research by Stolper & Walter (2017), Traders who lack financial knowledge are less likely to seek professional help or engage in high-risk assets. Financial inclusion benefits from financial literacy, according to Morgan & Long (2020). Making well-informed judgments and minimizing financial problems are made possible by financial knowledge. Wijaya & Zunairoh (2021) examined the relationship between stock trading decisions and heuristic and herding characteristics, taking financial literacy into account as a moderating factor. Morgan & Long (2020) illustrated the need to possess a high level of financial knowledge to make informed trading choices that would improve the financial well-being of individuals, businesses, and real investors. Therefore, this research looked at how financial knowledge might mitigate the effects of behavioural biases on cryptocurrency trading decisions.

Kuria (2024) researched the moderating effect of financial knowledge on the association between behavioural biases and the performance of real estate investments in Kenya. He concludes that higher financial literacy altered (typically lessened) the detrimental effect of behavioural biases on investment performance in the Kenyan real estate market. The study's participants were mostly selected from Kenyan real estate investors; it excluded retail investors, young digital investors, and cryptocurrency users, where bias-driven decision-making would be more noticeable. As a result, a more thorough empirical study is required to determine how financial knowledge influences the way that various behavioural biases influence cryptocurrency trading choices made by various investor groups in Kenya.

2.4 Summary of the knowledge gap

Significant gaps still exist in the vast body of research on behavioural biases and cryptocurrency trading decisions. Research was conducted by Ranaweera & Kawshala (2022) on the moderating effect of financial knowledge and the impact of behavioural biases on trading decision-making. Information gathered from 110 individual investors who are regular Colombo Stock Exchange traders. The study finds that financial knowledge mitigates behavioural biases and that overconfidence positively affects investing decision-making. Nevertheless, a conceptual gap resulted from the attention being restricted to a small number of behavioural biases. To account for a wide and varied population throughout the bitcoin marketplaces, this

gap necessitates the conceptual framework's enlargement to incorporate additional behavioural biases.

Rajapaksha (2023) concludes that judgments on cryptocurrency trading decisions are strongly correlated with overconfidence bias. The study identifies a contextual gap whereby the size, structure, volatility, and liquidity of the Sri Lankan market differ from those of the Kenyan market. Therefore, because Kenya is an emerging economy, the findings may not be generalizable. The purpose of the current study is to evaluate how overconfidence bias affects retail traders' choices in the Kenyan emerging market.

Kuria (2024) concludes that behavioural biases hurt investment performance in the Kenyan real estate market, which can be changed (usually mitigated) by more financial knowledge. This is because the relationship between behavioural biases and the success of real estate investments is moderated by financial literacy. Because bias-driven decision-making is more evident among retail traders, young digital investors, and cryptocurrency users, the study's participants were mostly drawn from Kenyan real estate investors. Therefore, a more comprehensive empirical investigation is needed to ascertain how different behavioural biases impact trading decisions made by different investor groups in Kenya in relation to financial knowledge.

Table 2. 1 Summary of Research Gaps

Author	**Focus of study**	**Findings**	**Research Gap**	**The focus of the current study**
Sezer and Demir (2015)	Impact of Financial Literacy on the Behavioral Biases of Individual Stock Investors: Evidence from Borsa Istanbul	No significant correlation between financial literacy and susceptibility to behavioral biases	Need to explore other factors influencing investor behaviour beyond	Examining the relationship between financial literacy and behavioral biases among cryptocurrency investors in Kenya
Corbet, Lucey, and Yarovaya (2018)	The Financial Market Effects of Cryptocurrency Energy Usage	Crypto assets show strong bubble patterns like historical financial crises	Conceptual Gap: Does not connect irrational investor behaviour to behavioral bias	This study contributes by applying behavioral theories specifically to the cryptocurrency domain, bridging traditional behavioral finance with modern, decentralized investment platforms

Kristoufek (2015)	What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis	Price is influenced by online activity and search interest over time	Conceptual Gap: No conceptual grounding in behavioral finance theories like heuristic theory or mental accounting	This study contributes by applying behavioral theories specifically to the cryptocurrency domain, bridging traditional behavioral finance with modern, decentralized investment platforms
Bouri, Pham, and Roubaud (2019)	The impact of investor sentiment on Bitcoin returns and volatility	Investor sentiment significantly affects both return levels and volatility in Bitcoin markets	Conceptual Gap: Does not explore specific behavioral biases like overconfidence or herding; lacks psychological framing	While behavioral finance literature identifies many biases (e.g., overconfidence, herd behaviour, loss aversion), their specific impact on cryptocurrency trading remains underexplored.
Yadav (2024)	Heuristic Theory Model for Cryptocurrency Returns	Investors exhibit strong loss aversion and probability weighting behaviour, as predicted by heuristic theory	Methodological Gap: No inclusion of investor-specific demographics or behavioral self-reporting	This research may employ primary data collection methods (e.g., surveys or interviews) from actual cryptocurrency traders in Nairobi, providing first-hand

				empirical evidence rather than relying solely on models or theoretical assumptions
Song (2025)	Behavioral Biases in the Cryptocurrency Market	Investor sentiment significantly correlates with short-term price anomalies (e.g., overreactions, anchoring)	Methodological Gap: Lacks primary investor perspective; findings are not localized (global scope only)	This research may employ primary data collection methods (e.g., surveys or interviews) from actual cryptocurrency tradesr in Nairobi, providing first-hand empirical evidence rather than relying solely on models or theoretical assumptions
Sachitra and Rajapaksha (2023)	Determinants of cryptocurrency and decentralized finance	Adoption is driven by complex configurations of technological, economic, social, cultural, and political factors; no single factor alone explains high adoption	Conceptual Gap: Need for exploring behavioural biases and demographic heterogeneity in configurational models	To map and analyse configurations of contextual factors promoting crypto/DeFi adoption in diverse emerging-market settings

Suchitra and Rajapaksha (2023)	Behavioral Biases in the Cryptocurrency Market:	Extreme optimism or pessimism in sentiment strongly correlates with price anomalies; composite sentiment indices outperform	Conceptual and Contextual Gap: Gap between aggregated market-level bias effects and individual investor behavioral antecedents; emerging markets are underexplored	To analyse how investor sentiment and behavioral biases (e.g., overconfidence, anchoring) manifest in cryptocurrency trading decision-making
Gunasena, Kuruppu, and Weerasinghe (2025)	Impact of Behavioural Biases on Cryptocurrency Investment Decisions with the Moderating Effect of Financial Literacy	Heuristic (especially availability bias) and prospect factors (loss aversion & regret aversion) significantly influence investment decisions; herding behaviour and financial literacy show no significant effect	Conceptual Gap and Contextual Gap: Small self-selected sample; cross-sectional design; limited to Sri Lanka; financial literacy did not moderate behavioural biases	Examine how behavioural biases drive crypto trading decisions and test whether there is any correlation between the variables.

2.5 Conceptual framework

The conceptual framework diagrammatically explains the relationship between the independent variables, the dependent variable (crypto trading decision), and the moderating variable (Financial knowledge) in the context of the Kenyan crypto market. Independent variables comprise the traders' overconfidence, a key factor influencing crypto trading decisions. According to behavioural finance theory, investor overconfidence translates to irrationality of an investor, leading to suboptimal decision-making.

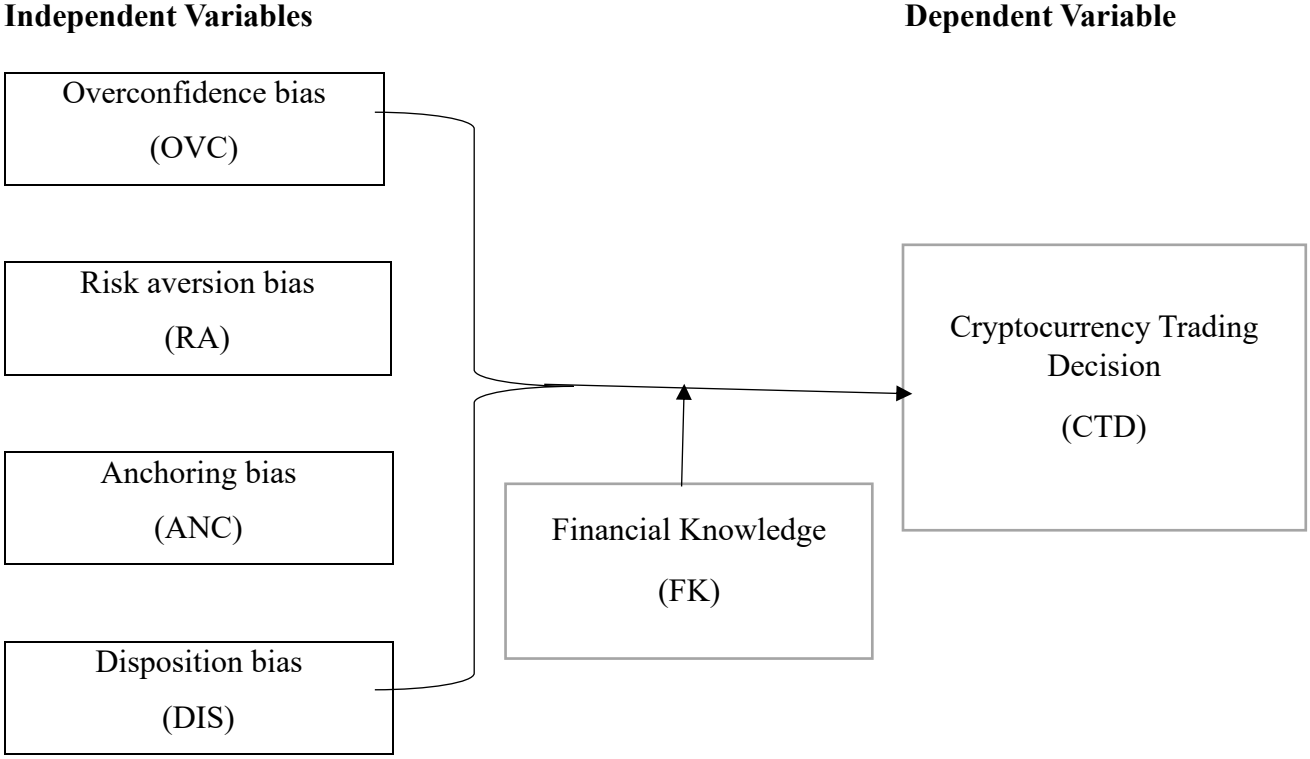
Risk aversion is another factor that influences crypto trading decisions. The prospect theory reveals that an individual values their choice under possible loss or gain. Individuals are less willing to gamble with profits than they are with losses. Kahneman & Tversky (1979) concluded that investors feel more pain from the loss than the pleasure they get from gains of the same amount, therefore, the reason for the prospect S-shaped utility curve.

The anchoring bias is another form of behavioural bias where investors tend to rely on the first piece of information they receive from others to make a trading decision. According to the heuristic theory, a person's behaviour may be motivated by the expectations and actions of others. Disposition bias is another form of behavioural bias that affects investors' ability to make rational investment decisions. It happens when an investor regrets disposing of a profitable investment portfolio in a short period of time and keeps on holding the losing portfolio for a long period of time.

The heuristic theory explains why investors detest losses more than they do comparable profits. They keep losing stocks in the hopes that prices will rise to prevent suffering a loss. The moderating variable is financial knowledge, while the dependent variable, which is the crypto trading decision, is measured by risk tolerance, return expectation, and the available information. The control variables that are not considered by this study are age, gender, and income level; these factors can affect the trading decision, but they are outside of this study’s scope.

The research seeks to understand the relationship between the independent and dependent variables in this study using the conceptual framework (Figure 2.1).

Figure 1.1 Conceptual Framework



Source: Author's (2025) compilation based on the literature review

2.6 Operationalization of Variables

Table 2.2 Operationalization of Variables

#	Type of Variable	Variable	Measurement Indicator	Measurement scale	Data Analysis	Source
1	Dependent Variable	Trading decision	1. I am comfortable taking high risks in my cryptocurrency trading decisions for the chance of higher returns. 2. I often make cryptocurrency trading decisions quickly to avoid missing out on a potential opportunity (FOMO). 3. I trade cryptocurrencies very frequently (e.g., daily or weekly).	5-point Likert Scale 1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree 5. Strongly disagree	Quantitative analysis	(Nofsinger,2017), (Jinesh,2019)
		Risk tolerance	1. The investor's willingness to take financial risk for high reward 2. The investor reaction to market losses 3. Preference level for high risk, high return	5-point Likert Scale 1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree 5. Strongly disagree	Quantitative analysis	(Grable & Lytton, 1999), (Omanovic,2024), (Kawshala, 2022), (Arthur, 2014)
		Information availability	1. The level of personal financial knowledge 2. Frequent use of online resources 3. Reliance level of the financial advisors	5-point Likert Scale 1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree 5. Strongly disagree	Quantitative analysis	(Lusardi & Mitchell, 2014), (Sally Wanjiru, 2019), (Munyoki & Uliana,2008) (Suchitra & Rajapaksha,2023)
		Return Expectation	1. I consider the expected rate of return	5-point Likert Scale	Quantitative analysis	(Barberis,2013),

			2. I prioritize short-term over long-term profits 3. Investors/Traders: I differentiate Capital gain versus income orientation	1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree 5. Strongly disagree		(Aigbovo & Ilaboya,2019) (Kristoufek ,2015),
2	Independent Variable	Investors Overconfidence bias	1. I trust my own analysis; thus, I trade often 2. I make trading decisions based on my own judgment rather than seeking professional guidance 3. I believe my trading skills are better than those of most other investors 4. I do not doubt that I can beat the market.	5-point Likert Scale 1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree 5. Strongly disagree	Quantitative analysis	(Ahmad et al. 2025), (Mohanraj, 2021)
		Risk aversion bias	1. I prefer keeping my money in a savings account rather than trading 2. I avoid trading assets with uncertain rewards 3. Even if low-risk trading provides lower returns, I still favour it 4. When the value of my trading assets changes a lot, I get uneasy.	5-point Likert Scale 1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree 5. Strongly disagree	Quantitative analysis	(Omanovic,2024),
		Anchoring bias	1. I don't change my original evaluation even when new information becomes available 2. I base my	5-point Likert Scale 1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree	Quantitative analysis	(Ahmad et al.2025), (Sachdeva,2024)

			trading choices on the asset's original purchase price 3 I'm hesitant to purchase assets whose value has just improved 4. When deciding to sell, I compare the current price to the purchase price rather than the intrinsic value	5. Strongly disagree		
		Disposition bias	1. I avoid selling assets that have decreased in value, hoping they will rebound 2. I tend to sell assets that have increased in value quickly to realize gains 3. Even when it makes sense, I frequently hesitate to acknowledge a loss 4. I monitor my profitable assets more closely than my losing ones.	5-point Likert Scale 1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree 5. Strongly disagree	Quantitative analysis	(Knüpfer,2021), (Adil et al,2022)
3	Moderating Variable	Financial Knowledge	Financial education 1. I understand the relationship between risk and reward 2. I can distinguish different trading products 3. I understand the impact of inflation on asset trading in the market	5-point Likert Scale 1. Strongly agree 2. Agree 3. Relatively agree 4. Disagree 5. Strongly disagree	Quantitative analysis	(Lusardi 2024), (Arifin, 2022),
			Financial Behaviour 4. I have a budget for my crypto trading	5-point Likert Scale 1. Strongly agree 2. Agree	Quantitative analysis	

			5. Often, I monitor my savings and investments 6. I evaluate the performance of different financial products before trading	3. Relatively agree 4. Disagree 5. Strongly disagree		
			Financial Attitude 7. I believe that increasing my financial literacy improves the results of my trading outcomes 8. I believe financial planning is essential for long-term success 9. I'm comfortable making my own financial decisions.		Quantitative analysis	(Lusardi 2024), (Arifin, 2022),

Source: Author's (2025) compilation based on the literature review

2.7 Chapter Summary

This chapter reviewed literature on cryptocurrency trading decisions, focusing on the influence of behavioural biases, which are traders' overconfidence, risk aversion, anchoring bias, and disposition bias. The theoretical framework includes behavioural fiancé theory, the heuristic theory, and the adaptive market efficiency theory linking the behavioural biases and cryptocurrency trading decisions.

Empirical studies revealed underexplored gaps in behavioural biases and cryptocurrency trading decisions, with a moderating effect of financial knowledge. The conceptual framework provides a diagrammatic integration of the two variables with financial knowledge as the moderating variable, offering a foundation to examine the influence of behavioural biases on cryptocurrency trading decisions among retail traders in Nairobi County.

CHAPTER THREE:

RESEARCH METHODOLOGY

3.1 Introduction

This chapter emphasised the fulfilment of research objectives and the analysis of the research problem. Additionally, it provided a detailed account of the research design, population frame, sample selection methods, data collection techniques, and data analysis strategies that were employed to achieve the objectives effectively.

3.2 Research Philosophy

Research philosophy refers to the set of beliefs concerning the nature of reality (ontology) and how knowledge about that reality can be acquired (epistemology). Several research philosophies were addressed in this study, including interpretivism, pragmatism, and positivism.

Interpretivism focuses on comprehending social processes and subjective meanings from the viewpoints of the participants. It is frequently used in qualitative research where the objective is to investigate perceptions, experiences, and interpretations. Although interpretivism would have helped examine how retail traders view behavioral biases in cryptocurrency trading, it was inappropriate for this study since the goal was to test predetermined hypotheses and quantify relationships between variables, rather than produce in-depth subjective insights (Saunders & Rojon, 2011).

Pragmatism places a strong emphasis on using techniques that best solve the study challenge, frequently fusing qualitative and quantitative methodologies. Although pragmatism permits flexibility and methodological pluralism, it was not used in this study because the goal was to use a structured approach to statistically examine quantifiable relationships between trading decisions, financial knowledge, and behavioral biases, rather than to combine methods (Ishtiaq, 2019).

The study adopted a positivist research philosophy to examine the impact of behavioral biases on crypto trading decisions among retail traders in Nairobi County. Financial knowledge was employed as the moderating variable between the two variables. According to Mohammad Ali (2024), Positivism assumes that reality is objective and can be observed and measured

independently of the researcher. This approach was appropriate for this research, as it allowed the investigation of quantifiable relationships between aspects of behavioural biases, such as traders' overconfidence bias, risk aversion bias, anchoring bias, and disposition bias, and crypto trading decisions.

According to Alharahsheh and Pius (2020), The positivist stance supports structured surveys and statistical analysis for testing predefined hypotheses, thereby ensuring objectivity and reliability. This approach aligns with deductive reasoning, as it starts with broad behavioural finance theories and tests them against data from the specific population of retail traders in Nairobi County. This enables the development of findings that can be generalised, and that may influence financial education and policy (El Khawli et al.,2025). Furthermore, positivism facilitates the replication and validation of findings across various contexts, which is essential for research intended to impact policy and practice.

Its focus on empirical and observable phenomena renders it particularly suitable for comprehending the behavioural patterns and decision-making processes of retail traders (Lusardi & Mitchell, 2014). The positivist paradigm assumes that social phenomena can be explained by applying the same scientific method used in the natural sciences, and thus was used in studying how behavioural biases, expressed in terms of traders' overconfidence bias, risk aversion bias, anchoring bias, and disposition effect, affect the crypto trading decisions among retail traders in Nairobi County.

The choice of positivism was driven by its capacity to operationalise behavioural biases into measurable variables, including traders' overconfidence bias, risk aversion bias, anchoring bias, and disposition bias, thus allowing systematic hypothesis testing as well as the establishment of correlations (Alharahsheh & Pius, 2020). The methodology ensured that the results produced are objective, replicable, and highly generalizable, offering insights that can be utilised to improve the crypto trading decision-making processes of the retail traders in Nairobi County.

This research philosophy ensured that the study remains grounded in scientific methodology, fostering a systematic understanding of how behavioural biases impact crypto trading behaviour (Alharahsheh & Pius, 2020). Positivism assisted this study by offering a scientific framework that stresses objectivity, quantification, and generalisation. This resulted in evidence-based conclusions that were dependable, reproducible, and valuable for shaping real-world financial decision-making, investment, and trading decision programmes and policies.

3.3 Research Design

There are several study designs, each appropriate for a particular question. When a topic is poorly known, and the goal is to provide novel concepts or hypotheses, exploratory research is employed (Stebbins, 2001).Although descriptive research offers a thorough description of a phenomenon's features, it is unable to elucidate its underlying causes (Emon, 2024).Without proving cause and effect, correlational research looks at how variables relate to one another (Cohen et al., 2005).Control groups and variable manipulation are used in experimental research to ascertain causal links (Babbie, 2020). Using quantitative data and statistical analysis to test hypotheses, explanatory research aims to explain the connections between variables (Blatter & Haverland, 2012).

The explanatory research design was employed in this study as it aims to identify and explain the relationships between behavioural biases and crypto trading decisions among retail traders in Nairobi County, with moderating financial knowledge through quantitative data analysis. This design was crucial for understanding how variables interact and affect each other, providing actionable insights for retail traders, financial advisors, and policymakers in identifying the most common behavioural biases towards crypto trading decision-making (Blatter & Haverland, 2012) It enabled the testing of effects, making it ideal for this research.

The target population consisted of individual (retail) traders who are engaged in crypto trading activities in Nairobi County (Business Daily, 2025). A snowball sampling method was used to select respondents who participate in crypto trading. This approach ensures that the study captures insights from individuals whose experiences are most relevant to the research objectives. Yamane’s formula was employed to ascertain the sample size, ensuring statistical significance.

Data collection was carried out using structured questionnaires that feature closed-ended items as well as Likert-scale questions. This approach aimed to measure the behavioural factors, which are traders' overconfidence bias, risk aversion bias, anchoring bias, and disposition bias, and elucidate the characteristics of crypto trading decisions. Dimensions of behavioural biases, including traders' overconfidence bias, risk aversion bias, anchoring bias, and disposition bias of crypto trading options, were assessed by the questionnaire (Lusardi & Mitchell, 2014).

The research instruments were evaluated by specialists in finance and research methodology to ensure their validity. A pilot study was used to test reliability, and Cronbach’s alpha was employed to evaluate internal consistency (Quansah, 2017). The analysis of data encompassed

descriptive statistics (such as frequencies, means, and standard deviations) as well as inferential statistics, particularly regression analysis, to assess the strength and direction of the link between behavioural biases and crypto trading decision-making (Flick, 2013). We strictly adhered to ethical considerations, including confidentiality, informed consent, and voluntary participation. The results of this study provided a guide for policymakers, financial institutions, and educators in improving and identifying the prevalent behavioural biases to enhance personal financial decision-making towards investment and crypto trading.

3.4 Target Population

This study focused on the retail traders in Nairobi County who were actively engaged in crypto trading. According to Business Daily (2025),The study population is retail crypto traders in Nairobi County(N =733,300).According to Mumo (2024) Retail traders are increasingly trading cryptocurrencies as they are open to innovative financial instruments and actively engaged in digital investment and trading platforms.

According to Bodie et al (2014) Retail traders are characterized as individuals who are not professionals but engage in the buying and selling of financial instruments, such as mutual funds, stocks, bonds, real estate, cryptocurrency, and other personal investment products, with their own money. Unlike institutional investors, these investors usually invest smaller sums and may lack access to advanced financial advisory services.

To align with the definition of retail traders, the study focused on individuals who (1) are aged 18 and above, (2) are currently living in Nairobi, and (3) have actively participated in crypto trading. The purpose of these criteria was to ensure that respondents have relevant and current experience in making personal financial decisions. Ingram & Schneider (1991)state that a clear definition of the target population helps in determining the study's boundaries and in selecting an appropriate sample.

Understanding the characteristics of this group will help in developing a research tool that is better suited to its needs and more accurate, a tool that is better tailored to its needs and more precise. Nairobi County has a relatively high concentration of financially active individuals due to its position as Kenya's economic and financial hub. This made it the perfect location for the study since it offers a representative and varied group of individual traders whose financial knowledge and behavioural biases may affect their choices about crypto trading (Mumo, 2024).

3.5 Sampling

The study employed a non-probability snowball sampling method to engage retail crypto traders in Nairobi. Snowball sampling is a suitable method for hard-to-reach populations due to the lack of a formal sampling frame, and particularly in online communities (Goodman, 2011).Cryptocurrency traders in Nairobi fit this description due to anonymity preferences, decentralized trading platforms, and reliance on encrypted digital networks.

The sampling process began by identifying several crypto traders from the blockchain meetup, including but not limited to Telegram crypto forums, TikTok platform, WhatsApp trading groups, and personal networks. The initial participants were screened to ensure they met the study criteria, such as actively trading crypto, residing in Nairobi, and regularly engaging in retail crypto trading. Each group was asked to recommend another eligible active user, who would then be asked to refer others as well, allowing the sample to grow progressively.

To reduce the referral bias and network clustering, the study considered using multiple snowball chains, focusing on diverse digital and physical entry points (Atkinson,2001). This approach enhanced the representativeness of the resulting sample, capturing a broader spectrum of investor demographics, trading behaviours, and financial knowledge levels. Although snowball sampling introduces risks such as selection bias and over-representation of specific networks, it is justified given the hidden nature of crypto traders and the absence of an accessible sampling frame in Kenya (Browne, 2005). It was therefore the most practical and methodologically sound strategy for this study.

The study adopted Yamane's (1967) formula to calculate the sample size since it offers a simplified and statistically sound method for determining the sample size for a limited target population when the size of the population (N=733,300) is known.

Yamane's formula is as follows.

$$n = \frac{N}{1+N(e)^2}$$

Where:

n = sample size

N = total population size (733,300)

e = margin of error (0.05 at 95% confidence level)

$n=1+733,300\times0.0025733,300=1+1,222733,300=1,223733,300\approx400$

Therefore, the sample size of 400 respondents was targeted and obtained from the total population of 733,300.

3.6 Data collection method

Systematic approaches, such as structured questionnaires for gathering information through data collection methods, were used for research, analysis, and/or decision-making. The study adopted primary data collection. Primary data was collected directly from first-hand sources. This is typically more reliable and relevant to specific research questions. The questionnaire tools were used to gather data through structured questions. They were administered in various formats, including online, paper-based, and face-to-face. Surveys are effective for collecting data from large populations efficiently (Lutfi et al., 2023). The purpose of these surveys was to collect quantitative data so that trends and patterns in the information that respondents submitted could be systematically examined.

The effectiveness of questionnaires in gathering standardized data from a wide range of participants, their cost-effectiveness and accessibility, and their provision of anonymity and privacy, especially considering recent technological advancements, make them extremely significant. They support diverse demographics and research goals, provide effective data processing, and may be modified for feedback or cross-sectional studies. Researchers, educators, and organizations may gain important insights, evaluate opinions, and monitor trends in a variety of subjects and situations with the use of questionnaires.

The study used questionnaires to gather pertinent data on the behavioural biases, such as traders' overconfidence, risk aversion, anchoring bias, and disposition effect in cryptocurrency trading decisions, and financial knowledge, which was used to inform the impact level of the connection between the behavioural biases and cryptocurrency trading decisions. The questionnaire used in this study was adapted from previously validated instruments used by Lutfi et al. (2023).

Minor modifications were made to align the items with the crypto trading decisions in the Kenyan context and the objectives of the current study. Additionally, the selection of a structured questionnaire with closed-ended questions as the appropriate tool in this research was used to allow the gathering of huge amounts of data from various respondents over a small period (Lutfi et al., 2023).

3.7 Data collection procedure

The researcher obtained a research authorization from the National Commission for Science, Technology, and Innovation (NACOSTI), an introduction letter from the institution, and clearance from the Strathmore Institution Ethical Review Committee. On the appointed day, the researcher delivered and retrieved the questionnaires that were given to the participants. To make sure the surveys adequately address the research, more follow-ups were done.

3.8 Data Analysis

Data analysis in this study focused on converting the raw data into a structured format to portray meaningful insight and establish reliable conclusions about the influence of behavioural biases on cryptocurrency trading decisions, with moderating financial knowledge (Flick, 2013). This was achieved through both descriptive and inferential statistical techniques. Similarly, the process was initiated with the proper data-cleaning phase to ensure that the collected data would be complete, clear, and consistent. The process involved identifying and fixing any missing values or inconsistencies to enhance the accuracy of the data. Once cleaned, the data were systematically coded and categorized to convert the responses into numerical and categorical values that could be analysed efficiently.

The Statistical Package for the Social Sciences (SPSS), selected due to its robust capabilities in managing large datasets and conducting a range of statistical analyses, served as the primary data analysis tool. Thus, SPSS version 27 was used to analyse data. It provided the ability to conduct an extremely thorough descriptive and inferential analysis, which precisely allowed for the investigation of patterns and correlations within the data. The dataset's features were presented using descriptive statistics initially to gain a better grasp of the distribution and trends before moving on to inferential analysis.

The study used inferential statistics, particularly Pearson's correlation analysis, to investigate the nature of the relationships between the dependent variable (cryptocurrency trading decisions) and the independent variables (investor overconfidence, risk aversion, anchoring bias, and disposition effect). Pearson's correlation coefficient, which has a range of -1 to +1, was used to quantify the direction and intensity of these correlations; the closer the correlation is to +1 or -1, the greater the positive or negative association, respectively. This investigation was employed to demonstrate the impact of several behavioural biases on cryptocurrency trading decisions.

Because the cryptocurrency trading decision variable is ordinal in nature, the study employed an Ordinal Logistic Regression (OLR) model (proportional odds model) to examine the influence of behavioural biases on cryptocurrency trading decisions and the moderating role of financial knowledge. The model estimated the log-odds of a respondent being at or above a certain level of trading decision.

To examine the impact of behavioural biases on crypto trading decisions among retail traders in Nairobi County, two econometric models were specified. The first model captures the direct effects of behavioural biases on trading decisions, while the second model incorporates financial knowledge as a moderating variable.

The general model 1 was expressed as:

logit[P(CTD≤j)] =αj−(β1OC+β2RA+β3AB+β4DE+εi

for $j = 1,2, \dots, k-1$, where $k$is the number of ordered categories of the dependent variable.

Where:

CTD= Cryptocurrency trading decision (ordinal outcome)

TOC= Traders Overconfidence

RA= Risk aversion

AB= Anchoring bias

DE= Disposition effect

α_j= Threshold (cut-point) parameters

$\beta_1 - \beta_4$= Coefficients of explanatory variables

ε_i= Error term

This model (1) examines the direct relationship between behavioural biases and crypto trading decisions:

The general model 2 was expressed as:

logit[P(CTD≤j)]=αj−(β1OC+β2RA+β3AB+β4DE+β5FK+β6(OC×FK)+β7(RA×FK)+β8 (AB×FK) +β9(AB×FK) +β10(DE×FK) +εi

for $j = 1,2, \dots, k-1$, where $k$is the number of ordered categories of the dependent variable.

Where:

CTD= Cryptocurrency trading decision (ordinal outcome)

TOC= Traders Overconfidence

RA= Risk aversion

AB= Anchoring bias

DE= Disposition effect

FL= Financial Knowledge (moderator)

α_j= Threshold (cut-point) parameters

$\beta_1 \dots \beta_9$= Regression coefficients

ε_i= Error term

Model 2 tested whether financial knowledge strengthens, weakens, or changes the relationship between behavioural biases and trading decisions.

This model allowed the study to determine both the direct effects of behavioural biases on cryptocurrency trading decisions and how financial knowledge moderates these relationships, under the proportional odds assumption.

Finally, the findings were summarized systematically, with tables showing major statistics, including correlation coefficients, mean scores, and frequency distributions. The findings from these analyses were examined considering the study's objectives, with an emphasis on how each behavioural bias (investor overconfidence, risk aversion, anchoring bias, and disposition effect) influences the cryptocurrency trading decision, and to what extent the impact of moderating financial knowledge on the connection between behavioural biases and cryptocurrency trading decisions.

3.9 Research Quality

The main tool for gathering data was a structured questionnaire. Closed-ended questions were included in the survey. As the proper method for this study, a structured questionnaire was used for the efficient collection of a lot of data from various respondents in a short period of time, and data collection will turn out to be economical (Lutfi et al., 2023)To get quantitative insights, the research method entailed gathering numerical data.

A pilot study was conducted as a simulation and replication of the actual study, aimed at identifying weaknesses in the instrument and allowing necessary adjustments (Kothari, 2004).The pilot stage was carried out as pre-testing of the questionnaire within the Nairobi County, which is an area with characteristics like those of the actual study location and target population. The instrument was pre-tested on a sample of 42 participants online. This constitutes 10% of the total sample size. Patten (2016) Recommend that the pretest use a sample of 10% to 20% of the sample.

3.9.1 Reliability of the Research Instruments

According to Patten (2016),Reliability is the extent to which a research tool consistently yields reliable outcomes under similar circumstances. The instrument's dependability was assessed in this study using the split-half reliability approach. The survey was randomly divided into two halves, with odd-numbered questions in one half and even-numbered questions in the other. After giving the respondents the first section of the instrument and recording the findings, the researcher gave them the second section. After that, the sum of the two sections' scores was determined. Cronbach's Alpha was used to calculate the reliability analysis for internal consistency. Additionally, Patten (2016) states that the threshold for Cronbach's Alpha is set as 0.7. Every objective will be analysed for reliability.

3.9.2 Validity of the Research Instruments

This pilot study was to facilitate the interpretation of the questions by the respondents and thus contribute to the validity and reliability of the data to be collected. The accuracy of the data gathered was considered in this investigation. According to Saunders and Rojon (2011), validity is the degree to which a data collection technique achieves the goals of the study by measuring the variables that are appropriately targeted. Pre-testing the questionnaire through pilot research increased the validity of the instrument in this investigation. Additionally, content validity was used to evaluate validity, and the researcher conferred with supervisors and

colleagues in this process. These people reviewed the questionnaire's content before it was administered and provided feedback and suggestions for improvement.

Construct validity was addressed by ensuring that the questionnaire items were aligned with the theoretical concepts and constructs derived from existing literature. Each construct was operationalized based on established definitions and prior empirical studies to ensure that the items accurately reflect the intended variables (Tavakoli & Wetzel, 2020). Internal validity was enhanced by carefully designing the questionnaire to minimize measurement errors and bias, ensuring consistency in the administration of the instrument, and using clearly structured and logically sequenced questions. This helped establish credible relationships between the study variables (Clark & Watson, 2019). External validity, which concerns the generalizability of the study findings, was strengthened by using a representative sample drawn from the target population and by applying standardized data collection procedures. This allowed the findings of the study to be reasonably generalized beyond the sample to the wider population under investigation (Clark & Watson, 2019).

3.10 Ethical Considerations

To guarantee that the integrity of the study was maintained, ethical principles were strictly followed during the data collection and administration phases of the project. Before starting data collection, ethical permission from the National Commission for Science, Technology, and Innovation (NACOSTI) and the Strathmore University Institutional Scientific and Ethical Review Committee (SU-ISERC) was acquired. To boost responders' confidence, Strathmore University Business School sent an introductory letter.

An essential component was informed consent, in which participants were provided written assent after being fully informed about the intent, methods, and rights of the proposed research, according to the terms of the participant information and consent form (Ishtiaq, 2019).They specifically comprehended the nature of taking part in this research. Since data was anonymised, stored securely, and private information was kept private, it was impossible to link specific responders to the data (Osborne et al., 2024).

The importance of voluntary involvement was emphasized, and participants were made aware of their right to discontinue the study at any time without facing any consequences to their connection with the researcher or their company (Bryman, 2016). The dignity of every participant was preserved throughout the study process by enforcing politeness and respect in all interactions.

3.11 Chapter summary

This chapter explains the research methodology. The study adopted a positivist paradigm to assess the influence of behavioral biases on cryptocurrency trading decisions among Nairobi retailers by utilizing objective measurement methods and quantitative methods. To understand the connection between the two variables, the study used an explanatory research design. From the total of 733,300 active crypto traders, a Sample size of 400 respondents was used to gather information. A structured questionnaire was used to gather quantitative responses from the sampled participants.

The study used SPSS version 27 for statistical analysis, which integrates descriptive procedures with correlation analysis and Ordinal Logistic Regression (OLR) inferential techniques. A diagnostic test was carried out to confirm the correct function of the regression model when dealing with the ordered nature of the dependent variable. The pilot study took place in Kiambu County to validate and establish the reliability of the research measurement tools, and Cronbach's alpha was used to analyse internal consistency. The study strictly maintained the ethical standards by acquiring consent from the respondents and getting permission from NACOSTI and Strathmore University research permits throughout the entire study duration.

CHAPTER FOUR

PRESENTATION OF FINDINGS

4.1 Introduction

The study's main goal was to evaluate the effect of behavioral biases on cryptocurrency trading decisions with moderating financial knowledge. The research findings are presented in this chapter along with discussions that follow in accordance with the study's goal. To achieve this, this chapter includes the response rate, demographic data about the respondents, conclusions drawn from the objectives using descriptive statistics, and the outcomes of inferential statistics.

4.2 Response Rate

The target population for this study was 733,300 crypto traders in Nairobi County. Using the snowballing sampling method, a sample of 400 users of cryptocurrency was chosen for data collection. The study achieved a response rate of 98.25% (393 out of 400), which is exceptionally high. This indicated strong participant engagement and suggested that the data collected was highly representative of the target population. Consequently, the findings of the study can be considered reliable, with minimal risk of non-response bias (N. Barberis & Thaler, 2003). To assess the possibility of non-response bias, an independent samples t-test was conducted between early respondents and late respondents based on the key study variables. The results indicated no statistically significant differences between the two groups ($p > 0.05$), suggesting that non-response bias was minimal and that the responses obtained were representative of the target population. Consequently, the data collected was considered reliable and suitable for drawing valid conclusions regarding cryptocurrency traders in Nairobi County.

Table 4.1Response Rate

	Frequency	**Percentage**
Complete questionnaires returned	393	98.25
Questionnaires not returned	7	1.75
Questionnaires distributed	**400**	**100.00**

Source: Researcher (2026)

According to Stedman et al (2019)A return rate of more than 70% is great; therefore, the researcher proceeded to examine the data. One crucial factor that supports the validity of a study is the response rate.

4.3 Demographic Data of Respondents

This section details the demographic profile data that was gathered from research participants, including their age, gender, employment situation, education level, Income level, and expertise with cryptocurrencies. Table 4.2 provides an overview of the respondents' demographic data.

Table 3.2: Respondents' Demographic Profile Information

		Frequency	**Percentage**
Gender	Female	180	45.80
	Male	174	44.30
	Prefer not to say	39	9.90
	Total	**393**	**100.00**
Age (Yrs)	18-25	196	49.90
	26-35	143	36.30
	36-Above	54	13.80
	Total	**393**	**100.00**
Education Level	Secondary School	56	14.20
	Technical Training	104	26.50
	Bachelor's Degree	151	38.40
	Postgraduate Degree (Master's/PhD)	46	11.70
	Other	36	9.20
	Total	**393**	**100.00**
Employment Status	Employed (Full-time)	93	23.70
	Employed (Part-time)	92	23.40
	Self employed	113	28.80
	Students	95	24.20
	Total	**393**	**100.00**
Income level (PM)	< 30,000	115	29.30
	30,000–59,999	95	24.20
	60,000–99,999	100	25.40
	100,000–199,999	52	13.20
	200,000+	31	7.90
	Total	**393**	**100.00**

Crypto Trading Experience	Less than 6 months	109	27.70
	6 months – 1 year	72	18.30
	1 – 3 years	64	16.30
	More than 3 years	76	19.30
	I have never traded cryptocurrencies	72	18.30
	Total	**393**	**100.00**

Source: Researcher (2026)

Male participants made up 44.30% of the sample size, with female participants making up the majority (45.80%). 9.90% of respondents chose not to disclose their gender identity. Just 9.90% of the sample opted to withhold their gender identity. Because women make up a small majority, the participation pool demonstrates fair gender equality.

Furthermore, most respondents (49.90%) were between the ages of 18 and 25, while the second-highest percentage of respondents (36.30%) was between the ages of 26 and 35.13.80% of the population was over 45. Most participants were in the youth group, suggesting that young people were exposed to digital platforms, mobile apps, and the internet as children. Compared to prior generations, this makes it simpler for them to comprehend and utilize cryptocurrency exchanges, wallets, and trading apps

The findings indicate that most retail cryptocurrency traders in Nairobi possess relatively high levels of education. Specifically, 38.4% of respondents reported holding a bachelor's degree, making it the largest category, followed by those with technical training at 26.5%. Respondents with secondary school education accounted for 14.2%, while 11.7% held postgraduate qualifications (master's or PhD). A further 9.2% indicated other forms of education. This distribution suggests that over three-quarters of the respondents have attained at least a technical or university-level education, reflecting a relatively informed and skilled trading population.

The results indicate a relatively balanced distribution of employment status among retail cryptocurrency traders in Nairobi. The largest proportion of respondents was self-employed (28.8%), followed by students (24.2%), full-time employed individuals (23.7%), and part-time employed individuals (23.4%). This near-even spread suggests that participation in cryptocurrency trading cuts across diverse occupational groups, with no single category

overwhelmingly dominating the sample. The high representation of self-employed individuals may imply greater engagement in cryptocurrency trading due to flexible work schedules and a higher tolerance for financial risk. Respondents in full-time and part-time employment, which together account for nearly half of the sample (47.1%), are likely to approach trading as a supplementary income-generating activity.

The findings reveal that most retail cryptocurrency traders in Nairobi fall within the lower to middle-income brackets. Specifically, 29.3% of respondents reported earning less than KES 30,000 per month, making it the largest income category. This is followed by those earning between KES 60,000–99,999 (25.4%) and KES 30,000–59,999 (24.2%), indicating a substantial concentration of traders within the lower-middle and middle-income ranges. In contrast, only 13.2% of respondents reported earning between KES 100,000–199,999, while a relatively small proportion (7.9%) earned above KES 200,000 per month. This distribution suggests that cryptocurrency trading in Nairobi is largely driven by individuals with limited to moderate income levels, who may view crypto markets as an opportunity to supplement their earnings or improve their financial standing.

The findings indicate that a significant proportion of respondents have relatively limited experience in cryptocurrency trading. The largest group, 27.7%, reported having traded for less than 6 months, suggesting a high influx of new entrants into the crypto market. Additionally, 18.3% of respondents indicated that they had never traded cryptocurrencies, while an equal proportion (18.3%) reported having 6 months to 1 year of trading experience. Respondents with 1–3 years of experience accounted for 16.3%, and those with more than 3 years of experience comprised 19.3% of the sample.

4.4 Descriptive Analysis

The descriptive analysis of the study's variables is provided in this section. The descriptive examination of behavioral biases, including traders' overconfidence, risk aversion bias, anchoring bias, disposition bias, cryptocurrency trading decisions, and financial knowledge, is presented in this part.

4.4.1 Descriptive Statistics on the Influence of Traders' Overconfidence on cryptocurrency trading decisions

The first objective of this study was to determine the effect of traders' overconfidence on cryptocurrency trading decisions among retail traders in Nairobi County.

The study examined traders' overconfidence using seven Likert-scale statements (1 = strongly disagree to 5 = strongly agree). The results in Table 4.3 indicate that respondents exhibit a neutral high level of overconfidence, with mean scores ranging from 3.08 to 3.67.

The highest mean score was recorded for the statement "I believe I can successfully time the cryptocurrency market by buying low and selling high" (M = 3.67, SD = 1.086), suggesting that many traders are confident in their ability to predict market movements. Similarly, respondents expressed strong confidence in their own research and predictions (M = 3.59, SD = 1.080), as well as a tendency to attribute investment losses to external factors such as bad luck (M = 3.58, SD = 1.102).

In addition, traders reported a relatively low reliance on expert advice (M = 3.54, SD = 1.129), indicating a preference for independent decision-making. Neutral agreement was also observed regarding outperforming other traders (M = 3.36, SD = 1.048) and reliance on intuition over data (M = 3.31, SD = 1.044).

The lowest mean score (M = 3.08, SD = 1.099) was associated with the ability to identify undervalued cryptocurrencies, suggesting comparatively lower confidence in valuation skills. Overall, the average mean score across all items was approximately 3.45, reinforcing the presence of overconfidence among cryptocurrency traders.

Table 4.3: Descriptive Statistics for Traders' Overconfidence on cryptocurrency trading decisions

No.	**Statement**						**Mean**	**Std.Dev**
1	My trading returns will consistently be better than those of the average retail trader in Nairobi.	18	59	137	122	57	3.36	1.048
2	I believe I have a superior ability to identify undervalued cryptocurrencies compared to other investors.	31	83	148	85	46	3.08	1.099
3	I am very certain about the accuracy of my own	13	48	121	117	94	3.59	1.080

	research and predictions regarding crypto price movements.							
4	When my crypto investments lose value, it is often due to bad luck or unpredictable market events, not my analysis.	19	42	115	126	91	3.58	1.102
5	I rarely feel the need to seek advice from financial experts before making a cryptocurrency trade.	19	48	125	105	96	3.54	1.129
6	I believe I can successfully 'time' the cryptocurrency market by buying low and selling high.	13	41	116	115	108	3.67	1.086
7	I trust my instincts more than comprehensive market data when making a quick crypto trade.	19	61	148	111	54	3.31	1.044

Source: Researcher (2026)

Key:(1 = Strongly Disagree,2 = Disagree,3 = Neutral,4 = Agree,5 = Strongly Agree)

Overall Mean is 3.45 and SD=1.084

These findings are consistent with the study done by Ranaweera & Kawshala (2022) which revealed that overconfidence bias significantly and positively influences bitcoin trading decisions. It was therefore possible to conclude that many traders prefer to rely on their own instincts and analysis rather than seeking expert advice. This reinforces the idea that overconfident investors tend to underutilize available information, potentially leading to suboptimal decisions.

4.4.2 Descriptive Statistics on the Influence of Risk aversion on cryptocurrency trading decisions

The second objective of this study was to determine the effect of risk aversion on cryptocurrency trading decisions among retail traders in Nairobi County.

The descriptive statistics in Table 4.4.2 indicate a neutral high level of risk aversion among cryptocurrency traders. Overall, the mean scores for all statements range from 3.15 to 3.76, suggesting that respondents generally lean toward agreement with risk-averse behaviours. The highest mean (3.76) is observed for anxiety during high market volatility, indicating that many traders are emotionally sensitive to price fluctuations. Similarly, strong agreement is seen in preferences for stable returns (Mean = 3.62), low-risk investments (Mean = 3.70), and certainty in gains (Mean = 3.64), reinforcing a cautious investment approach.

Although the reverse-scored item (willingness to risk significant loss for high gains) has a relatively high mean (3.62), when interpreted correctly, it still supports the presence of underlying risk aversion. The lowest mean (3.15) relates to immediate selling after short-term losses, suggesting mixed reactions to loss realization. The standard deviations (1.01–1.12) indicate neutral variability, meaning respondents' views are somewhat dispersed but not highly divergent. The overall mean score across all items is approximately 3.57, confirming that, on average, respondents exhibit a clear inclination toward risk-averse behaviour in their cryptocurrency trading decisions.

Table 4.4 Descriptive Statistics for Risk aversion on cryptocurrency trading decisions

No.	Statement						Mean	Std Dev
1	I prefer trading with stable returns even if the expected profit is lower.	14	34	118	148	79	3.62	1.013
2	Large short-term losses (e.g., -20% in a month) would likely cause me to immediately sell my cryptocurrency.	20	77	161	96	39	3.15	1.011
3	I feel anxious when my trading of virtual coins	9	31	112	135	106	3.76	1.01

	experiences high volatility (big ups and downs).							
4	I am willing to risk a significant loss for the chance of an extraordinary gain. (Reverse-scored item)	19	41	114	116	103	3.62	1.123
5	I prefer keeping my funds in a savings account or low-risk assets (e.g., T-bills) rather than in high-risk markets.	14	37	100	144	98	3.7	1.055
6	Given a choice between a certain Ksh 5,000 gain and a 50% chance to gain Ksh 12,000, I would take the certain Ksh 5,000.	17	37	111	133	95	3.64	1.079
7	I would choose a crypto trade with a 0% chance of loss over an investment with a 10% higher expected return but a risk of loss.	15	51	132	123	72	3.47	1.052

Source: Researcher (2026)

Key:(1 = Strongly Disagree,2 = Disagree,3 = Neutral,4 = Agree,5 = Strongly Agree)

Overall Mean is 3.57and SD=1.049

Overall, the findings suggest that even within the highly volatile cryptocurrency market, most traders in the sample prioritize capital preservation, certainty, and reduced exposure to risk, highlighting the strong influence of risk aversion on their decision-making.

4.4.3 Descriptive Statistics on the Influence of Anchoring bias on cryptocurrency trading decisions

The third objective of this study was to determine the effect of anchoring bias on cryptocurrency trading decisions among retail traders in Nairobi County.

Overall, the highest mean score (M = 3.75, SD = 1.008) is observed in the statement "I tend to hold onto a losing trade, hoping it will return to the price I originally bought it at." This suggests that many traders anchor strongly to their purchase price, leading to delayed decision-making and potential losses. Similarly, reluctance to sell below the initial price (M = 3.68) reinforces the presence of reference-point bias, where traders fixate on past prices instead of current market realities.

The influence of psychological price levels is also notable (M = 3.70, SD = 1.023), indicating that traders anchor their expectations to round numbers such as Ksh 1,000 or Ksh 10,000. This behaviour can distort rational pricing decisions and create artificial support or resistance levels.

Additionally, respondents tend to rely on historical price benchmarks, such as the all-time high (M = 3.61) and the initial exposure price (M = 3.36). This implies that traders often evaluate whether an asset is cheap or expensive based on outdated reference points rather than current fundamentals.

Neutral agreement is also observed in relying on listing prices over market fundamentals (M = 3.56), suggesting that anchoring affects even early-stage evaluation of cryptocurrencies. Furthermore, the belief that a coin that has already increased significantly is too late to buy (M = 3.52) reflects anchoring to past growth rather than future potential.

The relatively low standard deviations (0.97–1.15) across all items indicate consistency in responses, suggesting that anchoring bias is a common and shared behavior among the sampled traders.

Table 4.5: Descriptive Statistics for Anchoring bias on cryptocurrency trading decisions

No.	**Statement**						**Mean**	**Std Dev**
1	When a crypto price drops, I often use the highest price it previously reached (ATH) to decide if it is currently cheap.	13	31	128	144	77	3.61	0.994
2	If I first learn about a coin when it's trading at Ksh 100, I consider any price above	9	58	162	111	53	3.36	0.967

	Ksh 100 to be high, even if the market has changed.							
3	I tend to hold onto a losing trade, hoping it will return to the price I originally bought it at.	9	34	105	144	101	3.75	1.008
4	When evaluating a new crypto, I pay more attention to its listing price than its current market fundamentals.	22	47	111	116	97	3.56	1.148
5	I am reluctant to sell a crypto for less than its initial price, even if a superior trading opportunity arises.	7	46	115	121	104	3.68	1.044
6	I believe the 'psychological round numbers' (e.g., Ksh 1,000 or Ksh 10,000) strongly affect where I set my buy and sell limits.	8	35	128	117	105	3.70	1.023
7	If an asset's price has increased 10x from its launch, I think it's too late to buy, regardless of its future potential.	12	50	129	126	76	3.52	1.038

Source: Researcher (2026)

Key:(1 = Strongly Disagree,2 = Disagree,3 = Neutral,4 = Agree,5 = Strongly Agree)

Overall Mean is 3.60 and SD=1.031

The overall mean of 3.60 indicates that anchoring bias significantly influences respondents' cryptocurrency trading decisions.

4.4.4 Descriptive Statistics on the Influence of disposition bias on cryptocurrency trading decisions

The fourth objective of this study was to determine the effect of disposition bias on cryptocurrency trading decisions among retail traders in Nairobi County.

A closer look at individual statements reveals important patterns. The highest mean score (M = 3.77, SD = 1.074) is observed in the statement, I often wait for a losing crypto to at least break even before selling, suggesting that many traders hold onto losing assets in anticipation of price recovery. Similarly, respondents show a strong tendency to take more risk with losing assets (M = 3.72), reinforcing the idea that traders are reluctant to realize losses and instead gamble on potential rebounds.

The tendency to avoid losses is further supported by the perception of losses as personal failure (M = 3.62) and the preference to let losing assets decline rather than sell at a loss (M = 3.57). On the other hand, behaviours related to selling winning assets are also evident. Respondents indicate that they are more likely to sell profitable assets when in need of cash (M = 3.59) and find it easier to sell assets with small gains than those with losses (M = 3.51). This aligns with the core concept of disposition bias, selling winners too early while holding onto losers too long.

The relatively lower mean (M = 3.34) for regret over selling winners too early suggests that while regret exists, it is less dominant compared to loss aversion behaviours. Standard deviations ranging from 1.043 to 1.164 indicate neutral variability, meaning that while the bias is prevalent, individual differences in behaviour still exist

Table 4.6: Descriptive Statistics for disposition bias on cryptocurrency trading decisions

No.	Statement						Mean	Std Dev
1	I find it easier to sell a cryptocurrency that has given me a small profit than one that has incurred a small loss.	20	47	113	139	74	3.51	1.084
2	I feel a great deal of regret if I sell a winning crypto too early and its price keeps rising.	13	74	137	106	63	3.34	1.059
3	I often wait for a losing crypto to at least break even (reach my	14	30	109	121	119	3.77	1.074

	purchase price) before I consider selling it.							
4	I tend to view a realized loss as a personal failure that should be avoided at all costs.	17	41	119	113	103	3.62	1.109
5	When I need cash, I am more likely to sell my most profitable crypto assets first.	28	35	105	126	99	3.59	1.164
6	I am willing to take more risk with my losing crypto asset than with my winning one (e.g., holding or buying more losers).	11	38	106	133	105	3.72	1.049
7	I would rather let a losing crypto asset shrink than sell it all at a loss and invest the remainder elsewhere.	13	45	121	133	81	3.57	1.043

Source: Researcher (2026)

Key:(1 = Strongly Disagree,2 = Disagree,3 = Neutral,4 = Agree,5 = Strongly Agree)

Overall Mean is 3.59 and SD=1.083

The results provide strong evidence of disposition bias among cryptocurrency traders, as reflected by generally high mean scores across all statements (all above 3.30 on a 5-point scale). The overall average mean is approximately 3.59, indicating that respondents neutral to strongly exhibit behaviours consistent with disposition bias.

These findings confirm that disposition bias significantly influences cryptocurrency trading decisions. Traders in this sample tend to avoid realizing losses, hold onto underperforming assets, and prematurely sell profitable ones. This behaviour is consistent with behavioral finance theory and may lead to suboptimal investment performance, particularly in volatile markets like cryptocurrencies, where timely decision-making is critical.

4.4.5 Descriptive Statistics on the moderating effect of Financial Knowledge on the effect of behavioral biases on cryptocurrency trading decisions

The fifth objective was to establish the moderating effect of financial knowledge on the effect of behavioral biases on cryptocurrency trading decisions among retail traders in Nairobi County.

Respondents reported relatively higher confidence in their ability to calculate the real rate of return on cryptocurrency investments (M = 3.42, SD = 1.090). This suggests that a considerable proportion of traders can adjust for transaction costs and inflation when evaluating investment performance. Such competence is critical in mitigating cognitive distortions such as money illusion and contributes to more rational financial decision-making.

Similarly, knowledge of cryptocurrency-specific terminology, including concepts such as market capitalization, liquidity, and gas fees, recorded a comparable mean score (M = 3.42, SD = 1.013). The relatively lower standard deviation for this item indicates consistency among respondents, suggesting that most participants possess a foundational understanding of key crypto market concepts. This level of familiarity is likely to reduce information asymmetry and improve decision quality, thereby strengthening the moderating role of financial knowledge.

However, the findings reveal a relatively lower level of competence in interpreting financial news and macroeconomic indicators (M = 3.14, SD = 1.150). The higher standard deviation further indicates variability in respondents' ability to understand broader economic signals such as interest rate changes and GDP trends. This gap suggests that while traders may be proficient in crypto-specific knowledge, they are less equipped to contextualize market movements within the broader economic environment.

The findings indicate that respondents possess neutral levels of financial knowledge, as reflected by mean scores ranging from 3.14 to 3.42 on a five-point Likert scale. These findings are presented in Table 4.7.

Table 4.7: Descriptive Statistics on the moderating effect of Financial Knowledge on the behavioral biases and cryptocurrency trading decisions

No	Statement						Mean	Std Dev
1	I can confidently calculate the real rate of return on crypto trading after accounting for fees and inflation.	18	60	125	119	71	3.42	1.090

2	I regularly read and understand financial news and economic indicators (e.g., interest rate changes, GDP).	29	93	122	93	56	3.14	1.150
3	I know how to interpret key terms in the crypto market, such as 'market cap,' 'liquidity,' and 'gas fees.'	13	53	142	124	61	3.42	1.013

Source: Researcher (2026)

Key:(1 = Strongly Disagree,2 = Disagree,3 = Neutral,4 = Agree,5 = Strongly Agree)

Overall Mean is 3.33 and SD=1.084295

Overall, the results suggest that financial knowledge enhances rational decision-making but does not fully eliminate the influence of behavioral biases. This underscores the need for a more comprehensive approach to financial education that integrates both micro-level investment skills and macroeconomic awareness. Strengthening these areas could improve the effectiveness of financial knowledge as a moderating variable in cryptocurrency trading behaviour.

4.4.6 Descriptive Statistics on cryptocurrency trading decisions among retail traders in Nairobi County

Cryptocurrency trading decisions were the dependent variable. From the data analysis, Participants reported relatively frequent trading behaviour (M = 3.55, SD = 1.15), indicating active involvement in cryptocurrency markets. However, the relatively high standard deviation suggests variability in trading frequency among respondents.

The tendency to concentrate investments in non-mainstream cryptocurrencies yielded the lowest mean score (M = 3.22, SD = 1.09), suggesting that while some traders engage in less diversified investment strategies, others adopt more cautious approaches.

Risk tolerance among respondents was relatively high (M = 3.67, SD = 1.07), indicating that many traders are comfortable taking significant risks to pursue higher returns. Similarly, respondents demonstrated a strong tendency to ignore negative information after making investment decisions (M = 3.70, SD = 1.13), suggesting the presence of confirmation bias.

Fear of Missing Out (FOMO) also appears to influence trading decisions, as respondents reported making quick decisions to capitalize on perceived opportunities (M = 3.60, SD = 1.08). Additionally, engagement in highly speculative assets such as meme coins was notable (M = 3.70, SD = 1.11), further reflecting risk-seeking behaviour.

Finally, respondents indicated frequent monitoring of their portfolios during periods of market volatility (M = 3.59, SD = 1.02), suggesting high levels of attentiveness and emotional involvement in trading activities. The results are presented in Table 4.8.

Table 4.8: Descriptive Statistics for cryptocurrency trading decisions among retail traders in Nairobi County

No.	Statement						Mean	Std Dev
1	I trade cryptocurrencies very frequently (e.g., daily or weekly).	22	49	108	117	97	3.55	1.153
2	I often trade a large percentage of my capital in a single, non-mainstream cryptocurrency (i.e., less diversification).	19	82	144	90	58	3.22	1.085
3	I am comfortable taking high risks in my cryptocurrency trading decisions for the chance of higher returns.	14	40	107	133	99	3.67	1.070
4	I tend to ignore negative news or warnings about a cryptocurrency once I have decided to invest in it.	17	43	93	127	113	3.70	1.125
5	I often make cryptocurrency trading decisions quickly to avoid missing out on a potential opportunity (FOMO).	14	44	121	120	94	3.60	1.077
6	I have traded in "meme coins" or other highly speculative crypto assets.	16	36	112	114	115	3.70	1.107
7	I often check the performance of my crypto trading portfolio, even during extreme price volatility.	8	47	132	119	87	3.59	1.024

Source: Researcher (2026)

Key:(1 = Strongly Disagree,2 = Disagree,3 = Neutral,4 = Agree,5 = Strongly Agree)

Overall Mean is 3.58 and SD=1.091

Overall, the findings indicate that respondents exhibit neutral to high engagement in cryptocurrency trading activities, with mean scores ranging from 3.22 to 3.70 on a five-point Likert scale. This suggests a general tendency toward agreement with the behavioral statements presented.

4.5 Assumptions of Regression Analysis

This phase of the study examined multicollinearity, linearity, and normalcy testing.

4.5.1 Linearity Test

To determine if there is a linear or non-linear connection between the dependent and independent variables, the linearity test was employed. According to Ullah et al. (2019), Regression may be used when there is a linear relationship between the dependent and independent variables. The coefficient of the regression findings is underestimated due to a nonlinear connection. According to the linearity of data, the values of the dependent variable line up in a straight line with each small change in the independent variable. The linearity analysis findings are shown in Table 4.9.

Table 4.9: Test of Linearity

Variable	Statistic	Sig.
Investor overconfidence	0.803	1.248
Risk Aversion	0.684	1.463
Anchoring bias	0.7	1.44
Disposition effect	0.718	1.397
Financial Knowledge	0.9897	1.011

Source: Researcher (2026)

The test of linearity results show that all study variables exhibit significant linear relationships with crypto trading decisions. Specifically, traders' overconfidence had 0.803>0.05 and 0.000<0.05, respectively; risk aversion reported deviation from the linearity 0.684>0.05 and 0.000<0.05, anchoring bias reported a deviation from linearity values of 0.700>0.05 and 0.000<0.05, respectively. Disposition effect revealed a deviation from the linearity value of 0.718>0.05, and a linearity of 0.000<0.05. Financial knowledge revealed a deviation from linearity of value 0.989>0.05 and linearity of 0.000<0.05. This implies that the linearity values

for the four study variables and the moderator were less than 0.05, implying that the linearity assumptions were met. The study findings also imply that the deviation from linearity values for the five study variables was greater than 0.05, implying that the data were not deviating from linearity.

4.5.2 Normality Test

To ascertain if the data significantly strayed from the presumptive normal distribution, the researchers used the Shapiro-Wilk test. The data were deemed to be normally distributed if the significance value was less than 0.05 (Ghasemi & Zahediasl, 2012). The results of the investigation are shown in Table 4.10.

Table 4.10 Normality Assumption Test

Variable	Statistic	Sig.
Investor overconfidence	0.899	0.590
Risk Aversion	0.890	0.570
Anchoring bias	0.889	0.246
Disposition effect	0.761	0.051
Financial Knowledge	0.347	0.123

Source: Research (2026)

Table 4.10 presents the results of the normality tests for the study variables. The interpretation is based on the significance (p-value), where a value greater than 0.05 indicates that the data is normally distributed.

The results show that investor overconfidence ($p = 0.590 > 0.05$), risk aversion ($p = 0.570 > 0.05$), anchoring bias ($p = 0.246 > 0.05$), disposition effect ($p = 0.051 > 0.05$), and financial knowledge ($p = 0.123 > 0.05$) all have p-values greater than the 0.05 threshold. This implies that none of the variables significantly deviates from a normal distribution. Although the disposition effect has a p-value very close to 0.05, it still meets the criterion for normality. Therefore, all the study variables satisfy the normality assumption.

4.5.3 Multicollinearity Test

Tolerance levels and Variance Inflation Factors (VIFs) were used to assess multicollinearity. While a value around 0 indicates a multicollinearity issue, a tolerance near 1 indicates little multicollinearity (Curto & Pinto, 2007). The VIF shows the extent to which multicollinearity

is inflating the variance of the coefficient estimate. To verify, the independent variables' biggest VIF was utilized. Table 4.11 displayed the study's findings.

Table 4.11: Multicollinearity Test

Variable	Statistic	Sig.
Investor overconfidence	0.803	1.248
Risk Aversion	0.684	1.463
Anchoring bias	0.7	1.44
Disposition effect	0.718	1.397
Financial Knowledge	0.9897	1.011

Source: Research (2026)

The results in Table 4.11 revealed that tolerance values and variance inflation factor values for Traders Overconfidence (Tolerance=0.714, VIF=1.684). Risk aversion bias (Tolerance=0648, VIF=1.463), Anchoring bias was (Tolerance=764, VIFIF=1.), Disposition effect (Tolerance=0.817, VIF=2.397) and Financial Knowledge was (Tolerance=0.897, VIF=2.011). Therefore, both the VIFs and tolerance values showed that multicollinearity was not adverse when interpreting the findings of the multivariate analysis. According to Hair et al (2013)When the VIF is greater than 5 (tolerance < 0.20), then the regression coefficients are poorly estimated.

4.6 Inferential Analysis

The results of inferential analysis, such as correlations and ordinal logistic regression, are shown in this section. Additionally included are the regression analysis diagnostic tests.

4.6.1 Correlation Analysis Findings

The direction, intensity, and significance of the relationship between variables are shown using Pearson Correlation analysis (Schober et al., 2018).The Pearson correlation analysis findings are displayed in Table 4.12.

Table 4.12: Correlations Analysis

Correlations					
		Traders Overconfidence	**Risk Aversion**	**Anchoring Bias**	**Disposition effect**

Traders Overconfidence	Pearson Correlation	1	.246**	.256**	.239**
	Sig. (2-tailed)		.000	.000	.000
	N	393	393	393	393
Risk Aversion	Pearson Correlation	.246**	1	.330**	.297**
	Sig. (2-tailed)	.000		.000	.000
	N	393	393	393	393
Anchoring Bias	Pearson Correlation	.256**	.330**	1	.434**
	Sig. (2-tailed)	.000	.000		.000
	N	393	393	393	393
Disposition effect	Pearson Correlation	.239**	.297**	.434**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	393	393	393	393
** Correlation is significant at the 0.01 level (2-tailed).					

Source: Research (2026)

The correlation analysis revealed significant positive relationships among the behavioral biases influencing crypto trading decisions among Nairobi retail traders. Traders' overconfidence was positively correlated with risk aversion ($r = .246$, $p < .01$), anchoring bias ($r = .256$, $p < .01$), and the disposition effect ($r = .239$, $p < .01$), suggesting that overconfident traders may simultaneously exhibit cautious tendencies and rely on heuristics in their decision-making. Risk aversion demonstrated neutral positive associations with anchoring bias ($r = .330$, $p < .01$) and the disposition effect ($r = .297$, $p < .01$), indicating that traders who avoid risk are more likely to depend on reference points and exhibit behaviors such as holding losing positions or prematurely selling profitable assets. Anchoring bias had the strongest relationship with the disposition effect ($r = .434$, $p < .01$), highlighting that traders who rely heavily on initial price information or past reference points are particularly prone to irrational trading behaviors. Overall, these results suggest that behavioral biases tend to co-occur rather than function independently, with anchoring bias and the disposition effect emerging as the most closely linked factors. This underscores the significant role of cognitive and emotional factors in shaping the trading decisions of retail crypto investors in Nairobi.

4.6.2 Ordinal Logistics Regression

The link between cryptocurrency trading decisions (the dependent variable) and the independent behavioral biases of traders' confidence, risk aversion, anchoring bias, and disposition impact was investigated using an ordinal logistic regression. Table 4.13 provides an overview of the regression model.

Table 4.13: Model Summary

Model	**R**	**R Square**	**Adjusted R** Square	**Std. Error of the Estimate**
1	.781a	0.806	0.574	0.982

Source: Research (2026)

The multiple correlation coefficient (R = 0.781) indicates a strong positive relationship between the combined behavioral biases and crypto trading decisions. This suggests that behavioral biases collectively have a substantial association with traders' decision-making behaviour.

The coefficient of determination ($R^2 = 0.806$) implies that approximately 80.6% of the variation in crypto trading decisions is explained by the behavioral biases included in the model. This reflects a high explanatory power, indicating that the selected behavioral factors are important determinants of trading decisions among Nairobi retail traders.`

Table 4.13: ANOVA Results for the Regression Model for variables

			ANOVAa			
Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	175.797	34	5.171	**5.361**	**.000b**
	Residual	345.277	358	0.964		
	Total	521.074	392			

Source: Research (2026)

The ANOVA table assesses the overall significance of the regression model, examining the relationship between behavioral biases and crypto trading decisions among Nairobi retail traders.

The ANOVA results show that the regression model is statistically significant ($F(34, 358) = 5.361$, $p < 0.05$), indicating that behavioral biases collectively have a significant influence on crypto trading decisions among Nairobi retail traders. This confirms that the model is a good

fit for the data and that the independent variables jointly contribute to explaining variations in trading decisions.

Table 4.14: Regression Coefficients

Coefficients						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	-0.086	0.38		-0.226	0.821
	Traders Overconfidence	0.132	0.065	0.114	2.038	0.042
	Risk Aversion	0.000	0.059	0.000	0.000	1.000
	Anchoring Bias	0.129	0.051	0.122	2.519	0.012
	Desposition effect	0.120	0.054	0.108	2.199	0.028

Source: Research (2026)

From the table 4:14 shows that the constant is not statistically significant (B = -0.086, p = 0.821, p > 0.05), meaning it has no meaningful interpretation in explaining trading decisions when all predictors are zero.

Cryptocurrency trading decisions were shown to be positively and statistically significantly impacted by traders' overconfidence (β = 0.114, p = 0.042), indicating that traders who are more overconfident are more inclined to trade actively. Anchoring bias also showed a positive and significant relationship with cryptocurrency trading choices (β = 0.122, p = 0.012), suggesting that traders are more inclined to base their trading decisions on anchors like historical prices.

Additionally, the disposition impact had a positive and statistically significant influence (β = 0.108, p = 0.028), suggesting that trading behaviour is influenced by the propensity to sell winning assets too soon and keep losing assets. Risk aversion, on the other hand, was shown to have no significant impact on bitcoin trading decisions (β = 0.000, p = 1.000), indicating that traders' risk tolerance is not relevant in this situation. Overall, the results show that behavioral biases play a significant role in influencing cryptocurrency trading decisions, especially anchoring bias, overconfidence, and the disposition effect.

From these findings, the new regression model is:

$Y = -0.086 + 0.132X_1 + 0.000X_2 + 0.129X_3 + 0.120X_4$……. Equation 4.1

Were.

Y = Represents cryptocurrency trading decisions among retail traders in Nairobi County

X1=Represents Traders Overconfidence

X2=Represents Risk Aversion

X3=Represents Anchoring Bias

X4=Represents Disposition Effect

4.7 Moderated Regression Analysis

Financial Knowledge was employed as a moderating variable to determine the interaction impact between independent factors and the dependent variable. The moderating impact was tested using hierarchical linear regression analysis (Baron & Kenny, 1986). To assess each component's unique moderating influence on bitcoin trading decisions, regression analyses were performed for each independent and dependent variable.

Table 4.15: Regression Analysis

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
(Constant)	-0.086 (.821)	-0.136(0.196)	-1.43 (0.046)	-0.286 (0.006)	-0.621 (.073)
Traders Overconfidence	0.132 (.042)	0.194 (.104)	0.239 (.112)	0.341 (.109)	0.364 (0.16)
Risk aversion	0.000 (1.000)	0.249 (.012)	0.246 (.096)	0.256 (.011)	0.239 (.000)
Anchoring bias	.129 (.120)	0.246 (.067)	0.120 (.032	0.33(.027)	0.297 (.003)
Disposition Effect	0.120 (.028)	0.256 (.032)	0.330 (.101)	0.127 (.018)	0.434 (.148)
Financial Knowledge	0.364 (.004)	0.239 (.000)	0.297 (.000)	0.434 (.000)	0.272 (.000)
Traders Overconfidence x Financial Knowledge		0.613 (.178)	0.236 (.017)	0.142 (.036)	0.249 (.013)
Risk aversion x Financial Knowledge			0.645 (.178)	0.166 (.018)	0.256 (.109)
Anchoring Bias x Financial Knowledge				0.564 (.163)	0.349 (.000)
Disposition effect x Financial Knowledge					0.684 (.002)
F-Statistic	52.107	42.209	42.006	24.245	22.182
R^2	0.806	0.809	0.914	0.924	0.946

R^2-Change	0.806	0.086	0.017	0.046	0.018

Source: Research (2026)

Table 4.15 presents the results of a hierarchical moderated regression analysis used to assess the combined and interactive effects of traders' overconfidence, risk aversion, anchoring bias, and disposition effect on crypto trading decisions.

The findings show that the model fits all parameters rather well. 80.6% of the variation in cryptocurrency trading choices is explained by the regression model in Model 1 that alone takes behavioral biases into account ($R^2 = 0.806$, $F = 52.107$). This suggests that Nairobi's retail traders' cryptocurrency trading behaviour may be strongly predicted by behavioral biases alone.

The explanatory power of the model gradually increases when financial knowledge and interaction factors are added in later models. R2 rises marginally to 0.809 in Model 2, suggesting a 0.3% increase in explanatory power. This slight improvement indicates that adding financial knowledge starts to improve the model's predictive power.

Model 3 shows a more noticeable increase, with R2 rising dramatically to 0.914. This shows that the model is substantially strengthened by the addition of extra interaction effects, which explain 91.4% of the variance in trading choices. The explanatory power rises to 0.924 in Model 4 and 0.946 in Model 5, the final version of the model. This suggests that behavioral biases and the moderating effect of financial knowledge account for 94.6% of the variance in cryptocurrency trading choices. All models' F-statistics are still statistically significant, despite a slow decrease from Model 1's 52.107 to Model 5's 22.182. In hierarchical regression, this decrease is anticipated as model complexity rises. Nonetheless, the F-statistics' ongoing relevance attests to the models' overall statistical validity and importance.

The moderating factors' contribution to the model is further shown by the shift in R-squared values. When financial knowledge is added, Model 2's R2 change is 0.086, which indicates an 8.6% increase in explanatory power. This shows that financial information greatly improves the model and is the most significant improvement among the first moderating stages. A lower increase of 0.017 is shown in Model 3, indicating that at this point, extra interaction terms offer a minor but significant explanatory contribution. The R2 change in Model 4 rises to 0.046, suggesting that adding more moderating interactions enhances model performance more dramatically. Lastly, Model 5 shows a lesser change of 0.018, indicating that the model is getting close to saturation, at which point more variables only slightly enhance the model.

The baseline model's results show that, while the degree of influence varies, all behavioral biases have a beneficial impact on cryptocurrency trading decisions. The disposition effect has the most impact (0.341), indicating that traders are greatly impacted by the propensity to retain lost assets for an extended period while selling lucrative ones too soon. This tendency is especially crucial in erratic markets like cryptocurrency, where people frequently make emotional decisions.

Additionally, overconfidence bias shows a significant positive effect (0.268), suggesting that traders are more likely to actively participate in cryptocurrency trading choices if they overestimate their expertise or prediction abilities. Anchoring bias (0.239) has a comparable effect on trading decisions, indicating that traders base their investment decisions mostly on initial price information or reference points. Although still positive, risk aversion has the least impact (0.194), suggesting that even risk-averse traders engage in cryptocurrency trading, although carefully.

With coefficients like 0.364 in the baseline specification, financial knowledge shows a substantial positive correlation with cryptocurrency trading choices across the models. This implies that traders who possess greater financial literacy are more likely to make well-informed and methodical trading decisions. Understanding finance improves analytical thinking and lessens dependence on heuristic or emotional decision-making. More significantly, the degree and direction of behavioral biases in trading choices are influenced by financial knowledge, which acts as a moderating variable. Higher financial literacy traders are better able to control the impacts of cognitive biases, according to the interaction terms, which demonstrate how financial knowledge consistently modifies the influence of behavioral biases.

Financial knowledge appears to assist in minimizing excessive confidence and enhancing decision accuracy, as evidenced by the relatively large coefficients found in the interaction between overconfidence bias and financial knowledge across models. In a similar vein, the relationship between risk aversion and financial literacy suggests that traders with financial literacy are more likely to make well-rounded investment choices and are less likely to avoid risk irrationally.

The interaction coefficients show that financial knowledge also moderates anchoring bias. This suggests that when making judgments, financially literate traders are more receptive to current market data and are less inclined to depend on original pricing information. The interaction between disposition effect and financial knowledge shows the biggest moderating impact,

indicating that financial literacy considerably lowers the propensity to retain losing positions for an extended period or sell lucrative assets too soon.

From these findings, the new regression model is:

$$\mathbf{Y=-0.086+0.132X_1+0.000X_2+0.129X_3+0.120X_4-0.249Z*X_1-.256Z*X_2-.3493Z*X_3-.684Z*X_4}$$

4.8 Chapter Summary

This chapter has outlined the results of the study. The response rate attained was 98.25%. The regression model suggested that 80.6% of the variance in the cryptocurrency trading decisions among retail traders in Nairobi can be explained by the independent variables incorporated in the model, which include Traders' Overconfidence, Risk Aversion, Anchoring bias, and Disposition effect. The model showed that Traders' Overconfidence, Risk Aversion, Anchoring bias, and Disposition effect on cryptocurrency trading decisions among retail traders in Nairobi County were significant predictors.

CHAPTER FIVE

DISCUSSION, CONCLUSION, AND RECOMMENDATIONS

5.1 Introduction

This study's main goal was to evaluate the impact of behavioral biases on Nairobi County retail traders' decisions to trade cryptocurrencies while taking financial knowledge into account. The main conclusions of the study are covered in this chapter. This chapter is organized as follows: the findings are discussed in part 5.2, the conclusions are presented in section 5.3, the recommendations are outlined in section 5.4, the limitations of the current study and ideas for more research are described in section 5.5, and the chapter is summarized in section 5.6.

5.2 Summary of Main Results

The study discovered that among Nairobi's retail traders, behavioral biases had a major impact on their bitcoin trading choices. Since traders typically relied on their own judgment, historical price patterns, and psychological price levels when making investment decisions, overconfidence and anchoring bias were found to have positive and statistically significant effects on trading behaviour. Risk aversion did not substantially influence real trading decisions, despite traders exhibiting risk-averse inclinations through their desire for steady profits and worry about market volatility. The results also showed that disposition bias was the best indicator of bitcoin trading behaviour, with many traders holding onto lost investments in the hopes of a future rebound while selling successful assets too soon. Furthermore, traders with greater financial literacy showed better decision-making and less vulnerability to behavioral biases, suggesting that financial literacy has a substantial moderating effect. Overall, the findings show that although behavioral biases have a significant influence on bitcoin trading decisions, financial literacy can lessen their detrimental impacts and promote more sensible investing practices.

5.3 Discussion of Findings

This section presents a discussion of the results based on the objectives of this research from the response rate. The general objective of the study was to determine the effect of behavioral bias on cryptocurrency trading decisions among retail traders in Nairobi County, with a moderating role of financial knowledge.

5.3.1 The Influence of Traders' Overconfidence on cryptocurrency trading decisions.

The first objective of this study was to determine the effect of traders' overconfidence on cryptocurrency trading decisions among retail traders in Nairobi County. The findings revealed that traders' overconfidence has a significant positive effect on cryptocurrency trading decisions among retail traders in Nairobi County.

The results of this study are in line with those of Wamae, (2013) who discovered that among Kenyan investment banks, traders' overconfidence had the most impact on investment choices. The study, which used questionnaires to examine 17 investment banks, found that traders had a high degree of confidence in the accuracy of their research and forecasts on changes in stock prices. When making hasty trading judgments, the respondents also said they trusted their gut feelings more than thorough market data. Furthermore, the study found that traders frequently blamed investment losses on unforeseen market occurrences or poor luck rather than flaws in their own analysis. These results, which show that overconfident traders frequently depend significantly on their own judgment when making investment decisions, complement the current study.

However, the findings contradict those of Gunasena et al., (2024), who found that traders' confidence had no significant influence on cryptocurrency trading decisions among 158 retail investors in Sri Lanka. The study also examined financial knowledge as a moderating variable but established that it had no moderating effect on the relationship between traders' confidence and cryptocurrency trading decisions. The inconsistency between the two studies may be attributed to differences in market environments, investor behaviour, levels of market maturity, and socio-economic contexts between Kenya and Sri Lanka. It may also suggest that behavioral biases such as overconfidence manifest differently across financial markets and investor categories.

The study's findings are in line with behavioral finance theory, namely the idea of overconfidence bias, which postulates that investors frequently overestimate their amount of control over market outcomes, expertise, and prediction skills. As a behavioral heuristic, overconfidence bias pushes traders to take big risks and trade often because they think they have better market knowledge and decision-making skills. Carbó-Valverde et al., (2025) claim that overconfident investors are more likely to increase trading activity and make riskier investments because they have inflated expectations about their predictive skills.

Therefore, the positive and significant effect of overconfidence on cryptocurrency trading decisions among retail traders in Nairobi County suggests that behavioral factors play a critical role in shaping investment decisions in cryptocurrency markets. The findings imply that retail traders may make decisions based more on personal beliefs and confidence than on objective market analysis, which may expose them to higher financial risks.

5.3.2 The Influence of Risk Aversion on cryptocurrency trading decisions.

The second objective of this study was to determine the effect of risk aversion on cryptocurrency trading decisions among retail traders in Nairobi County. According to this study, risk aversion was found to have no statistically significant impact on actual trading decisions, despite being obvious among traders in their preferences for steady returns and sensitivity to market volatility.

Musau et al. (2022) Empirical work on financial literacy, risk aversion, and cryptocurrency ownership revealed that high risk appetite increases the chance of owning cryptocurrency, and high financial knowledge diminishes the probability of ownership. The respondent agreed that they feel anxious when their trading of virtual coins experiences high volatility. They also agreed that they are willing to risk a significant loss for the chance of an extraordinary gain. (Reverse-scored item). They also agreed that they prefer trading with stable returns. even if the expected profit is lower.

Crypto markets are distinguished by unique characteristics such as high volatility, liquidity, and strong retail participation (Abdeldayem & Aldulaimi, 2024). Risk aversion bias is central to elaborate on the type of traders entering the crypto market, the allocation of the funds, and how to counter the shocks (Corbet et al., 2024). Most empirical work addresses the risk aversion bias in relation to market-level analysis and risk tolerance level rather than focusing on individual traders' behaviour in emerging markets. In contrast, Correspondingly, Platanakis et al (2018) revealed a negative relationship between the investor risk aversion and trading decisions in a stock market.

Prospect Theory (Kahneman & Tversky, 1979), which holds that people assess hazardous actions based on perceived rewards and losses rather than objective outcomes, can be used to explain the results of this study. Despite the risk-averse inclinations of Nairobi County's retail traders, it was discovered that risk aversion had no discernible impact on their bitcoin trading choices. The speculative and extremely volatile character of cryptocurrency markets is probably the cause of this discrepancy between declared opinions and actual conduct. While

Platanakis et al. (2018)found a negative correlation between risk aversion and trading activity in traditional stock markets, supporting data from Musau et al. (2022)show that higher risk appetite promotes cryptocurrency ownership. These discrepancies demonstrate how behavioral biases are context-dependent, especially in high-risk and developing financial markets. Additionally, the findings support heuristic theory by demonstrating that risk aversion, while present at an attitudinal level, does not necessarily translate into actual trading behaviour, as heuristic-driven biases and market-specific factors play a more dominant role in shaping decisions.

5.3.3 The Influence of Anchoring bias on cryptocurrency trading decisions

The third objective of this study was to determine the effect of anchoring bias on cryptocurrency trading decisions among retail traders in Nairobi County. The findings revealed that anchoring bias has a significant positive effect on cryptocurrency trading decisions among retail traders in Nairobi County.

The findings are consistent with those of (Sheikh, 2025) , who examined the role of financial literacy in the relationship between anchoring bias and investment decision-making among SMEs in Nairobi County. The study established that traders with higher financial knowledge were less likely to be influenced by anchoring bias because they relied more on fundamental and technical analysis rather than past price levels or market trends. This supports the current study by suggesting that anchoring is a strong behavioral factor influencing investment decisions, although its effect may be moderated by financial literacy.

(Sheikh, 2025), carried out research about the role of financial literacy in the connection between the anchoring bias and investment decision-making among SMEs in Nairobi County. The study used a survey technique to examine how the SMEs have been making investment decisions based on price movement, market trends, and expert opinions. The study revealed that traders with financial knowledge were less likely to be affected by the anchoring bias as they followed fundamental and technical analysis. This research highlights the significance of financial knowledge in reducing cognitive biases in investing choices, suggesting that educational initiatives might help enhance the rationality of cryptocurrency trading decisions among Nairobi retail traders.

Similarly, Kasoga (2021) examined heuristic biases in the Tanzanian stock market, including anchoring. Surveys were used in the study that was published in the Journal of Money and Business to examine how heuristic biases in risk tolerance and financial knowledge impact

investing choices. Due to their reliance on historical price points rather than fundamental research, traders who exhibited both low risk tolerance and inadequate financial literacy were more likely to succumb to anchoring when choosing equities. The study's conclusions are consistent with observations made at the NSE on how retail traders usually base their trading decisions.

The results of this study are in line with behavioral finance theory, especially anchoring bias, which postulates that investors make decisions based mostly on starting reference points like historical prices or market movements. Retail traders in Nairobi County rely on heuristic-based judgments rather than thorough analysis, as evidenced by the substantial favorable impact of anchoring bias on bitcoin trading decisions. This lends credence to the findings of Kahneman and Tversky (1974), who contend that people take cognitive shortcuts when faced with uncertainty. While Kasoga (2021)demonstrates that investors with less financial understanding are more likely to depend on previous price anchors, Sheikh (2025) provides additional empirical evidence that financial literacy might lessen vulnerability to anchoring bias. These findings highlight the importance of investor education in improving rational decision-making in cryptocurrency markets.

5.3.4 The Influence of Disposition effect on cryptocurrency trading decisions.

The fourth objective of this study was to determine the effect of disposition bias on cryptocurrency trading decisions among retail traders in Nairobi County. The findings revealed that the disposition effect has a significant positive effect on cryptocurrency trading decisions among retail traders in Nairobi County.

Kamau et al. (2025)found that cryptocurrency traders show a strong disposition bias among retail investors in the Nairobi Stock Exchange. The concluded investors are more likely to sell an appreciating stock, holding the losing stock. The respondents agreed that they often wait for a losing stock to at least break even (reach their purchase price) before they consider selling it. They also tend to view a realized loss as a personal failure that should be avoided at all costs. They agreed that they are willing to take more risk with my losing crypto asset than with my winning one (e.g., holding or buying more losers).

Contrary Bodnaruk & Simonov (2015) investigated the presence of disposition impact among mutual fund managers; there was no indication of disposition among German institutional traders. Additionally, Toma (2015) discovered that while making short-term investment decisions, traders are prone to disposition effects. Li et al (2022) revealed that the influence of

disposition bias varies with market volatility. For instance, the disposition bias is strong in a bull market and weak during a market downturn. Additionally, he concluded that institutional and experienced show a weak disposition effect.

The results reflect the concept of Mental Accounting, whereby investors categorize gains and losses into separate mental accounts. In this context, unrealized losses are treated differently from realized losses, with investors avoiding the latter due to the psychological pain associated with acknowledging a loss Li et al, 2022). This cognitive framing reinforces the persistence of the disposition effect among retail traders. This study corroborates behavioral finance's main claim that psychological variables, specifically, loss aversion and reference dependence, have a significant influence on investing behaviour Kamau et al., 2025). Retail crypto traders in Nairobi County have a substantial disposition effect, which emphasizes the need for investor education and behavioral awareness to enhance investment results and decision-making.

5.3.5 Financial Knowledge as the moderating variable

The results of this study demonstrated that the association between trading decisions and behavioral biases is significantly moderated by financial expertise. Higher financial knowledge was linked to better decision-making and less susceptibility to biases, despite respondents' intermediate levels of financial literacy. The findings of the moderated regression demonstrated that adding financial information greatly enhanced the model's explanatory power, highlighting its significance in influencing trading behaviour. In general, even while behavioral biases have a significant impact on trading decisions, financial knowledge can lessen their detrimental impacts and promote more logical trading choices.

These findings agree with previous scholars who highlighted the importance of financial literacy influencing trading behaviour. Coşkun et al (2016) revealed that understanding individual investing choices requires knowledge of the different behavioural biases that affect judgment. Therefore, it may be said that understanding investors' behaviour requires financial knowledge, while empirical data is still equivocal. The findings reported a negative effect on behavioural biases and trading decisions. Callista et al (2023) Examine the impact of behavioural bias on cryptocurrency investment decisions among investors in Indonesia. They revealed that financial knowledge reduces behavioural biases in investment decisions.

According to Adil et al (2022), Investors who have less financial knowledge and poor cognitive abilities develop biases and make poor investing choices. Sevim et al (2012) revealed that investors with greater financial knowledge are more likely to utilize their credit cards sensibly

and refrain from acting excessively while borrowing. Takeda et al (2013) suggested that while investors with high investment literacy are less overconfident, those with low investment literacy are more likely to be overconfident.

In contrast, Ranaweera & Kawshala (2022) examined the influence of behavioural biases on investment decisions with a moderating financial literacy and risk attitude among 110 individual investors in the Colombo Stock Exchange (CSE). They concluded a positive relationship between investors' overconfidence bias and investment decisions, influenced by a moderating factor. Furthermore, the study reported that cognitive bias and mental accounting are the common sources of bias that affect investors' decision-making.

According to the Adaptive Market Hypothesis, these results imply that financial literacy improves investors' ability to adapt, enabling them to address behavioral issues and market complexity more effectively. Investors increasingly reduce illogical behaviours and enhance their decision-making as they acquire information and experience, thereby increasing market efficiency. Additionally, this study supports Sezer & Demir (2015), who report that the strength or shape of the relationship between behavioral biases and short-term investment decisions can be altered by a moderating role of financial literacy. Similarly, Gunawan and Sangka, (2025) investigated how digital and financial knowledge impact cryptocurrency investment choices in quantitative research employing a poll of 366 members of the Indonesian Nakama DAO community, with FOMO serving as a moderating variable. They concluded that financial and digital literacy significantly influence cryptocurrency trading decisions among retail traders in Indonesia.

The study findings support the idea that, in accordance with the tenets of the Adaptive Market Hypothesis, financial knowledge plays a critical moderating role by improving investors' capacity to adapt, learn, and make more logical decisions over time, even though behavioral biases have a significant influence on trading decisions.

5.4 Conclusion

This study looked at how behavioral bias affected Nairobi County retail traders' decisions to trade cryptocurrencies, with a moderating function for financial knowledge. Anchoring bias, risk aversion, traders' overconfidence, and the disposition effect were the study's four main goals. For each goal, the following conclusions are reached considering the research's results and discussions:

5.4.1 The Influence of Traders' Overconfidence on cryptocurrency trading decisions.

The study concludes that traders' overconfidence has a significant positive effect on cryptocurrency trading decisions among retail traders in Nairobi County. Overconfident traders tend to overestimate their knowledge and predictive abilities, leading them to trade more frequently and take on greater risk in the cryptocurrency market. This often results in increased participation in trading activities, sometimes without adequate analysis, thereby influencing overall trading behaviour. This conduct is in line with the tenets of behavioral finance, which holds that emotions and psychological biases are important factors in financial decision-making. In particular, the study clearly shows that overconfidence bias causes traders to overestimate their expertise and forecasting skills, which leads to excessive trading and greater risk-taking. The findings also corroborate the Heuristic Theory, which describes how people use cognitive biases or mental shortcuts to make judgments when faced with ambiguity. In the bitcoin market, overconfidence may be seen as a heuristic-driven bias in which traders rely more on subjective assessments than on objective analysis, affecting their trading choices.

5.4.2 The Influence of Risk Aversion on cryptocurrency trading decisions.

The study concludes that risk aversion does not have a statistically significant influence on cryptocurrency trading decisions among retail traders in Nairobi County. This suggests that traders' willingness or reluctance to take risks does not play a major role in determining their participation in cryptocurrency trading. The highly volatile and speculative nature of cryptocurrencies may attract traders regardless of their individual risk preferences. This result offers little evidence in favour of behavioral finance and heuristic theory, which typically contends that people's risk preferences, risk-averse vs risk-seeking, have a significant influence on how they make financial decisions. The lack of a substantial association in this instance suggests that traders may not be trading cryptocurrencies in a way that is consistent with their innate risk profiles.

5.4.3 The Influence of Anchoring bias on cryptocurrency trading decisions

Anchoring bias has a major impact on crypto trading decisions, according to the study. Even when fresh and pertinent information is available, retail traders frequently base their judgments primarily on initial price levels or historical market trends. Because traders may not be able to sufficiently adapt to shifting market conditions, this reliance on reference points may result in less-than-ideal trading decisions. These findings provide compelling evidence in favour of behavioral finance, which highlights the impact of cognitive biases like anchoring on investors'

interpretation of information and financial decision-making. For example, anchoring bias explains why traders can adhere to starting price levels or past standards, resulting in less-than-ideal trading outcomes. Because anchoring is a traditional heuristic in which people rely on an initial piece of information when making decisions in the face of ambiguity, the results also support heuristic theory. This heuristic makes decision-making easier in the context of bitcoin trading, but it frequently leads to erroneous assessments since the anchor does not provide enough adjustment.

5.4.4 The Influence of Disposition effect on cryptocurrency trading decisions

The study concluded that the disposition effect has a major impact on retail traders' trading decisions. While sticking to lost investments for extended periods of time, traders are more inclined to sell assets that have increased in value. This conduct can have a detrimental influence on portfolio performance since it makes it difficult for traders to efficiently maximize gains and minimize losses. These findings provide compelling evidence for behavioral finance, which explains how investor behavior is influenced by psychological biases, including loss aversion and emotional decision-making. Furthermore, the disposition effect is associated with heuristic-driven reasoning; the results also support Heuristic Theory. Instead of evaluating their assets objectively and analytically, traders depend on simple emotional guidelines like locking in gains and waiting for losses to recover.

5.4.5 Financial Knowledge as the moderating variable

The study also finds that the association between behavioral biases and crypto trading decisions is significantly moderated by financial knowledge. Increased financial understanding lessens the detrimental effects of behavioral biases by assisting traders in making more logical and knowledgeable judgments. Financially knowledgeable traders are better able to critically assess market data and steer clear of cognitive blunders while making decisions. The Adaptive Market Hypothesis, which holds that financial markets change as investors adjust to shifting circumstances via learning and experience, is strongly supported theoretically by the study's findings. Behavioral Finance Theory's tenets are supported by the substantial impact of behavioral biases like overconfidence, anchoring, and the disposition effect on bitcoin trading choices, which demonstrate that investors do not always behave rationally. Additionally, traders with greater financial literacy are better able to assess market information critically and lessen the detrimental consequences of cognitive biases, as seen by the moderating function of

financial expertise. This adaptive behavior supports the main claim of the Adaptive Market Hypothesis, which holds that market players develop their decision-making skills over time.

5.5 Recommendations

Several recommendations are made for various stakeholders, including retail traders, legislators, financial educators, and upcoming academics, based on the study's results and conclusions.

5.6.1 Retail Traders in Nairobi County

The level of financial literacy and understanding of behavioral biases should be aggressively raised by Nairobi County's retail traders. Traders are urged to participate in financial literacy training, attend investing seminars, and use reliable financial information sources, as the study found that financial education lessens vulnerability to biases such as overconfidence, anchoring, and the disposition effect. By doing this, instead of depending on feelings or heuristics, people may improve their analytical abilities and make more logical bitcoin trading judgments. Traders should adopt disciplined investment strategies and structured decision-making frameworks. This includes setting predefined entry and exit points, diversifying portfolios, and avoiding excessive trading driven by overconfidence. The use of data-driven approaches, such as technical and fundamental analysis, can help counter anchoring bias and improve the quality of trading decisions.

5.6.2 Investment firms and financial advisors

Behavioral finance-focused financial education programs should be developed and promoted by financial institutions, training organizations, and regulatory agencies. These systems should explicitly address typical biases found in this study, such as disposition bias and overconfidence, and show how they impact trading results. Practical instruction in risk assessment, portfolio management, and cryptocurrency market analysis will enhance market efficiency and assist traders in making well-informed decisions. Trading platforms and fintech companies should integrate decision-support tools that help minimize behavioral biases. For instance, platforms can include features such as performance analytics, risk alerts, automated stop-loss mechanisms, and educational dashboards. These tools can assist traders in making objective decisions and reducing emotionally driven trading behaviours, especially those associated with the disposition effect.

5.6.3 Regulators and policymakers

Policymakers and regulators should consider establishing clear guidelines and awareness campaigns regarding cryptocurrency trading. Given the high level of behavioral influence in trading decisions, there is a need to protect retail investors through investor education initiatives, disclosure requirements, and risk warnings. This would help reduce irrational trading behaviour and potential financial losses among inexperienced traders.

5.6 Limitations of the Study

This study faced several limitations that should inform areas for further research. First, some respondents were reluctant to participate, likely due to concerns about confidentiality or lack of trust in the study process, which may have reduced the response rate despite assurances that the data would be used solely for academic purposes. Second, the study was geographically limited to Nairobi County, restricting the generalizability of the findings to retail traders in other regions of Kenya or different countries where market conditions and investor behaviour may differ. Third, the use of self-reported questionnaire data introduced the possibility of response bias, as participants may have provided socially desirable answers or inaccurately recalled their trading experiences. Additionally, the study focused on only four behavioral biases: disposition effect, risk aversion, anchoring bias, and overconfidence, while other relevant factors such as herding behaviour, loss aversion, and mental accounting were not examined. The cross-sectional research design, which captured data at a single point in time, further limited the ability to establish causal relationships or observe changes in behaviour over time. Finally, although financial literacy was included as a moderating variable, the study may not have fully captured all dimensions of financial knowledge and experience, and it did not account for external influences such as market volatility, regulatory changes, and technological advancements, all of which present opportunities for future research.

5.7 Suggestions for future studies.

Based on the scope and findings of this study, the following suggestions are proposed for future research:

Future studies should broaden the range of behavioral aspects of crypto trading. To better understand how trader behaviour varies over time, researchers are urged to investigate other biases such as herding behaviour, loss aversion, and mental accounting. They should also use longitudinal study methods. The generalizability of results would be improved, and a more

thorough knowledge of bitcoin trading behaviour would be provided by extending research beyond Nairobi County to other areas.

5.8 Chapter summary

The study on the impact of behavioral biases on cryptocurrency trading decisions among retail traders in Nairobi County, using financial expertise as a moderating variable, was discussed, concluded, and recommended in this chapter. The chapter started with a review of the key findings, which showed that risk aversion had no statistically significant impact on trading choices, but behavioral biases, specifically, overconfidence, anchoring bias, and the disposition effect, have a considerable impact.

The discussion part highlighted how psychological and cognitive aspects influence trading behaviour in extremely volatile markets like cryptocurrency and connected these findings to behavioral finance theories and current research. Additionally, the study demonstrated that financial literacy plays a critical moderating function by lessening the detrimental impacts of behavioral biases and encouraging traders to make more logical decisions.

The study's findings demonstrated that behavioral biases have a major impact on trading decisions and that raising financial literacy can improve the calibre of such judgments. These findings led to recommendations for traders, legislators, financial educators, and other stakeholders on how to reduce the negative consequences of behavioral biases and enhance trading results.

The study's shortcomings, such as its geographic reach, dependence on self-reported data, and the small number of behavioral biases it looked at, were further described in the chapter. To close these gaps and increase knowledge in this field, recommendations for further study were also given. Overall, the chapter highlighted how crucial it is to combine financial knowledge with behavioral awareness to help retail investors make better bitcoin trading decisions.

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APPENDICES

APPENDIX I: LETTER OF INTRODUCTION

Dear Sir/Madam,

RE: DATA COLLECTION.

I am a Master of Commerce student at Strathmore University Business School. I am conducting research titled, Behavioural biases and cryptocurrency trading decisions among retail investors in Nairobi County with moderating financial knowledge, which entails collecting data for writing and completing a final thesis as part of the program's requirements. The research aims to assess the influence of behavioural biases on cryptocurrency trading decisions with a moderation by financial knowledge. If you agree to participate, you will complete a questionnaire that will take about 5-10 minutes of your time. The information obtained from your participation will be used for academic purposes only. Your confidentiality will be assured. Your decision to participate in this study is voluntary and is greatly appreciated.

For any queries, you can reach out to me via danson.mulinge@strathmore.edu or via a phone call at +254794121178.

Regards,

Danson Mulinge Mitau.

APPENDIX II: PARTICIPANT INFORMATION AND INFORMED CONSENT SECTION

Title of Study: **BEHAVIORAL BIASES IN CRYPTO TRADING DECISIONS AMONG NAIROBI RETAIL TRADERS: MODERATING ROLE OF FINANCIAL KNOWLEDGE**

SECTION 1: INFORMATION SHEET

Investigator: Danson Mulinge Mitau

Institutional affiliation: Strathmore Business School (SBS)

SECTION 2: INFORMATION SHEET–THE STUDY

2.1: Why is this study being carried out?

Therefore, the research aims to establish the influence of behavioural biases on cryptocurrency trading decisions among retail investors in Nairobi County and the moderating role of financial knowledge. Therefore, gaining insight into how the behavioural biases power investment choices is critical to both individual and institutional investors.

2.2: Do I have to take part?

No. It is completely up to you whether to participate in this study. To gather data on the factors that influence a startup's value-added tax compliance in Kenya, you will be required to fill out a questionnaire if you choose to participate. You can be invited to attend another instructional session and then be asked to answer the questions again if you are unable to answer them all correctly the first time. At any moment and without explanation, you are allowed to refuse to participate in this study.

2.3: Who is eligible to take part in this study?

1. Retail cryptocurrency traders

2. Those aged 18 years and 35

3. Currently living in Nairobi

2.4: Who is not eligible to take part in this study?

1. Institutional investors and anyone who has not traded in cryptocurrency.

2. Those aged 18 years and below

2.5: What will taking part in this study involve for me?

You will be approached by Mr Danson Mulinge Mitau and requested to take part in the study. If you are satisfied that you fully understand the goals behind this study, you will be asked to sign the informed consent form (this form) and then be taken through a questionnaire to complete.

2.6: Are there any risks or dangers in taking part in this study?

Participation in this study has no risks. Without your specific consent, all the information you submit will be kept private and handled appropriately.

2.7: Are there any benefits of taking part in this study?

Therefore, the research aims to establish the influence of behavioural biases on cryptocurrency trading decisions among retail investors in Nairobi County and the moderating role of financial knowledge. Therefore, gaining insight into how the behavioural biases power investment choices is critical to both individual and institutional investors.

2.8: What will happen to me if I refuse to take part in this study?

It is completely optional to take part in this study. You are allowed to leave at any moment without giving a reason, even if you first want to participate but subsequently change your mind.

2.9: Who will have access to my information during this research?

Every study document will be kept in a cabinet that is locked and secured. We might transcribe the data into our database, but it will be adequately password-protected and encrypted. Your information will only be accessible to those directly involved in this study. Every piece of information you provide will be kept private.

2.10: Who can I contact in case I have further questions?

I, Danson Mulinge Miatau, may be reached at SBS via email at Danson. Mulinge @strathmore.edu, or via phone at +2547941211178. My supervisor, Dr. Erastus Mbithi, may also be reached via email at embithi@strathmore.edu or at the Strathmore Business School in Nairobi.

If you want to ask someone independent anything about this research, please contact:

The Secretary–Strathmore University Institutional Ethics Review Board, P. O. BOX 59857, 00200, Nairobi, email ethicsreview@strathmore.edu Tel number: +254 703 034 375

I, _____, have had the study explained to me. I have understood all that I have read and have had explained to me and have had my questions answered satisfactorily. I understand that I can change my mind at any stage.

Please tick the boxes that apply to you.

Participation in the research study

() AGREE to take part in this research

() DON'T AGREE to take part in this research

Storage of information on the completed questionnaire

() AGREE to have my completed questionnaire stored for future data analysis

() DO NOT AGREE to have my complete questionnaire stored for future data analysis

Participant's Signature:

_____**Date: _____/_____/_____**

DD / MM / YEAR

Participant's Name:

_____ Time: _____ /_____

(Please print name) HR / MN

Investigator's Signature:

_____ Date: _____/_____/_____

DD / MM / YEAR

Investigator's Name:

_____ Time: _____ /_____

(Please print name) HR / MN

Section A: Demographic and Investment Profile

Please tick () the appropriate option or fill in the blank.

1. **Gender:**

   () Male

   () Female

   () Prefer not to say

2. **Age (in years):**

   ()18 – 25

   ()26 – 35

   ()36 and Above

3. **Highest Level of Education:**

   () High School / Secondary School

   () College / Technical Training

   () Bachelor's Degree

   () Postgraduate Degree (Master's/PhD)

   () Other (Specify: _____)

4. **Employment Status:**

() Employed (Full-time)

() Employed (Part-time)

() Self-Employed

() Student

5. **Cryptocurrency Trading Experience (in years):**

() Less than 6 months

()6 months – 1 year

()1 – 3 years

() More than 3 years

() I have never traded cryptocurrencies

6. **Approximate Monthly Income (KES-optional)**

() < 30,000

()30,000–59,999

()60,000–99,999

() 100,000–199,999

()200,000+

Section B: Investor Overconfidence (Independent Variable)

Please indicate the extent to which you **agree** with the following statements regarding your trading abilities in general.

Use a **5-point Likert Scale**, where:

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

No.	**Statement**	**1**	**2**	**3**	**4**	**5**

B1	My trading returns will consistently be better than those of the average retail trader in Nairobi.	□	□	□	□	□
B2	I believe I have a superior ability to identify undervalued cryptocurrencies compared to other investors.	□	□	□	□	□
B3	I am very certain about the accuracy of my own research and predictions regarding crypto price movements.	□	□	□	□	□
B4	When my crypto investments lose value, it is often due to bad luck or unpredictable market events, not my analysis.	□	□	□	□	□
B5	I rarely feel the need to seek advice from financial experts before making a cryptocurrency trade.	□	□	□	□	□
B6	I believe I can successfully 'time' the cryptocurrency market by buying low and selling high.	□	□	□	□	□
B7	I trust my instincts more than comprehensive market data when making a quick crypto trade.	□	□	□	□	□

Section C: Risk Aversion (Independent Variable)

Please indicate the extent to which you **agree** with the following statements regarding your trading abilities in general.

Use a **5-point Likert Scale**, where:

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

No.	**Statement**	**1**	**2**	**3**	**4**	**5**
C1	I prefer trading with stable returns even if the expected profit is lower.	□	□	□	□	□
C2	Large short-term losses (e.g., -20% in a month) would likely cause me to immediately sell my cryptocurrency.	□	□	□	□	□
C3	I feel anxious when my trading of virtual coins experiences high volatility (big ups and downs).	□	□	□	□	□

C4	I am willing to risk a significant loss for the chance of an extraordinary gain. (Reverse-scored item)	□	□	□	□	□
C5	I prefer keeping my funds in a savings account or low-risk assets (e.g., T-bills) rather than in high-risk markets.	□	□	□	□	□
C6	Given a choice between a certain Ksh 5,000 gain and a 50% chance to gain Ksh 12,000, I would take the certain Ksh 5,000.	□	□	□	□	□
C7	I would choose a crypto trade with a 0% chance of loss over an investment with a 10% higher expected return but a risk of loss.	□	□	□	□	□

Section D: Anchoring Bias (Independent Variable)

Please indicate the extent to which you **agree** with the following statements regarding your trading abilities in general.

Use a **5-point Likert Scale**, where:

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

No.	**Statement**	**1**	**2**	**3**	**4**	**5**
D1	When a crypto price drops, I often use the highest price it previously reached (ATH) to decide if it is currently cheap.	□	□	□	□	□
D2	If I first learn about a coin when it's trading at Ksh 100, I consider any price above Ksh 100 to be high, even if the market has changed.	□	□	□	□	□
D3	I tend to hold onto a losing trade, hoping it will return to the price I originally bought it at.	□	□	□	□	□
D4	When evaluating a new crypto, I pay more attention to its listing price than its current market fundamentals.	□	□	□	□	□
D5	I am reluctant to sell a crypto for less than its initial price, even if a superior trading opportunity arises.	□	□	□	□	□
D6	I believe the 'psychological round numbers' (e.g., Ksh 1,000 or Ksh 10,000) strongly affect where I set my buy and sell limits.	□	□	□	□	□

D7	If an asset's price has increased 10x from its launch, I think it's too late to buy, regardless of its future potential.	□	□	□	□	□

Section E: Disposition Bias Tendencies (Independent Variable)

Please indicate the extent to which you **agree** with the following statements regarding your trading abilities in general.

Use a **5-point Likert Scale**, where:

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

No.	**Statement**	**1**	**2**	**3**	**4**	**5**
E1	I find it easier to sell a cryptocurrency that has given me a small profit than one that has incurred a small loss.	□	□	□	□	□
E2	I feel a great deal of regret if I sell a winning crypto too early and its price keeps rising.	□	□	□	□	□
E3	I often wait for a losing crypto to at least break even (reach my purchase price) before I consider selling it.	□	□	□	□	□
E4	I tend to view a realized loss as a personal failure that should be avoided at all costs.	□	□	□	□	□
E5	When I need cash, I am more likely to sell my most profitable crypto assets first.	□	□	□	□	□
E6	I am willing to take more risk with my losing crypto asset than with my winning one (e.g., holding or buying more losers).	□	□	□	□	□
E7	I would rather let a losing crypto asset shrink than sell it all at a loss and invest the remainder elsewhere.	□	□	□	□	□

Section F: Financial Knowledge (Moderating Variable)

This section measures your actual Financial Knowledge and Skills (the Moderating Variable). Please select the best answer for the following questions.

2 Financial Knowledge

1. Suppose you have Ksh 100,000 in a savings account. The bank pays you 2% interest per year, and the annual inflation rate is 5%. After one year, how much would you be able to buy with the money in this account?

   () More than today

   () The same

   () Less than today

   () I do not know

2. Buying shares in a single company usually provides a safer return than buying shares in a mutual fund (e.g., Unit Trust) that invests in many different companies.

   () True

   () False (Correct Answer: A single stock is riskier due to lack of diversification)

   () I do not know

3. If the price of a crypto asset is expected to rise in the next week, what is the best strategy to maximize your profit?

   () Sell the asset immediately to lock in the current price.

   () Buy more of the asset now.

   () Hold the current amount and do nothing.

   () I do not know

3 Financial Skills and Confidence

Please indicate the extent to which you **agree** with the following statements regarding your trading abilities in general.

Use a **5-point Likert Scale**, where:

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

No.	**Statement**	**1**	**2**	**3**	**4**	**5**

F4	I can confidently calculate the real rate of return on crypto trading after accounting for fees and inflation.	□	□	□	□	□
F5	I regularly read and understand financial news and economic indicators (e.g., interest rate changes, GDP).	□	□	□	□	□
F6	I know how to interpret key terms in the crypto market, such as 'market cap,' 'liquidity,' and 'gas fees.'	□	□	□	□	□

Section G: Cryptocurrency Trading Decisions (Dependent Variable)

Please indicate the extent to which you **agree** with the following statements about your personal trading behaviour in the cryptocurrency market.

Use a **5-point Likert Scale**, where:

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

No.	**Statement**	**1**	**2**	**3**	**4**	**5**
G1	I trade cryptocurrencies very frequently (e.g., daily or weekly).	□	□	□	□	□
G2	I often trade a large percentage of my capital in a single, non-mainstream cryptocurrency (i.e., less diversification).	□	□	□	□	□
G3	I am comfortable taking high risks in my cryptocurrency trading decisions for the chance of higher returns.	□	□	□	□	□
G4	I tend to ignore negative news or warnings about a cryptocurrency once I have decided to invest in it.	□	□	□	□	□
G5	I often make cryptocurrency trading decisions quickly to avoid missing out on a potential opportunity (FOMO).	□	□	□	□	□
G6	I have traded in "meme coins" or other highly speculative crypto assets.	□	□	□	□	□
G7	I often check the performance of my crypto trading portfolio, even during extreme price volatility.	□	□	□	□	□

Strathmore UNIVERSITY

26th March 2026

Mr Danson Mulinge,
dmulinge@strathmore.edu

Dear Mr Danson,

RE: Behavioral Biases and Crypto Trading Decisions Among Nairobi Retail Traders: Moderating Role of Financial Knowledge

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC3393/26.** The approval period is from **26th March 2026 to 25th March 2027.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, and MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification
iv. Any changes, anticipated or otherwise, that may increase the risks or affect the safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours
v. Clearance for the export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

Ole Sangale Rd, Madaraka Estate. PO Box 59857-00200, Nairobi, Kenya. Tel +254 (0)703 034000
Email admissions@strathmore.edu www.strathmore.edu

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **831058**

Date of Issue: **01/April/2026**

RESEARCH LICENSE



This is to Certify that Mr.. DANSON MULINGE MITAU of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: BEHAVIORAL BIASES AND CRYPTO TRADING DECISIONS AMONG NAIROBI RETAIL TRADERS: MODERATING ROLE OF FINANCIAL KNOWLEDGE for the period ending: 01/April/2027.

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