

The influence of behavioural biases on cryptocurrency adoption in South Africa

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Abstract

South Africa's investment landscape is being reshaped by fintech and decentralised finance, pressuring traditional financial institutions and accelerating retail interest in cryptocurrency. This makes it vital to understand the behavioural drivers behind adoption in an emerging market context. This study addresses a local research gap on how behavioural biases and financial literacy shape cryptocurrency adoption, and whether effects differ by age.

The objective is to test whether herding, disposition effect, overconfidence, loss aversion and heuristics influence cryptocurrency adoption, and whether financial literacy moderates these relationships; a secondary objective tests life-stage (age) differences. A positivist, quantitative, cross-sectional design was used, which gathered responses through an online survey. Structural equation modelling and a one-way ANOVA were employed to understand the direction, strengths and significance of the relationships.

Key findings indicate that herding and heuristics positively and significantly predict adoption. Disposition, loss aversion and overconfidence are not significant, while financial literacy shows no significant moderating effects. Age-group ANOVAs reveal no significant differences across behavioural factors or adoption. The implication is that South African investment platforms and institutions should anticipate socially driven and heuristic decision-making, embed pre-emptive nudges, simplify journeys, and target education where it reduces bias while recognising that age alone does not segment behaviour in this market.

Keywords

cryptocurrency, life-stage, herding, heuristics

Plagiarism Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other university. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

3 November 2025

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Chapter 1: Introduction

1.1. Research Problem

The competitive pressures and rapid rise of alternative fintech (financial technology) investment platforms have increased the strain on the traditional investment industry (Murinde et al., 2022). Over the last decade, cryptocurrency has emerged as a new investment asset class that has garnered significant interest. However, the reason for this behaviour is not well documented in emerging countries (Saiedi et al., 2020). In South Africa, there is limited research examining behavioural factors that influence the adoption of cryptocurrency, even as its popularity grows as a payment option and as an alternative asset (Cai & Zhao, 2023; Matsepe & Van der Lingen, 2022; Mofokeng et al., 2024). In addition, as this is a new asset class underpinned by new technology, education is key to its understanding and crucial for adoption, particularly in navigating the associated risks and opportunities (Banker et al., 2023; Islam et al., 2023). Furthermore, whether there are differences in age groups for the various behavioural biases, such as herd behaviour, overconfidence, fear of missing out, loss aversion, heuristics and disposition effects, remains under-researched regarding cryptocurrency adoption among South Africans (Ballis & Verousis, 2022; Fahlin & Gustafsson, 2024; Raut, 2020).

This study aims to bridge this knowledge gap by investigating the specific behavioural drivers underpinning cryptocurrency adoption in the South African context, whether financial literacy moderates these factors, and whether there are differences across age groups in cryptocurrency adoption.

With over 650 million people invested globally and a market capitalisation of over \$3.5 trillion, cryptocurrency is an asset class that has been gaining prominence among mainstream finance (CoinGecko, n.d.; Sergio & Wedemeier, 2025). Platforms such as Easy Equities, Luno, VALR, MetaMask, eToro, Robinhood and Polygon have reduced the barriers to alternative investments and payments such as cryptocurrency and attract professional and non-professional investors alike (Mattke et al., 2020). Blockchain and cryptocurrency enable faster and cheaper payment and remittance options for individuals and businesses seeking to bypass traditional banking fees and delays, thereby enhancing financial services and improving the ease of doing business (Jetha 2023; Mavilia & Pisani, 2019; Palmié et al., 2019). However, these inclusionary benefits are putting strain on the

traditional financial sector, prompting regulators to reassess compliance frameworks, risk management practices and financial institutions to reconsider their growth and acquisition strategies.

The launch of a Bitcoin Exchange Traded Fund by BlockRock, the world's largest asset manager, at the start of 2024 marked a significant event, achieving the most successful ETF launch in history, with over \$45 billion in assets under management within 12 months and \$88 billion by September 2025. The subsequent approval of 10 other Bitcoin ETFs by the Securities and Exchange Commission in the United States of America has heightened public awareness and may increase adoption pressures in South Africa, where institutional endorsement is still developing. Despite this “The 2024 Geography of Crypto Report” by Chainalysis, indicates that South Africa received between \$20 billion and \$30 billion in cryptocurrency, suggesting substantial inflows that necessitate an examination of how behavioural biases, including fear of missing out, herd behaviour and risk tolerance, shape South African investors' decisions regarding cryptocurrency adoption (Gerrans et al., 2023; Chainalysis, 2024; Rzaev et al., 2024).

Fintech platforms have the power to disintermediate the traditional banking system and pose a threat to the way people invest and bank due to agility and lower cost-to-income ratios (Broby, 2021; Elsaid, 2021). This shift necessitates a thorough examination of consumer behaviour in emerging markets such as South Africa, where cryptocurrency awareness, acceptance and adoption are influenced by unique factors which can vary depending on where people are in their life stages and level of education (Shahzad et al., 2024).

1.2. Theoretical Contribution

The theoretical problem is that previous studies do not provide a comprehensive understanding of the behavioural factors or perceptions driving cryptocurrency adoption among South African investors, nor whether life stage and financial literacy impact these decisions (Almansour, 2020; Mata et al., 2011; Nyakurukwa & Seetharam, 2022; Sergio & Wedemeier, 2025). This limits the ability of financial institutions and policymakers to effectively engage with and regulate this emerging asset class. There is limited research on emerging markets that employ a behavioural theoretical framework overlaying cryptocurrency adoption, especially in a diverse country like South Africa with its socio-economic challenges.

The study is underpinned by Behavioural Finance Theory, which posits that psychological factors significantly influence investor decision-making processes (Bhilawadikar & Garg, 2020; Jankeeparsad & Tewari, 2022). Specifically, this framework acknowledges that individuals often deviate from purely rational economic behaviour due to cognitive biases and emotional heuristics, which are particularly relevant in volatile and speculative markets such as cryptocurrency (Bui & Sällberg, 2022; Hackethal et al., 2021).

This study investigates the behavioural factors influencing South African adults' adoption of cryptocurrencies and whether financial literacy serves as a mediator, in addition, determining if this differs across age groups. This provides valuable insights for the financial sector, including banks and investment institutions, as they assess the competitive threat posed by this asset class. The emergence of cryptocurrencies represents a significant departure from traditional, centralised and heavily regulated financial systems, presenting both opportunities and challenges for investors, regulators and existing financial institutions (Kumar et al., 2022).

The study's findings will extend the existing literature on the application of Behavioural Finance Theory in finance, technology and investments by examining emerging market trends in cryptocurrency adoption by South Africans. It will also highlight South Africa's specific socio-demographic and behavioural influences, focusing on factors driving cryptocurrency adoption to develop more client-centric solutions. The research aims to determine the significance of these factors on cryptocurrency adoption and whether financial literacy moderates their effect.

Financial literacy is crucial for investors, particularly in the volatile cryptocurrency market and South African demographic landscape, as it is meant to enable informed decision-making and help understand the inherent risks involved. However, previous research indicates a gap in understanding how financial literacy specifically interacts with behavioural biases in the context of cryptocurrency adoption in South Africa (Adil et al., 2021; Walton & Johnston, 2018).

1.3. Business Contribution

The surge of fintech and blockchain technology has rapidly altered the financial landscape, driven by factors such as the sharing economy, evolving regulations and advancements in information technology (Suryono et al., 2020). Start-ups and fintechs are

capitalising on these advancements and entering the financial services sector, using business models that focus on payments, lending, investing, insurance and security, all of which are threatening the traditional financial institutions and making consumers question the value that these institutions add (Elsaid, 2021; Sergio & Wedemeier, 2025; Suryono et al., 2020). Consequently, South African banks must redesign their service models, risk frameworks and strategy to retain relevance in an ecosystem increasingly shaped by decentralised finance (Moyo, 2018).

The increase in financial inclusion is important for addressing South Africa's financial challenges, but innovative financial technology is a key driver of it (Baker et al., 2018; Telukdarie & Mungar, 2023). This is evident in the growth of companies such as Luno, VALR and Ovex, which are cryptocurrency exchanges with over 15 million clients globally.

To remain competitive, financial institutions must adapt to the evolving expectations of technology-savvy consumers and develop a deeper understanding of the behavioural factors influencing decision-making across age groups. Investors increasingly prioritise seamless, intuitive and easily accessible financial solutions (Neves et al., 2023). This highlights the imperative for established financial South African entities to integrate technological advancements and behavioural insights into their strategic frameworks to retain market share and relevance, and to obtain a first-mover advantage on the global stage (Mazambani & Mutambara, 2019). Furthermore, the democratisation of financial markets through online platforms, as seen with apps like Easy Equities in South Africa, has lowered entry barriers, but simultaneously amplified the need for enhanced financial literacy among retail investors to navigate increasingly complex financial products and inherent risks (Nyakurukwa & Seetharam, 2022).

Emerging global data indicate that investors between 18 to 45 years of age are more likely to invest in cryptocurrencies than older generations, driven by the promise of higher returns (Kumar et al., 2022; Liu & Tsyvinski, 2020). There is also a lack of empirical studies globally on cryptocurrency adoption, yet it has grown at 60% annually for the last five years (Saiedi et al., 2020). Concurrently, the growing awareness and legitimacy of cryptocurrencies signal a shift in investment behaviour, warranting further exploration.

This evolution in the financial and technology world has already changed the way we analyse and view problems; it now begs the question of how we can approach this differently. There is increasing competition between traditional finance institutions and

fintech companies; therefore, understanding the importance of behavioural factors and its influence on adoption across age groups is vital to creating robust business strategies.

The research question derived from the business problem is “What are the key behavioural determinants influencing cryptocurrency adoption among South African adults and how does financial literacy moderate this relationship?” and whether the impact differs by age group, providing actionable insights for targeted interventions.

The rest of this document will outline the theoretical framework (Chapter 2), describe the hypotheses being tested (Chapter 3), explain the methodology used to conduct the research (Chapter 4), present the results and findings (Chapter 5), discuss the findings, and conclude with managerial implications, recommendations and further research (Chapter 7).

Chapter 2: Literature Review

Below is a graphical representation of the literature structure that highlights the flow and relationships between sections.

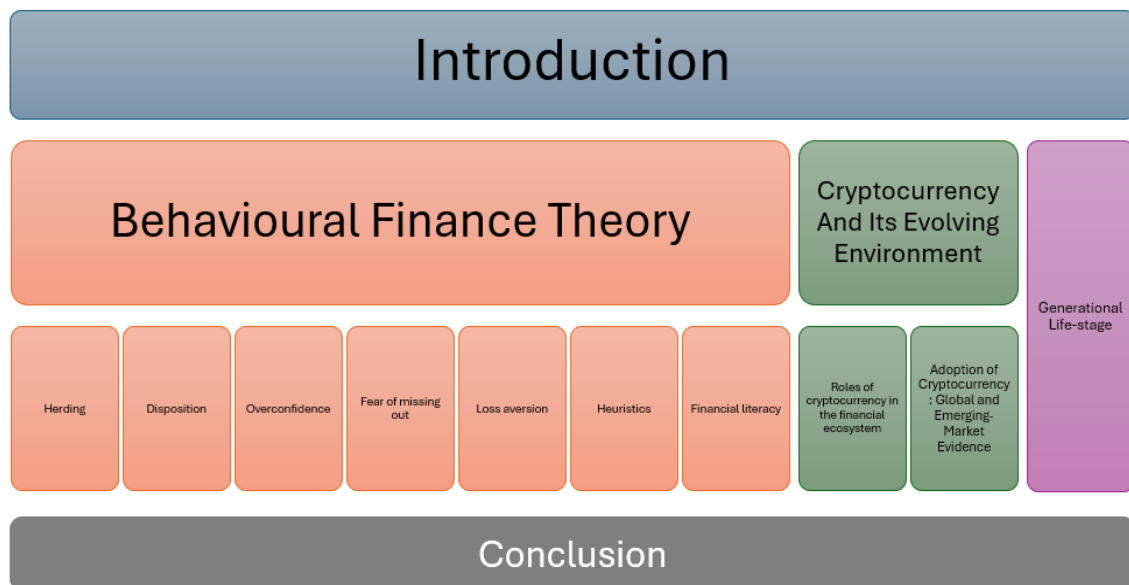


Figure 2.1: Literature Road Map

(Source: Author)

2.1. Introduction

This chapter thoroughly reviews existing theoretical frameworks, including Behavioural Finance Theory, the impact of financial literacy on investment decisions, and the adoption of cryptocurrency and blockchain technologies, with relevance to emerging markets. It also examines the awareness and adoption of cryptocurrencies, investigating whether generational cohorts or life stages influence investment choices. Furthermore, the review synthesises findings from studies conducted in developed economies and critically evaluates their applicability to South Africa's unique socio-economic landscape.

Previous studies by Pokharel and Maharjan (2024), Hashim et al. (2024) and Almansour (2020) have utilised frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT), Behavioural Finance Theory, Generational Theory and the Theory of Planned Behaviour. However, research examining behavioural factors that influence the adoption of cryptocurrency has been limited in South Africa, even as its popularity grows (Mofokeng et al., 2024; Cai & Zhao, 2023; Matsepe & Lingen, 2022).

Additionally, there is a lack of investigation into significant differences in bias factors across life stages among South Africans. This chapter analyses the current literature to identify these gaps and proposes a research framework to understand cryptocurrency adoption and the specific behavioural biases influencing South African end-user decisions.

2.2. Behavioural Finance Theory

Behavioural Finance Theory offers a compelling framework, blending psychology and economics to illuminate the often-irrational decisions of investors (Almansour, 2020; Kaur et al., 2023). The fundamental principles of Behavioural Finance Theory were first established by Kahneman and Tversky (1977) through their seminal research on Prospect Theory. This theory was a cornerstone of behavioural economics and posits that individuals do not consistently make rational decisions when faced with risk. Instead, they assess potential outcomes in relation to a reference point, demonstrating a greater sensitivity to losses than to comparable gains, called loss aversion, which can substantially influence an individual's choices (Lisauskiene & Darškuvienė, 2021).

Behavioural Finance Theory is crucial in understanding how psychological factors and cognitive errors influence decision-making, particularly with complex and uncertain investments such as cryptocurrency (Altaf & Jan, 2023). It explains how investors deviate from rational economic models by incorporating insights from psychology to understand investment behaviour. This theoretical lens is particularly pertinent to cryptocurrency markets, given their inherent volatility and susceptibility to phenomena such as herding, overreaction and sentiment-driven trading (Bui & Sällberg, 2022). However, some authors argue that while behavioural finance offers valuable insights into investor psychology, it may overemphasise deviations from rationality, potentially neglecting the role of efficient market principles and rational decision-making, especially in more mature markets. Poyser (2018) and Ballis and Verousis (2022) further this point by stating that Efficient Market Hypothesis (EMH) has numerous flaws in explaining market irrationality. In situations where irrational behaviour is evident, behavioural finance provides explanations for investor decision-making.

2.3. Behaviour Finance Theory and the Efficient Market Hypothesis

Behavioural finance is built on the premise that cognitive and emotional factors often lead individuals to make suboptimal financial decisions, as traditional financial models assume that investors are rational and make decisions based on logical evaluations of available information (Adil et al., 2021; Rahman & Gan, 2020). This assumption is built on the Efficient Market Hypothesis introduced by Fama and French, who propose that the market is thought to incorporate all available information and that investors are rational and make rational decisions (Malkiel, 2003; Raut, 2020). Research has divergent views on whether the highly volatile cryptocurrency market is efficient or inefficient under this theory and whether investors can realise abnormal returns, but rather make decisions based on behavioural traits, which effectively is in contradiction to the Efficient Markets Hypothesis (Bui & Sällberg, 2022; Malkiel, 2003).

2.4. Behavioural Factors

Behavioural factors include cognitive and emotional factors that affect how individuals perceive risk, assess opportunities and act in financial markets. Such factors include mental accounting, herd behaviour, anchoring, loss aversion, disposition effect, overconfidence effect, optimism bias, confirmation bias, loss aversion, fear of missing out and sentiment (Altaf & Jan, 2023; Baker et al., 2018; Rahman & Gan, 2020). Consequently, these biases can intensify cryptocurrency price volatility and impede rational investment decisions, highlighting the importance of incorporating behavioural interventions into adoption strategies (Almansour, 2020; Altaf & Jan, 2023)

Pokharel and Maharjan (2024) looked at the investment behaviour of Millennials and Gen Z and found that financial literacy, ethics and attitude significantly differed between these two generations. India currently has the largest population of Millennials, and a study conducted by Bhilawadikar and Garg (2020) concluded that Millennials have an increasing risk appetite in comparison to other generations in the adoption of cryptocurrency. However, it is argued that the high volatility and speculative nature of cryptocurrencies may deter some investors, particularly those with a lower risk tolerance or less financial literacy, from engaging with this asset class. Empirical evidence indicates that individuals with higher financial literacy are less susceptible to biases such as overconfidence and confirmation bias, thereby exhibiting a greater propensity to adopt cryptocurrencies (Armansyah et al., 2023).

One of the key elements that influences behavioural factors is demographics, such as age, gender, level of education, profession and income, which have a direct influence on factors that later affect investment decisions (Baker et al., 2018). This is echoed by Fahlin and Gustafsson (2024) and Pokharel and Maharjan (2024), who stated that psychological factors can influence investors and that different age groups tend to have varying risk tolerances, investment strategies and perspectives on long-term goals, which highlights a downward sloping risk tolerance curve as one gets older. Given South Africa's high levels of inequality and lower literacy rates, the findings of this study hold significant potential value for practical applications across various industries.

This research will consider the following factors on the adoption of cryptocurrency, as they are most commonly supported in the literature regarding cryptocurrency investments (Almansour, 2020). Herd behaviour describes how investors follow the actions of a group of people without conducting their own due diligence on whether to invest or not, but rather following the decision of others, even if it contradicts their own beliefs (Gupta & Shrivastava, 2021). This is followed by heuristics, where, in conjunction with herd behaviour, investors create mental shortcuts to simplify their decision-making process and are often based on limited information and past experiences (Almansour, 2020). Gupta and Shrivastava (2021) found that an individual's investment decision is significantly impacted by loss aversion, the herding effect and fear of missing out (FOMO). This leads to FOMO, which is particularly relevant to cryptocurrency adoption among the generational cohorts in this study. The influence of social media and online sentiment on cryptocurrency suggests that individuals may be driven by FOMO on potentially profitable investments, which is also very closely related to herding. (Barry & Wong, 2020). An et al. (2018) described the disposition effect as having an inverse relationship to gains and a positively disproportionate one to losses. Basically, investors sell winners too early and hold onto losers longer than they should, which falls out of the realm of rationality. The sixth behavioural factor considered is overconfidence, which is the overestimation of one's ability in making investment decisions. This can be fuelled by large gains in the crypto market, which can cause this bias to contribute significantly to explaining adoption (Adil et al., 2021; Fahlin & Gustafsson, 2024).

In addition to the aforementioned factors that will be analysed, financial literacy will be used as a moderating variable for the six behavioural factors. A moderating variable can strengthen, diminish, negate or otherwise alter the relationship between independent and

dependent variables (Adil et al., 2021). Financial literacy has been found to have a significant relationship with behavioural factors, where it decreases the impact of the behavioural factor, on decision-making. However, it has also been noted that higher financial literacy can lead to overconfidence in investment decisions (Adil et al., 2021; Baker et al., 2018; Lone & Bhat, 2022; Sabir et al., 2019).

2.4.1. Herding

Bias in the form of herding describes investors' disregarding their own information and instead copying the actions of a larger group, which can appear as informational cascades, positive feedback trading or reputational herding (Coskun et al., 2020; Poyser, 2018; Youssef, 2020). Such herd-driven dynamics have been shown to amplify price swings in cryptocurrency markets, as investors collectively chase rising assets without independent analysis (Ballis & Verousis, 2022; Kyriazis, 2020). Consequently, this herd-driven momentum exacerbates price volatility and may be amplified by FOMO, a mechanism empirically linked to both herd behaviour and loss aversion in retail investors (Gupta & Shrivastava, 2021). Fuelled by social influence and market sentiment, herding fosters speculative bubbles and heightened trading activity in South Africa's cryptocurrency market (de Almeida & Gonçalves, 2023; Bouri et al., 2018).

Youssef (2020) and Bouri et al. (2018) demonstrated that herding is a significant contributor to an individual's intention to adopt cryptocurrency, thereby highlighting its importance as a key behavioural driver. However, Coskun et al. (2020) explained that herd behaviour is not linear. They suggested that investors prioritise information from other investors over their own, particularly in less volatile markets. However, overconfident investors disregard market signals and exhibit anti-herding behaviour when faced with uncertainty. Handoko et al. (2024) found a similar trend, whereby herding was found to be an insignificant contributor in explaining cryptocurrency adoption with experienced and inexperienced investors. However, Baker et al. (2018) elucidated how herding can lead to poor investment decisions and reinforce the disposition effect, while Raut (2020) indicated that social influence can significantly sway investors and often lead to irrational choices. In contrast, the findings by Adil et al. (2021) revealed that herding behaviour negatively impacted investment choices for both male and female investors within their study.

The interaction between overconfidence and herding can thus either reduce or increase the likelihood of cryptocurrency adoption, contingent on investors' risk perception. Given

the asset's high volatility, this behaviour is intensified, subsequently boosting adoption intentions among risk-seeking investors who interpret collective buying as a signal of potential high returns in a market characterised by limited informational asymmetry (Bui & Sällberg, 2022; Prasetyo et al., 2023). Balutel et al. (2022) showed that adoption is shaped by shared beliefs about cryptocurrency utility and trust, where lower institutional trust correlates with a greater likelihood to “follow the crowd”.

Herd behaviour has also been shown to have an inverse relationship with age in some studies. Younger investors tend to herd more strongly, while older investors exhibit comparatively lower herd-driven adoption rates, reflecting a difference in risk tolerance (Makapchuk et al., 2023; Senarathne & Wei, 2020). In addition, Colline and Hermawan (2025) found this to be empirically true among younger investors displaying a stronger tendency to herd, especially with cryptocurrency. This was supported by Prasetyo et al. (2023) and Bui and Sällberg (2022), who attributed this to the high information asymmetry. Speculative trading among younger cohorts seeking rapid gains is consequently amplified. In contrast, older investors tend to rely more on personal due diligence and are less susceptible to herding, which may temper their cryptocurrency adoption (Fahlin & Gustafsson, 2024).

Bogdan et al. (2023) and De Almeida and Gonçalves (2023) introduced the notion that social media sentiment is connected to herd-like behaviour, as digital communication amplifies this tendency. In South Africa, surges in social media discussions correlate with increased herd-driven trading, reinforcing the relationship between online sentiment and adoption trends (Dickason-Koekemoer & Ferreira-Schenk, 2018; Raut, 2020). Extending the social-signal mechanism that underpins the herding bias, endorsements by celebrities or governments precipitate synchronised retail reactions and short-run volatility bursts coordinating collective entry and exit (Ullah et al. 2022). Studies of South African equity investors and trading teams report imitation tendencies and reputational herding when local information is scarce, which is very common in crypto markets due to the asymmetry of information (Dickason-Koekemoer & Ferreira-Schenk, 2018; Shandu & Alagidede, 2022). Heightened social media discussion and sudden retail inflows on South Africa's exchanges have corresponded with surges in trading and price momentum, consistent with herd-driven behaviour (Bui & Sällberg, 2022; Gupta & Shrivastava, 2021; Kaiser & Stöckl, 2019).

Financial literacy appears to influence herding behaviour, while South African studies indicate that education can reduce copy trading; however, this effect remains unconfirmed for cryptocurrencies (Walton & Johnston, 2018). Individuals with lower financial literacy are significantly swayed by social media sentiment, but Gupta et al. (2020) highlighted that education and transparency can weaken herd behaviour. Alongside immature market structures such as thin order books and fewer institutional market-makers on local exchanges, the price impact of retail herding is increased, amplifying volatility (Almansour, 2020; Bui & Sällberg, 2022; de Almeida & Gonçalves, 2023; Kallinterakis et al., 2010; Silva et al., 2019). This strengthens the need for retail-level empirical studies that measure the significance of herding among South African crypto investors or identify how this varies across age groups.

2.4.2. *Disposition effect*

This established pattern is formalised by Shefrin and Statman (1985) as the disposition effect, whereby investors systematically realise gains too early and defer losses, consistent with prospect-theoretic framing and realisation utility. This effectively means investors sell winning positions prematurely while holding onto losing ones, a pattern observed among South African cryptocurrency investors (Dickason-Koekemoer & Ferreira-Schenk, 2018; Kaur et al., 2023).

According to Kahneman and Tversky (1977), Prospect Theory provides an explanation for this behaviour by highlighting loss aversion and reference dependence. In financial markets, this behaviour reduces ex-post portfolio performance and can exaggerate return disparities, as trades driven by collective disposition result in selling pressure during upswings and decreased trading during downswings. Such behaviour not only amplifies realised losses during market downturns but also reinforces risk-seeking tendencies that can exacerbate portfolio volatility in emerging cryptocurrency markets (Bui & Sällberg, 2022). This behaviour could easily be misinterpreted as that of a risky investor or trader seeking abnormal returns, but disposition bias generally has a low risk tolerance (Dickason-Koekemoer & Ferreira-Schenk, 2018). These investors tend to purchase more of the depressed asset to mitigate losses or average down their position. This disposition-driven trading aligns with evidence that loss-aversion bias exerts a strong influence on cryptocurrency investment choices, manifesting in heightened sell-pressure during market rallies and prolonged holding during downturns (Bui & Sällberg, 2022; Kaur et al., 2023).

This investor persona also suffers from mental accounting bias, which leads investors to compartmentalise gains and losses. Recent transaction-level studies show that investors' psychological biases affect how they buy and sell on cryptocurrency exchanges and are found to exacerbate the disposition effect by encouraging the reinvestment of realised profits into underperforming assets (Dickason-Koekemoer & Ferreira-Schenk, 2018; Kaur et al., 2023). However, Son et al. (2025) suggested that mental accounting can also lead investors to set aside funds for specific purposes, potentially acting as a buffer against impulsive reinvestment in underperforming assets. This dual nature indicates that mental accounting can, under certain circumstances, foster discipline rather than invariably leading to negative outcomes. Nevertheless, in the highly volatile cryptocurrency markets, the segmentation of gains and losses tends to reinforce dispositional biases, as the prominence of past acquisition prices and the emotional weight of unrealised losses tend to dominate decision-making frameworks.

Recent empirical work shows the disposition effect is observable in cryptocurrency markets as well as in traditional assets. Research by Schatzmann and Haslhofer (2023) on cryptocurrency trading indicates that retail investors display disposition-type behaviour, with intensity that varies across market regimes, which is more pronounced during boom-bust episodes and when inexperienced retail participants flood markets (Haryanto et al., 2019). These findings indicate that the disposition effect in cryptocurrency markets fluctuates over time. During periods of market growth, a greater number of investors tend to secure their profits. Conversely, during significant downturns, investors often hold onto assets that are losing value or increase their holdings to recoup losses, which amplifies market volatility. In cryptocurrency markets, which are frequently dominated by retail investors with limited diversification, such portfolio-level dynamics may magnify the disposition effect (Schatzmann & Haslhofer, 2023). An et al. (2018) showed that disposition-type rebalancing emerges from portfolio thresholds locking in winners while holding losers whose strength varies across market states. Moreover, the interaction with financial literacy is complex, where greater knowledge can reduce naive mistakes but may also allow experienced investors to rationalise holding losers for strategic reasons, blurring the line between rational strategy and bias-driven inertia (Adil et al., 2021; Baker et al., 2018; Raut, 2020).

Evidence of the disposition effect within South Africa is predominantly found in studies on equity investors and trading teams, with scant research specifically addressing

cryptocurrency markets (Shandu & Alagidede, 2022). The interaction between financial literacy and disposition in South Africa remains underexplored, although international research suggests that financial literacy and experience can moderate certain behavioural biases, potentially reducing or merely altering disposition patterns among South African crypto investors (Guenther & Lordan, 2023). Furthermore, Schatzmann and Haslhofer (2023) highlighted that studies on cryptocurrency disposition rely on exchange-level data with few studies integrating survey-based measures of investor psychology. Recognising these gaps, there is a need to investigate the significance of disposition in cryptocurrency adoption and whether financial literacy serves as a moderating function. In addition, there is limited research to determine if biases are significantly different across age groups.

2.4.3. Overconfidence

Overconfidence, a cognitive bias, involves individuals' overestimating their knowledge or abilities, often resulting in excessive risk-taking (Altaf & Jan, 2023). In finance, overconfident investors tend to trade more frequently and underestimate potential risks. Several studies link overconfidence to increased cryptocurrency adoption and investment. For instance, research by Kim et al. (2021) indicated that overconfident investors were more likely to invest in cryptocurrency and, similarly, Kaur et al. (2023) demonstrated that overconfidence significantly influences cryptocurrency investment decisions. Therefore, overconfidence can stimulate cryptocurrency adoption by fostering greater optimism towards volatile assets. A recent integrative review also situates overconfidence within a broader taxonomy of investment biases and cross-bias interactions, clarifying the contextual triggers under which the effect materialises (Sathya & Gayathiri, 2024).

This overestimation of one's own judgment can lead individuals to participate in risky investment activities, particularly within the nascent and often unpredictable cryptocurrency market (Poyser, 2018). This phenomenon is often linked to the "better-than-average effect" or an "illusion of control", where individuals perceive their investment acumen to be superior to others, leading them to overlook inherent risks and make suboptimal decisions (Kaur et al., 2023). This behaviour is particularly pronounced when investors exhibit a divergence between their objective and subjective financial knowledge, where a false sense of understanding complex investment concepts leads to greater engagement in speculative assets (Kim et al., 2021). Extending this moderation view, higher financial literacy can temper the influence of overconfidence by narrowing the gap

between perceived and actual knowledge (Sabir et al., 2019). Investment experience together with literacy jointly shapes cryptocurrency participation, mitigating miscalibration even as experience may sustain confidence (Zhao & Zhang, 2021).

Overconfidence is also reinforced by the decentralised nature of the asset class, where information is often opaque, complex and propagated via unregulated forums such as chat rooms and peer-driven discussions. This further reinforces individual biases rather than promoting informed decision-making (Kim et al., 2021). Complementing the classic trading-frequency channel, evidence from online message boards links overconfidence and confirmation bias to attention-driven trading surges and subsequent performance drag mechanisms plausibly mirrored in cryptocurrency discussion venues (Barber & Odean, 2001; Park et al., 2010). Notably, some studies also found that overconfidence distinguishes crypto investors from non-investors, underscoring heterogeneity when confidence translates into entry (Iamin, 2025).

Despite these empirical findings, much of the evidence is from international samples, and there is little research on South African investors specifically. Walton and Johnston (2018) explored Bitcoin adoption in South Africa but focused on factors such as perceived benefit and complexity, not overconfidence bias. Beyond geography, the expression of confidence itself is culturally conditioned and cross-cultural work shows reported financial confidence reflects cultural display rules as much as true knowledge, with classic evidence of systematic cross-national differences in calibration (Ooi, 2022; Yates et al., 1996). Demographic nuance also matters, where wealthier male investors can display stronger overconfidence, and gender gaps in crypto consideration are partly mediated by financial overconfidence and personality traits (Nyhus et al., 2023; Xiao et al., 2022). In behavioural finance, foundational studies by Barber and Odean (2001) and Kahneman and Tversky (1977) provided insights into overconfidence as a bias in stock trading, but specific data on overconfidence among South African cryptocurrency investors remains limited. This deficiency highlights the need to investigate whether overconfidence similarly influences crypto adoption within South Africa, considering potential differences in market experience and educational backgrounds among local investors and across age groups (Walton & Johnston, 2018).

2.4.4. Fear of missing out (FOMO)

FOMO describes the emotional impulse to act quickly to avoid missing perceived gains observed in others (Gupta & Shrivastava, 2021; Kaur et al., 2023). FOMO can be a strong motivator for investing in cryptocurrencies, especially when seeing others profit from a rising market. This is the case with cryptocurrency, where double-digit gains are common and more probable than with other asset classes (Bhilawadikar & Garg, 2020). Gupta and Shrivastava (2021) found loss aversion, herd behaviour and FOMO to be significant contributors, which was also supported by Altaf and Jan (2023), however, FOMO only partially mediated these relationships. This mediation is complementary, meaning that the presence of FOMO amplifies the impact of loss aversion and herd behaviour on the investment decisions of investors. Empirically, FOMO has been associated with herd behaviour and the desire for earning greater returns, yet there is limited empirical evidence to support this claim, especially in developing countries such as South Africa (Gupta & Shrivastava, 2021).

As described by Altaf and Jan (2023), FOMO is a social emotion intertwined with social comparison and inadvertently influences their public persona. Such socially-driven FOMO, amplified by visible peer successes on digital platforms, can spur cryptocurrency adoption among South African investors even when financial literacy is low. This is true since FOMO has been shown to positively influence crypto price dynamics and mediate the impact of herd behaviour and loss aversion (Gupta & Shrivastava, 2021). However, research by Zhao and Zhang (2021) found social influence was not significant in their study, which contradicts the notion that socially driven FOMO dictates cryptocurrency investment decisions (Friederich et al., 2023; Gupta & Shrivastava, 2021).

Friederich et al. (2023) posited that social norms and the fear of missing out are often perceived as separate concepts, but social norms can fuel FOMO. Adhering to group expectations can intensify this bias, influencing the relationship between social norms and behaviours such as phubbing (Li et al., 2021). From this viewpoint, temporary FOMO triggered by specific information can encourage consumers to make timely, and sometimes better-informed, purchasing decisions, reflecting a focus on the present. However, there is a potential downside that FOMO might boost engagement and encourage purchases and lead to impulsive and less rational decision-making. This highlights that social influences and FOMO, while capable of positively shaping behaviour,

can also detract from consumer well-being by increasing choices driven by biases. In the South African context, given the significant income inequality, this amplifies FOMO-driven adoption, as lower-income investors are more inclined to pursue perceived quick gains despite increased risk exposure (Kaur et al., 2023).

Limited understanding and education within the cryptocurrency sector, exacerbated by information asymmetry, foster speculative behaviour, thereby leading investors to rely on peer influence and social media trends, amplifying the fear of missing out and solidifying biased adoption patterns in South Africa (Gupta & Shrivastava, 2021). Observations across age groups suggest that younger investors exhibit markedly higher susceptibility to FOMO-driven adoption than older cohorts, who tend to adopt more cautiously (Anaza et al., 2023). This is due to the natively digital media consumption patterns of younger cohorts, which heighten exposure to FOMO-inducing cues (Barry & Wong, 2020; Friederich et al., 2023). Platform user experience and design also contribute to FOMO. Features such as instant-buy buttons, real-time price movement notifications and gamified interfaces can shorten the time for consideration and encourage impulsive purchases. Platforms such as X, YouTube and TikTok, which are popular with younger demographics, tend to reinforce this bias, confirming with existing literature (Walton & Johnston, 2018).

The relevance of this narrative to cryptocurrency adoption in South Africa has not yet been examined, and it would be beneficial to ascertain the impact of FOMO on retail investors. Friederich et al. (2023) identified this bias as a significant factor in decision-making, thus warranting further investigation into this potential behavioural driver's local relevance. The question is then, does FOMO significantly influence cryptocurrency adoption among South African investors, particularly when moderated by financial literacy, and do age groups differ in this regard? Preliminary evidence suggests that lower financial literacy amplifies FOMO's impact, especially among younger South African investors, underscoring the need for targeted empirical research (Gerrans et al., 2023; Gupta & Shrivastava, 2021).

2.4.5. Loss aversion

Loss aversion describes the tendency for individuals to experience the negative impact of losses more intensely than the positive impact of equivalent gains (Gupta & Shrivastava, 2021). Investors exhibiting loss aversion typically demand significantly higher returns to compensate for potential losses, which often leads them to sell profitable investments prematurely while holding onto underperforming ones. Loss aversion and the disposition

effect are intertwined, with loss aversion serving as the underlying psychological driver for the disposition effect.

Both concepts are rooted in Prospect Theory, which suggests that individuals assess potential outcomes against a reference point, usually their initial investment, and display an asymmetrical response to gains and losses, where the psychological distress from a loss outweighs the pleasure derived from an equivalent gain (Kahneman & Tversky, 1977; Schatzmann & Haslhofer, 2023; Shandu & Alagidede, 2022). In portfolio terms, realisation patterns that look like “selling winners and holding losers” can arise as investors manage positions around reference points and thresholds, connecting loss aversion to disposition-type rebalancing across market states (An et al., 2018).

This leads to the possibility that loss aversion is significantly pronounced with cryptocurrency due to its extreme volatility and the amplified emotional responses it elicits in investors. This heightened emotional response often leads to irrational decision-making, such as panic selling during market downturns, which is predominantly experienced during the halving cycle of Bitcoin, resulting in a contagion effect across the cryptocurrency market (Almansour, 2020). Investors then hold onto depreciating assets in the hope of recovery, exacerbating the impact of volatility (Schatzmann & Haslhofer, 2023). Kaur et al. (2023) reinforced this by stating that loss aversion is a significant factor in cryptocurrency investments. Their study found that investors with higher loss aversion exhibit distinct investment behaviours and that FOMO partially mediates the influence of loss aversion on crypto investment decisions, suggesting that those fearful of losses might still purchase if they are afraid of missing out. Empirically, this dovetails with evidence that losses “hurt about twice as much” as equal-sized gains (Camerer & Loewenstein, 2003; Kahneman & Tversky, 1977; Kaur et al., 2023).

However, it is important to note that not all investors exhibiting loss aversion will necessarily make irrational decisions. Some may use their risk aversion to make more calculated choices, carefully managing their exposure to volatile assets (Guenther & Lordan, 2023). This nuance suggests that while loss aversion is a pervasive behavioural driver, its manifestation in cryptocurrency markets is complex, potentially leading to both detrimental and protective investment strategies, depending on individual financial literacy and market conditions.

Specific evidence on loss aversion among South African crypto investors is under-researched and indicates strong roles for perceived usefulness, ease of use and social influence (Almeida & Gonçalves, 2023; Walton & Johnston, 2018). This implies possible self-selection into cryptocurrency by more risk-tolerant cohorts, which would bias observed loss aversion effects at entry (Mazambani & Mutambara, 2019). Relative to non-holders, cryptocurrency holders tend to exhibit higher risk tolerance, impatience and lower self-control, and are more willing to accept drawdowns for potential upside (Fujiki, 2021; Hackethal et al., 2021; Steinmetz et al., 2021; Stix, 2021). Relatedly, null or attenuated bias effects in some are also observed, consistent with risk-tolerant or experienced groups shaping observed relationships (Fahlin & Gustafsson, 2024). These patterns align with a broader contextual view in which macroeconomic conditions and institutional features with inflationary pressure or limited access to traditional finance, therefore leading to investors' tolerating higher volatility and refraining from cryptocurrency participation despite potential losses (Auer & Tercero-Lucas, 2022; Balutel et al., 2022; Carbó-Valverde et al., 2024).

Given these considerations, loss aversion often coexists with social and informational forces in cryptocurrency markets. Existing research suggests that loss aversion can operate alongside herd behaviour and FOMO, but mental accounting can blunt loss-averse responses at entry by quarantining “speculative capital”, thereby tolerating drawdowns while seeking rebound opportunities (Almansour, 2020; Kaur et al., 2023; Schatzmann & Haslhofer, 2023). In an emerging market context such as South Africa, characterised by economic and political volatility and strong social dynamics, tolerance for downside risk may differ from advanced economies, and prospective adopters may accept cryptocurrency's downside risk for perceived diversification or high-return potential (Carbó-Valverde et al., 2024; Stix, 2021). Accordingly, one cannot assume that loss aversion functions identically across emerging markets like South Africa. Instead, its stage-dependence (entry versus post-adoption trading and age), interaction with other biases (e.g. FOMO/herding) and conditioning by investor characteristics (e.g. literacy, experience) should be anticipated in both design and interpretation of empirical tests, even across age cohorts.

2.4.6. *Heuristics*

Heuristics are mental shortcuts or simple rules used to make decisions under uncertainty (Almansour, 2020). They allow investors to make quick judgments without analysing all

the information, but they often introduce biases. Common heuristics in investing include availability (relying on recent or vivid information), representativeness (expecting trends to continue) and anchoring (fixating on reference points) (Baker et al., 2018; Sathya & Gayathiri, 2024). However, Mardiana et al. (2025) suggested that not all sub-biases act uniformly and are significant. Confirmation bias can impair choices, representativeness can increase participation, while anchoring and availability are sometimes insignificant, underscoring that not all heuristics have the same impact. In the rapidly evolving and often opaque cryptocurrency landscape, investors frequently resort to mental shortcuts in an attempt to act quickly (heuristics) to navigate complex information and highly volatile markets like cryptocurrency (Hackethal et al. 2021). Almansour (2020) discovered that heuristics influence mental accounting, a behaviour also observed in investors experiencing the disposition effect. This reliance on heuristics can lead to systematic errors in judgment, as investors may oversimplify complex market dynamics or base decisions on readily available but potentially irrelevant information (Handoko et al., 2024).

Research by Mulyadi et al. (2025) indicated that heuristics, particularly availability bias and overconfidence, are the most significant factors influencing cryptocurrency investment decisions, a finding supported by Almansour (2020). Furthermore, Handoko et al. (2024) emphasised the importance of measuring the impact of herding and heuristics, as these two biases encompass the varied psychological dynamics that shape investment choices, offering a more thorough and insightful perspective (Jain et al. 2019). Complementing this process, literature shows heuristic simplifications influence judgment steps but not always final allocations, yielding modest net effects in certain markets (Piotrowski & Bünnings, 2022). This is vital for creating more effective strategies and reducing risks tied to investor behaviour and biases.

Experienced investors, however, are better equipped to mitigate these biases through enhanced risk evaluation and learning from past mistakes, unlike novice investors who are more prone to emotional reactions and social pressures (Ahmad & Shah, 2020; Handoko et al., 2024). The study by Handoko et al. (2024) observed an interesting pattern where heuristics did not significantly influence investment decisions in cryptocurrency for investors with less than two years of experience. However, for those with more than two years of experience, heuristics became a significant factor, highlighting an experience effect.

Financial literacy has been shown to reduce the reliance on certain heuristics, with educated investors being less susceptible to herding and availability bias (Mulyadi et al., 2025). However, Mulyadi et al. (2025) also suggested that even financially literate individuals can be influenced by heuristic biases, especially in volatile and speculative markets such as cryptocurrency.

This is particularly pertinent in the South African context, where financial education levels vary drastically in South Africa, and the allure of quick returns in cryptocurrency markets may amplify the impact of these cognitive shortcuts, potentially leading to suboptimal investment outcomes (Asbaruna, 2023; Handoko et al., 2024). Despite this, heuristic biases in the South African crypto context are under-researched. Given that Walton and Johnston (2018) noted that age, complexity and education are barriers in adoption, it is plausible that South Africans rely on heuristics when considering cryptocurrency investments. This highlights the need to investigate the specific influence of heuristic biases on South African cryptocurrency investors, particularly given the documented impact of such biases in other emerging markets, where results have varied. This research gap is further supported by the findings of Ahmad (2022), which emphasised the importance of understanding heuristic biases to prevent costly mistakes in investment management.

2.4.7. Financial literacy

Financial literacy is widely recognised as a factor that can improve investment decision-making by mitigating certain cognitive biases (Adil et al., 2021; Baker et al., 2018). For instance, Adil et al. (2021) found that investors with higher financial literacy were less susceptible to overconfidence when making investment decisions. This aligns with the observations of Sabir et al. (2019) and Raut (2020), who established that financially literate investors or those who are improving their knowledge tend to make more rational financial choices compared to those with low literacy. Financial literacy, therefore, enhances an investor's confidence, reducing cognitive errors and leading to improved investment decisions (Adil et al., 2021; Kaur et al., 2023; Sabir et al., 2019).

Recent studies indicate that greater financial knowledge actually makes individuals less likely to invest in highly speculative assets like cryptocurrency (Carbó-Valverde et al., 2024; Hayashi & Routh, 2025). Kim et al. (2021) reported that investors who truly know more about finance tend to be more cautious and hold fewer cryptocurrencies, while those

who merely think or perceive they know a lot are more prone to invest heavily in cryptocurrency. This overinvestment is due to overconfidence in one's ability, fostered by limited education. This observation is further supported by Zhao and Zhang (2021), who found that while real-world financial knowledge deterred participation in cryptocurrencies, a greater perceived understanding of this asset class often encouraged it. Overconfidence in one's financial understanding thus appears to raise cryptocurrency investment, whereas genuine expertise or domain knowledge can temper it.

The influence of financial literacy on biases is not uniformly advantageous, as it can act as a double-edged sword, as highlighted by Zhao and Zhang (2021). Extending this view, Mulyadi et al. (2025) found that availability and overconfidence are among the strongest predictors of cryptocurrency choices and that financially literate investors remain susceptible in speculative, high volatility settings, suggesting literacy mitigates but does not immunise against heuristic influence. Specifically, while financial literacy can attenuate the negative impact of information cascade on investment decisions, it does not eliminate the influence of behavioural biases (Handoko et al., 2024; Wangzhou et al., 2021). Consistent with this, Handoko et al. (2024) showed that even knowledgeable investors continue to rely on heuristic shortcuts under volatility and time pressure, with the salience of these shortcuts increasing with market experience. This reveals that literacy alone does not extinguish System 1 decision rules. Financial literacy can also amplify certain biases, such as overconfidence, leading to excessive risk-taking, especially in novel and complex markets such as cryptocurrency (Adil et al., 2021; Darwish, 2025).

Financial literacy levels in developing nations vary drastically, with South Africa being a prime example. This disparity leaves its investors more vulnerable to behavioural biases. This concern was highlighted by Walton and Johnston (2018), who emphasised the critical role of financial literacy for novice investors. This is particularly relevant in a developing country such as South Africa, which is characterised by significant inequality and uneven access to education (Seraj et al., 2022). This lack of understanding can make less experienced investors prone to FOMO or herd-driven behaviour. However, research in South Africa is limited in examining whether financial literacy moderates the influence of behavioural factors. The research is inconsistent and limited due to the nature of cryptocurrency markets, considering it is still a relatively young asset class (Almeida & Gonçalves, 2023; Walton & Johnston, 2018). Even global studies offer mixed insights into this issue. A recent study indicated that the link between financial literacy and

cryptocurrency ownership differs among investor demographics, where younger investors are males and those with higher incomes tend to own more cryptocurrency (Hayashi & Routh, 2025; Steinmetz et al., 2021). Hayashi and Routh (2025) and Carbó-Valverde et al. (2024) elucidated that investors with a greater willingness to take on financial risk is a significant positive indicator of cryptocurrency ownership, and the interplay between financial literacy and risk tolerance shows that even for those who are risk-tolerant, higher financial literacy reduces the probability of investing in crypto. On the other hand, Steinmetz et al. (2021) found that higher education is correlated with high cryptocurrency ownership along with higher income. This illustrates that the impact of literacy on cryptocurrency behaviour is complex and context dependent. Therefore, a deeper investigation into how financial literacy influences cryptocurrency adoption and investment decisions within the specific demographic and economic landscape of South Africa is warranted (Carbó-Valverde et al., 2024).

2.5. Cryptocurrency and its Evolving Environment

Since Bitcoin's introduction by its purported creator Satoshi Nakamoto in 2008 (Nakamoto, 2008), blockchain technology has evolved considerably, transitioning from a niche technological concept to a foundational element for a wide array of decentralised applications and digital assets (Chang et al., 2020; Mavilia & Pisani, 2019). This evolution has broadened its scope beyond merely a medium of exchange to encompass complex smart contracts, decentralised finance (DeFi) protocols and non-fungible tokens (NFTs) (Steinmetz et al., 2021). Stablecoins by Tether and Circle (the largest by market capitalisation) emerged to address price volatility and cross-border payments by pegging to fiat values. In the past five years, decentralised finance NFTs have broadened use cases and attracted both retail and institutional interest (Cong et al., 2020; Sánchez, 2022; Thakor, 2019).

Blockchain applications have also matured beyond finance into logistics, supply-chain verification and digital identity. The core characteristic is decentralisation, which minimises reliance on a single authority. Blockchain technology is considered to improve transparency and inadvertently trust through its decentralised nature (Rehman, 2023; Sánchez, 2022). As accessibility through mobile applications and exchanges has improved, and as cryptocurrency becomes more integrated into mainstream finance, individual financial decisions increasingly mirror this evolving environment (Osakwe et al.,

2024). National efforts to legalise cryptocurrency and widespread media coverage may influence perceptions of its legitimacy, even within South Africa. Nevertheless, knowledge deficits and adoption persist but vary across age groups (Hashim et al., 2024). Many investors, particularly new entrants, lack sufficient financial literacy to navigate the complexities of investing, which reinforces the reliance on behavioural factors (Baker et al., 2018; Raut, 2020; Walton & Johnston, 2018).

2.5.1. Roles of Cryptocurrency in the financial system

Cryptocurrency is widely discussed as an alternative investment due to its low correlation with traditional asset classes, prospect of high returns and the ability to bypass traditional financial intermediaries (Fujiki, 2021; Hackethal et al., 2021; Kim et al., 2021). Beyond investment, users value low-cost, peer-to-peer transfers that may disrupt conventional banking and enhance financial inclusion. However, motivations for investing in cryptocurrencies remain under-researched in developing markets (Osakwe et al., 2024; Steinmetz et al., 2021; Walton & Johnston, 2018).

Bitcoin and gold are frequently regarded as comparable in their capacity as stores of value and their ability to hedge portfolios; however, research indicates that Bitcoin delivers exceptionally high returns and demonstrates low, time-varying correlations with equities across diverse timeframes but with higher volatility compared to gold (Saiedi et al., 2020). This suggests that even small allocations of Bitcoin can enhance short-term diversification and improve risk-adjusted returns while its digital native attributes further appeal to users in jurisdictions with capital controls or weak institutions (de Almeida & Gonçalves, 2023).

Mthembu et al. (2022) and Mattke et al. (2020) highlighted limitations of Bitcoin's store of value due to its significant volatility, especially during a crisis, which diminishes its credibility as a safe haven asset. Unlike gold, which exhibits negative correlations with troubled and equity markets, Bitcoin often moves in tandem with equities during periods of acute stress. The European Central Bank shares this concern regarding its potential impact on various asset classes and implications for financial system stability, thereby underscoring the need for further research. Bitcoin can supplement portfolios as a high-return, time-varying diversifier or occasional inflation hedge, but it is not a direct replacement for gold's more dependable safe-haven characteristics. Small, actively managed allocations with robust risk controls are advisable.

2.5.2. Adoption of cryptocurrency: Global and emerging market evidence

Global adoption has expanded since 2009, driven by innovation, inclusion and speculative interest with added uptake in developing countries (Hackethal et al., 2021; Sergio & Wedemeier, 2025). The surge in media coverage has elevated public awareness of cryptocurrency. In Austria, 64% of the population reported awareness, yet 37% expressed no interest (Stix, 2021). In 2018, awareness rates reached 89% in Canada and 80% in Japan (Balutel et al., 2022; Fujiki, 2021). Furthermore, compared with non-holders, cryptocurrency investors were more risk-seeking and held a larger share of other risky assets in their portfolios (Fujiki, 2021). Studies noted that widespread acceptance in environments with high inflation, weak banking access or capital controls can influence perceptions of legitimacy. However, a lack of infrastructure and established regulatory frameworks might hinder widespread integration (Saiedi et al., 2020). A study by Shahzad et al. (2024) showed that awareness exerts a direct, positive and significant effect on intention to use, with perceived ease of use and usefulness mediating this effect and trust acting as a cornerstone. Trust has not been universally established in the cryptocurrency market, particularly given its historical association with illicit activities, scams and pronounced price volatility, which makes adoption even more difficult (Saiedi et al., 2020).

The relationship between financial literacy and investing in risky assets is well-established, but its implications for cryptocurrency are less clear due to factors such as volatility, regulatory uncertainty and significant behavioural influences (Carbó-Valverde et al., 2024; Gerrans et al., 2023; Kim et al., 2021). Demographics play a role, with Millennials typically demonstrating greater financial literacy than Gen Z and showing a higher propensity to diversify their portfolios with various asset classes, including crypto (Hashim et al., 2024; Pokharel & Maharjan, 2024). While Millennials tend to incorporate crypto into broader investment strategies, Gen Z, despite their digital nativity, exhibit distinct expectations and risk perceptions. However, the motivations behind these generational differences remain largely unexplored (Fahlin & Gustafsson, 2024; Hashim et al., 2024). Addressing these knowledge gaps is crucial for advancing sector development and fintech innovation.

Cryptocurrency adoption globally remains uneven. While high-income economies often integrate cryptocurrency into portfolios and payments, developing economies may prioritise remittances or use cryptocurrency as an alternative store of value (Fujiki, 2021; Sergio & Wedemeier, 2025). In South Africa, despite increased awareness from media

coverage and fintech offerings, concerns about volatility, scams and regulation hinder widespread adoption. South African users report ease of use as a key factor but perceive cost and technical complexity as barriers (Walton & Johnston, 2018). Existing local research has primarily focused on payments and policy rather than the behavioural motivations for investment. This gap in understanding behavioural drivers is particularly relevant in a South African context.

2.6. Generational Life-Stage

A widely held view in investing is that risk tolerance declines with age, implying that early-career investors are more willing to experiment with alternative, more volatile asset classes like cryptocurrency, whereas those nearing retirement prefer safer allocations (Bhilawadikar & Garg, 2020; Bui & Sällberg, 2022; Rauvola et al., 2019). In parallel, Generational Theory proposes that cohorts such as Millennials, Gen Z and Gen X develop distinct preferences because shared formative events shape values and behaviours (Altaf & Jan, 2023; Rauvola et al., 2019). Applied to cryptocurrency, these perspectives would predict that Millennials and Gen Z, having grown up as digital natives and through the 2008–2009 crisis that catalysed Bitcoin, should display stronger adoption and different bias profiles than older cohorts like Gen X (Altaf & Jan, 2023; Bharadwaj & Deka, 2021; Rosdiana, 2020).

Consistent with this intuition, surveys and ownership studies show that younger, more educated, higher-income groups are more likely to hold cryptocurrency while investor level evidence indicates that cryptocurrency investors are younger, trade more actively and tolerate risk to a greater degree (Hayashi & Routh, 2025; Steinmetz et al., 2021; Krause, 2024; Hackethal et al., 2021). Industry and international evidence likewise suggest that younger generations are more open to cryptocurrency, whereas older groups may be more sceptical of unregulated digital instruments (Osakwe et al., 2024). Contextual motives also matter in some settings; participation is driven more by speculation than distrust of traditional finance. An age and cohort dependent distinction can highlight observed adoption patterns (Auer & Tercero-Lucas, 2022).

Within South Africa specifically, adoption research highlights perceived usefulness, ease of use and social influence as important drivers, which may attenuate simple age-based differences in intention (Gupta et al., 2020; Mazambani & Mutambara, 2019). Moreover,

differential risk capacity (income stability, savings buffers) can vary with age and education, enabling younger, high-income professionals to assume more volatility even when their risk tolerance is not markedly higher, blurring pure cohort interpretations.

Conversely, the explanatory power of generational cohorts is contested. Age, period and cohort effects are intrinsically confounded, such that apparent generational differences may reflect ageing or lived experiences rather than stable cohort traits (Pokharel & Maharjan, 2024). While each generation can diverge due to distinct historical events, peer-group socialisation, evolving educational contexts, and generational categories rarely add predictive value beyond life-course indicators and can promote stereotyping (National Academies of Sciences, Engineering, and Medicine [NASEM], 2020; Pokharel & Maharjan, 2024; Rudolph et al., 2020). In finance, life-cycle theory provides a more precise lens where the optimal risky portfolio varies with horizon, income risk and preferences, typically declining as human capital is converted into financial wealth (Parker et al., 2025). Evidence from labour-income risk and household portfolios similarly supports life-stage variation in risk-taking (Antwi & Naanwaab, 2022). In addition, literature shows that experience-based learning, such as exposure to macro shocks, shapes risk attitudes and trading styles, while financial literacy predicts portfolio sophistication (Baker et al., 2018; Lusardi & Mitchell, 2007; Malmendier, 2021). Personality and demographic factors can also mediate or override simple age effects in explaining cryptocurrency participation (Honold & Oh, 2025). Methodologically, cross-sectional snapshots can exaggerate “generation gaps” by confounding period effects (e.g. bull runs) with cohort traits; therefore, longitudinal designs are better suited to disentangling these forces (NASEM, 2020; Rudolph et al., 2020).

This nuanced understanding is crucial for dissecting the behavioural drivers of cryptocurrency adoption, particularly within the South African context, where unique socioeconomic factors may amplify or mitigate these generational tendencies. Expanding fintech access and pervasive digital exposure can homogenise behaviours across age groups, while local drivers such as perceived usefulness and social influence can compress differences that might otherwise be attributed to generational labelling (Gupta et al., 2020; Mazambani & Mutambara, 2019). Consequently, life-stage resources (e.g. income stability, human capital horizon), experience (including macro-shock histories) and literacy may better account for adoption propensities than broad cohort labels (Baker et al., 2018; Lusardi & Mitchell, 2007; Malmendier, 2021; NASEM, 2020; Parker et al., 2025;

Pokharel & Maharjan, 2024; Rudolph et al., 2020). In emerging markets, these mechanisms interact with institutional features and media environments; thus, cohort patterns likely reflect who can access, understand and absorb the risks of cryptocurrency, rather than immutable generational essences.

2.7. Conclusion

This chapter critically examined the theoretical and empirical literature on behavioural finance, financial literacy and cryptocurrency adoption. The review highlights that while global research identifies a range of behavioural biases such as herding, heuristics, overconfidence, disposition effect and loss aversion as being influential in investment decisions. There is limited evidence on how these factors interact with the adoption of cryptocurrency and the mediation of financial literacy in emerging markets. Furthermore, the chapter highlights the evolving role of cryptocurrency as both an investment asset and a tool for financial inclusion, particularly in environments characterised by economic uncertainty and technological advancements. Notably, gaps remain regarding generational and life-stage differences in behavioural drivers. These insights inform the conceptual framework and hypotheses for this study, setting the stage for the empirical investigation that follows in subsequent chapters.

Chapter 3: Theoretical framework and Hypotheses

3.1. Introduction

In light of the literature review, there are two overarching research questions that have been identified that are relevant to South Africa. These questions aim to explore the complex interplay of cognitive biases, financial literacy and the differences between age groups that influence cryptocurrency adoption among South African investors.

3.2. Research Question One

The research question (RQ): Do behavioural biases influence the decision-making processes of South African cryptocurrency investors, and does financial literacy moderate these effects?

The associated hypotheses that were identified through the literature review are:

H1: Herding behaviour has a positive influence on the adoption of cryptocurrency.

H2: Disposition effect has a positive influence on the adoption of cryptocurrency.

H3: Overconfidence effect has a positive influence on the adoption of cryptocurrency.

H4: Fear of missing out has a positive influence on the adoption of cryptocurrency.

H5: Loss aversion has a positive influence on the adoption of cryptocurrency.

H6: Heuristics have a positive influence on the adoption of cryptocurrency.

H7: Financial literacy is a moderating variable between behavioural factors and cryptocurrency adoption.

As highlighted in the literature, there has been limited research on the specific behavioural factors impacting cryptocurrency investment decisions among South African retail investors (Ballis & Verousis, 2022; Walton & Johnston, 2018). Although studies have explored behavioural finance factors such as herding, Prospect Theory and heuristics in global cryptocurrency markets, there is a notable gap in understanding how these specifically manifest and interact within the South African context (Almansour, 2020; Pathak & Thapa, 2024). In addition, the landscape of cryptocurrency is evolving fast due

to technological improvement, adoption and regulatory maturity. Consequently, examining these behavioural drivers is crucial for a nuanced understanding of investment patterns and updating existing literature with timeous and relevant quantitative findings. Figure 3.1 depicts a conceptual framework for the adoption of cryptocurrency.

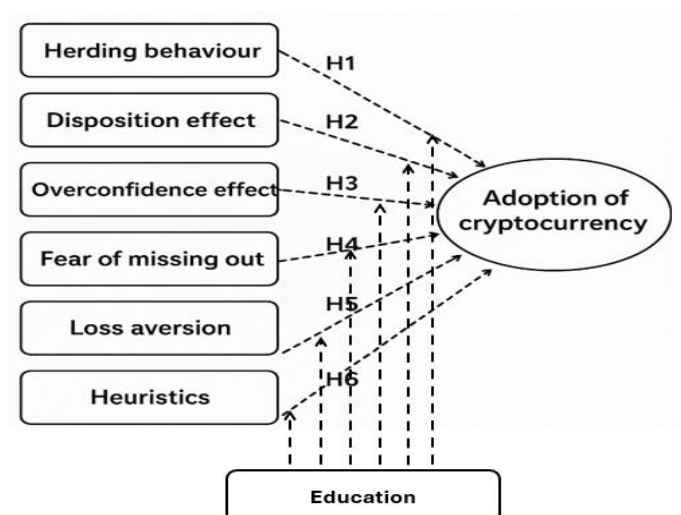


Figure 3.1: Conceptual Framework

(Source: Altaf & Jan, 2023; Gupta & Shrivastava, 2021; Jetha, 2023; Raut, 2020)

The conceptual framework in Figure 3.1 was created by derivation from prior studies on behavioural factors and biases by Altaf and Jan (2023), Jetha (2023), Gupta and Shrivastava (2021), Almansour (2020) and Raut (2020). The conceptual framework illustrates how each variable is related to one another, such as the independent, dependent and moderating variables.

3.3. Research Question Two

The research question (RQ): Do South Africans' behavioural drivers of cryptocurrency adoption differ by life stage?

RQ2 investigates whether the behavioural determinants influencing cryptocurrency adoption vary across different age cohorts among South African retail investors. The existing literature offers conflicting perspectives on how age affects risky choices, suggesting that life experience can either mitigate or intensify risk-taking behaviours (Auer & Tercero-Lucas, 2022; NASEM, 2020; Osakwe et al., 2024). Specifically, younger demographics, including Millennials and Gen Z, demonstrate a significantly higher propensity

for cryptocurrency adoption, often driven by factors like digital native fluency and openness to novel financial paradigms (Honold & Oh, 2025; Krause, 2024). Conversely, older generations often exhibit greater risk aversion and scepticism towards emergent technology and investments (Krause, 2024). This hypothesis aims to demystify this intergenerational variance by empirically assessing how specific behavioural biases manifest within distinct age groups, thereby enriching the understanding of cryptocurrency adoption dynamics in South Africa.

Chapter 4: Research Methodology and Design

4.1. Introduction

This chapter outlines the methodological approach adopted to investigate the behavioural drivers of cryptocurrency adoption in South Africa. Guided by a positivist paradigm, the study employs a quantitative, deductive strategy to test hypotheses derived from Behavioural Finance Theory. The research design is structured to measure the influence of cognitive biases and financial literacy on cryptocurrency adoption, as well as to explore differences across age groups. A structured online survey served as the primary data collection instrument, enabling the quantification of relationships between key variables. The survey targeted South African retail investors, ensuring a diverse demographic representation. Data analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) and a ANOVA analysis. This chapter details the research philosophy, sampling strategy, measurement instruments, data collection procedures and analytical techniques, ensuring transparency and replicability of the study's findings.

4.2. Philosophy

The philosophy of research design refers to the set of assumptions about reality (ontology), knowledge (epistemology), and values (axiology) that guide how a researcher frames questions, chooses methods, and interprets findings. This study adopts a positivist paradigm, rooted in the social sciences, which assumes that reality is objective and measurable (ontology) and that knowledge can be obtained through observation and statistical testing (epistemology). It reflects an axiological stance of researcher neutrality, where values are minimised to ensure objectivity.

Accordingly, the study seeks to understand the relationships between behavioural biases (independent variables) and cryptocurrency adoption (dependent variable) through hypothesis testing. This aligns with the structured, quantitative approach of positivism, where standardised survey instruments and statistical analysis are employed to test theory-driven propositions (Lim, 2024; Pandurugan & Shammakhi, 2024). The chosen design supports the aim of generating generalisable, replicable findings that contribute to existing behavioural finance literature.

4.3. Approach to Theory Development

Aligned with positivism, the study adopted a deductive approach where existing theories of investment behaviour and adoption were used to formulate specific hypotheses about how behavioural biases (e.g. overconfidence, herding) influence cryptocurrency adoption and to determine if these vary across age groups in South Africa. The deductive approach is underpinned by social theory, which then tests its implications with data that were collected via the online survey to identify if there are any causal relationships (Walton & Johnston, 2018).

Behavioural Finance Theory was the theoretical framework that was used to help understand the adoption of cryptocurrency. This framework played a significant role in helping to understand investment behaviour across age groups and to determine which bias constructs influence cryptocurrency adoption (Almansour, 2020; Bharadwaj & Deka, 2021; Hashim et al., 2024). Furthermore, financial literacy was used as the moderating variable between the constructs and cryptocurrency adoption. This approach facilitates the quantitative assessment of how cognitive biases and varying levels of financial literacy collectively shape the intent to adopt cryptocurrencies among South African investors (Bui & Sällberg, 2022; Mazambani & Mutambara, 2019).

Findings were then derived from the raw data received through the online survey and compared with existing literature to support or refute the findings. New insights in the field of study could be generated and added to the existing literature with more recent observations from an emerging country such as South Africa, while providing practical recommendations for relevant stakeholders.

4.4. Methodological Choice

Given the positivist paradigm and deductive objectives, the study considered a mono-method approach, which was quantitative in nature (Trương et al., 2020). The use of a structured survey in the form of an online questionnaire was the instrument of choice to gather primary data for the study. This method offered the ability to quantify the relationships between the variables and objectively analyse the data based on the hypotheses (Budree & Nyathi, 2022; Wellman et al., 2023; Saunders & Lewis, 2018). Using a quantitative method allowed for statistical inferences and predictions while providing insight into the topic being researched (Wellman et al., 2023). Quantitative

methodologies are well-suited for objectively testing theories regarding variable relationships. This approach also ensures consistency and objectivity in measurement, aligning with the positivist emphasis on replicability and generalisability (Barroga et al., 2023; Truong et al., 2020)

4.5. Purpose of Research Design

The purpose of the research design was descripto-explanatory, which aims to explain and quantify the influence of behavioural factors on cryptocurrency adoption and to determine if this varies across age groups (Bui & Sällberg, 2022; Walton & Johnston, 2018). The survey enabled the assessment of relationships among variables at a point in time. This is suitable for identifying associations and potential causal linkages. The aim is to test the significance of hypotheses about the relationships between the constructs and adoption of cryptocurrency while financial literacy serves as the moderating variable. Furthermore, the study aims to determine if this varies across age groups. An exploratory approach allows for a more comprehensive unpacking of the hypothesis being analysed (Mariani et al., 2022; Shahzad et al., 2024). This approach aligns with previous South African research that employed quantitative designs to understand cryptocurrency awareness, ownership and investment motivations, facilitating comparisons and broader theoretical development (Jetha, 2023; Walton & Johnston, 2018).

4.6. Research Strategy

Since the study applied a mono-method approach, a structured survey in the form of an online questionnaire was used to collect data on the participants' demographics, awareness, intention to invest in cryptocurrency and other factors. A Likert scale relating to each bias was used, as articulated in the literature review. This method is the most cost- and time-efficient within the parameters given (Almansour, 2020; Baker et al., 2018).

A Survey strategy is common in business research for measuring attitudes and testing theory-based models (Adil et al., 2021; Snyder, 2019). This approach enables the quantification of various constructs essential for this study, drawing from a broader sample than qualitative alternatives (Ahmad et al., 2019). The questionnaire incorporated validated multi-item scales for each behavioural construct and for the outcome. Upon data collection, descriptive and structural model analyses were performed using Partial Least Squares Structural Equation Modelling (PLS-SEM) on SmartPLS v4, facilitating the

simultaneous evaluation of measurement properties and hypothesis testing. PLS-SEM is particularly robust for exploratory research, complex models with varying paths, and when theoretical underpinning is still developing, as is the case with cryptocurrency adoption in emerging markets (Ahmed et al., 2022; Jariyapan et al., 2022; Loor-Zambrano et al., 2022; Shahzad et al., 2024).

4.7. Time Horizon

This study employed a cross-sectional time horizon where data were collected during a defined period (July–August 2025) without follow-up. A cross-sectional approach was suitable because the primary aim was to examine existing attitudes and biases of retail investors regarding cryptocurrency adoption at the time of study, rather than to observe changes or developments over time (Bui & Sällberg, 2022). While this limits causal inference, it offers practical advantages regarding time and resources. This approach is consistent with prior research on cryptocurrency adoption in South Africa and investor psychology in emerging markets, where cross-sectional designs have been effectively utilised to capture contemporary perceptions and behaviours (Mazambani & Mutambara, 2019; Osakwe et al., 2022)

4.8. Target Population

The target population was individual retail investors who are South African citizens and older than 18 years of age. The aim was to get an equitable disbursement of respondents across the various age groups (18–28; 29–37; 38–45 and 45+ years) to allow for reliable and in-depth findings. This focus aligns with the research question on behavioural drivers in a specific geographic and regulatory context. The study aimed to gather responses across various industries; however, this served as a limitation as the majority of the respondents were in the ICT and finance sector. This demographic skew may influence the generalisability of findings, as these sectors often exhibit higher digital literacy and financial sophistication compared to the broader populace (Hasan et al., 2021; Shahzad et al., 2024). Demographic variables (age, gender, education) were collected to describe the sample (Chapter 5), but these serve as context rather than units of analysis. The research also acknowledged the potential for self-selection bias given the survey methodology, as individuals more engaged with cryptocurrencies might be more inclined to participate.

4.9. Unit of Analysis

The unit of analysis in this study is the perceptions of the individual investor across the various age groups in South Africa as stipulated in the questionnaire. Each survey response corresponds to one person's attitudes and behaviours regarding cryptocurrency adoption. The analysis examines relationships at the individual level (e.g. an investor's overconfidence score predicting that same investors reported adoption level). This individual-level data offers detailed insights into the psychological elements influencing cryptocurrency engagement across different demographic groups in South Africa. This method yields granular data, facilitating the identification of specific psychological drivers and demographic impacts on investment choices, which is vital for developing targeted educational and regulatory frameworks within the South African context (Dabbous et al., 2022).

4.10. Sampling Method and Size

A non-probability purposive sampling strategy was employed, complemented by snowball sampling. This allowed participants to disseminate the questionnaire within their professional and personal networks (Gupta & Shrivastava, 2021). The sample size determination considered PLS-SEM requirements, with some research suggesting a minimum of 10 times the number of paths or indicators in the model (Rahman & Gan, 2020). Given the proposed model had 6 constructs and 1 dependent variable, with a maximum of 6 predictive paths, a minimum of 60 valid respondents was sufficient. However, for robust multivariate statistical analysis, sample sizes between 160 and 300 observations are often recommended for stable parameter estimates and acceptable power (Hair et al., 2018, 2021; Sarstedt & Liu, 2023).

Consequently, a target of at least 200 valid responses was set for ample statistical power for the analyses (Etikan et al., 2016; Rahman, 2023; Sibona et al., 2020). This approach aligns with previous South African research, where similar sample sizes have proven viable for studying cryptocurrency adoption determinants (Kumari et al., 2023). A total of 350 known potential respondents were contacted, with 234 responding, resulting in a 66.86% response rate. After meticulous screening for incomplete information and influential outliers, five responses were excluded as they were not South African citizens, a prerequisite for the study. An additional nine respondents were removed due to providing identical answers across all Likert scale items, indicating unreliable data. The final sample

for analysis comprised 219 valid responses. This sample size is considered robust for descriptive survey research, ensuring meaningful subgroup analyses and minimising the impact of sampling variability or small cell sizes on population parameter estimates.

4.11. Measurement Instrument

The measurement instrument was a structured survey (Appendix A) in the form of an online questionnaire that was self-completed and closed-ended. The survey questions were developed based on existing literature and peer-reviewed papers that are relevant to this paper's field of research (Section 3.2). These papers had relevance to behavioural factors, preferences and attitudes towards the adoption of cryptocurrency to ensure the validity of the questions.

The questionnaire was divided into five sections. The initial section focused on collecting demographic data, including age, gender, income, education, employment status and professional expertise. This information is pertinent as these factors can significantly influence financial literacy, risk tolerance and categorise respondents for comparative analysis, allowing for the identification of demographic-specific behavioural adoption and bias patterns (Shahzad et al., 2024). The second section explored cryptocurrency awareness and usage, which, when combined with demographic information, aimed to identify adoption patterns and behavioural intentions across different groups. This approach helped in understanding how participant profiles influenced the dependent variable. Section 3 focused on the six behavioural factors that may influence the adoption of cryptocurrency. The fourth section addressed financial literacy, which served as the moderating variable, while the fifth and final section assessed the participants' intention to adopt cryptocurrency.

Each behavioural construct in the study was measured using three questionnaire items on a five-point Likert-type scale (1 = strongly disagree to 5 = strongly agree). The constructs and their respective hypotheses were ordered as follows: H1: Herding behaviour was measured through items Q3.4.1–Q3.4.3, adapted from Altaf and Jan (2023); H2: Disposition effect through Q3.5.1–Q3.5.3 (Altaf & Jan, 2023); H3: Overconfidence bias through Q3.3.1–Q3.3.3 (Altaf & Jan, 2023); H4: Fear of missing out (FOMO) through Q3.2.1–Q3.2.3, based on (Altaf & Jan, 2023) and (Gupta & Shrivastava, 2021); H5: Loss aversion through Q3.6.1–Q3.6.3 adapted from (Gupta & Shrivastava, 2021); and H6: Heuristic bias through Q3.1.1–Q3.1.3 adapted from (Almansour, 2020).

Finally, H7: Financial literacy was incorporated as a moderating variable between behavioural factors and cryptocurrency adoption, measured through items Q4.1–Q4.3 to assess its moderating effect and statistical significance, adapted from Raut (2020).

4.12. Data Gathering Process

Primary data for the study were gathered via an online survey hosted on Microsoft Forms, which was then distributed through the author's social media channels and personal networks, including WhatsApp, email, LinkedIn and professional and academic contacts. The author's network was asked to forward the survey to their networks, creating a snowball effect (Saunders & Lewis, 2018). The data were exported from Microsoft Forms to Excel and coded for analysis. The online survey allowed geographically dispersed respondents across South Africa to participate at their convenience. Incomplete or out-of-scope responses (non-South Africans and incomplete questionnaires) were excluded. A cover page introduced the study and its purpose and provided informed consent information. All collected data were stored on the author's Google OneDrive for an intended period of 10 years, after which it will be destroyed in accordance with data privacy regulations set by GIBS or relevant authorities.

4.13. Analysis Approach

PLS-SEM suits this study's goal of explanation and prediction as it aims to maximise explained variance in cryptocurrency adoption and in path coefficients for each hypothesis outlined in Chapter 3 (Hair et al., 2018; Shahzad et al., 2024).

Descriptive statistics such as mean, frequency, standard deviation and averages were used to draw inferences about the demographic profile of the sample group and screened for missing data, outliers and normality before inferential statistics were applied (Adil et al., 2021; Barroga et al., 2023; Fujiki, 2021). The approach involved two stages. First, the model was evaluated for reliability and validity and tested to assess the hypothesised relationships. Convergent validity was evaluated using Average Variance Extracted (AVE) and standardised factor loadings, while internal consistency reliability was confirmed through Cronbach's alpha and composite reliability (Fornell & Larcker, 1981; Hair et al., 2018, 2021). Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio to ensure distinctness between constructs (Walton & Johnston, 2018).

Second, the structural model was analysed to test the proposed hypotheses by examining the path coefficients and their associated p-values to determine the significance and direction of relationships between constructs (Mazambani & Mutambara, 2019). Bootstrapping with 10,000 resamples was applied to generate t-values to obtain the level of significance for the path coefficients and the R^2 for the model was evaluated as a measure of explanatory power (Ahmed et al., 2022; Hair et al., 2018, 2021). Model fit was assessed using Stone-Geisser's Q^2 (via blindfolding) and the Standardised Root Mean Square Residual (SRMR) index. Moderating effects of financial literacy against the constructs were tested, including the significance of biases between age groups. To test for significance of biases between age groups, analysis of variance (ANOVA) was utilised (Steinmetz et al., 2021).

4.14. Ethics Research

Ethical guidelines and consideration were followed in this study to ensure that data were gathered and handled responsibly and morally for the intended purpose of this study. To ensure the integrity and ethical conduct of this research, ethical clearance was obtained from the Master's Research Ethics Committee of GIBS (MREC).

The informed consent cover page of the online survey explained the purpose of the research and assured respondents that data would be used for only academic purposes. Participation in the survey was voluntary, with informed consent being given when the respondent decided to continue with the survey.

The study complied with the Protection of Personal Information Act of South Africa, ensuring that all personal information was processed lawfully and securely. To protect the privacy of participants, anonymity was ensured. Personal identifying information was not collected, and responses were aggregated to prevent individual identification. Participants were informed of the study's purpose, their right to withdraw at any time and the measures taken to ensure confidentiality. Respondents were also made aware of the estimated time that it will take to complete the survey in order to know the time commitment on their part. By adhering to these ethical principles, the research aims to uphold the dignity and rights of participants while producing credible and valuable insights relevant to the study.

4.15. Quality Controls

To ensure the quality and validity of the data collected, the following were employed. A pilot was done to test the survey with a small sample of individuals to assess the clarity, relevance and flow of the survey questions. A participant should be able to answer all questions in four to six minutes based on a timed exercise conducted by the author. This was part of the pilot process to ensure the reliability of the survey.

Reliability was assessed using Cronbach's alpha (α). All constructs exceeded the minimum threshold of 0.70, except for disposition ($\alpha = 0.675$) and loss aversion ($\alpha = 0.648$) (Adil et al., 2021; Jadil et al., 2021; Mariani et al., 2022). However, this was not seen as a violation of the reliability test since this study is exploratory and values between 0.60 and 0.70 are deemed acceptable (Nicholls & Yitbarek, 2022; Taber, 2017).

Convergent validity was assessed through AVE with a minimum requirement value of ≥ 0.50 for each construct (Hair et al., 2018; Walton & Johnston, 2018). Discriminant validity was checked using the Fornell-Larcker criterion, where the square root of each construct's AVE exceeded its correlations with other constructs (Altaf & Jan, 2023; Fornell & Larcker, 1981). Normality was not assumed (PLS-SEM is non-parametric), but no severe skewness and kurtosis were detected. Multicollinearity was checked using Variance Inflation Factors (all VIF < 5), ensuring no redundant items (Altaf & Jan, 2023; Kaur et al., 2023; Walton & Johnston, 2018).

Collectively, these procedures ensured that the measurement model demonstrated adequate reliability, convergent and discriminant validity, and absence of multicollinearity, thereby supporting the robustness of the data used for hypothesis testing.

4.16. Limitations

There are limitations that may hinder the findings and data of the study. The data were self-reported so behavioural factors could potentially affect the accuracy of responses. The reliance on non-probability purposive sampling introduces limitations regarding generalisability, as the sample may not fully represent the broader South African population and its age demographics, particularly those aged 45 and above (Rahman & Gan, 2020). This limitation was evident in the sample data, where the ICT and finance sectors were predominantly represented. Additionally, the cross-sectional design captures insights only at a single point in time. This limits the study's ability to assess the constructs

and relationship evolution over time (Lim, 2024; Pandurugan & Shammakhi, 2024). Furthermore, the study's timing coincides with peak consumer interest in cryptocurrency, potentially skewing results due to socio-cognitive biases such as availability and anchoring, which may inflate reported behavioural intentions to use (Mahomed, 2017).

The measurement model showed acceptable validity; however, a few constructs (overconfidence and loss aversion) were below 0.65 and 0.70, suggesting caution in the interpretation of those specific constructs. Future work could refine the scales or employ mixed methods to deepen understanding. Regulations in South Africa pose another challenge; policy changes may significantly affect adoption trends after data collection. Events such as the inclusion of cryptocurrency in the FAIS legislation and the requirement for all financial service providers (FSPs) to be registered with the FSCA to provide crypto-related services impact adoption. Lastly, more behavioural factors could have been tested; however, these were the most relevant for this study.

Despite these limitations, the methodological approach remains appropriate for the study's objectives. The rigorous application of PLS-SEM, combined with extensive validity and reliability testing, supports confidence in the robustness of the key findings and their contribution to understanding behavioural factors in cryptocurrency adoption.

4.17. Conclusion

Chapter 4 has detailed the methodological framework underpinning this study to investigate the behavioural drivers of cryptocurrency adoption in South Africa. By adopting a quantitative, cross-sectional approach and leveraging a structured online survey, the study ensures objectivity, replicability and robust statistical analysis. While the chosen methodology offers significant strengths in terms of reliability and validity, acknowledged limitations such as potential sampling bias and the constraints of self-reported data are also addressed. Overall, the methodological rigour established in this chapter sets the stage for the presentation and interpretation of empirical findings in the subsequent chapter.

Chapter 5: Findings

5.1. Introduction

Out of the 234 individuals who responded, five were excluded as they were not South African citizens, which was a requirement to proceed with the questionnaire, and one respondent did not complete it. An additional nine respondents were removed due to providing identical answers across all Likert scale items, indicating unreliable data. The final sample size for analysis comprised of 219 valid responses.

5.2. Data Preparation and Assumption Checks

Since Likert scales inherently possess defined upper and lower limits, the presence of extreme values for individual items is anticipated. The raw dataset underwent scrutiny, with instances of inattentive responses, where respondents provided identical answers across all questions or completed the survey significantly faster than the average duration. Recognising the potential impact of outliers on ANOVA results, traditional ANOVA methods were augmented with robust alternatives. This confirmed that the study's conclusions remained consistent even after the exclusion of outliers. Such a precise methodology guaranteed the resilience of the statistical analyses and affirmed that the behavioural drivers pinpointed were genuine findings, not mere consequences of data irregularities.

Raw data were screened before analysis. Ineligible cases (age <18, outside SA, or incomplete consent) were removed. Reliability was verified (Cronbach's α) and items with low loadings were reviewed and dropped like FOMO. Normality was tested using histograms and reported skew and kurtosis, adopting practical thresholds to test for normality (skewness < 2.0 and excess kurtosis < 7.0). The skew and kurtosis for the constructs tested were within the range (-0.95 and .30 for skew and -.38 and 0.79 for kurtosis). This establishes a normal distribution with no significant outliers.

To calculate financial education, three yes/no questions were asked and coded as true/false, and a percentage was computed out of the three to create the financial score variable for moderation in the model. Furthermore, FOMO was removed from the original model (Figure 5.1) as it proved to be unreliable (factor loading of 0.4) in the analysis. It was therefore removed from the final structural model and results discussion. Figure 5.1 shows the initial model with FOMO included for completeness.

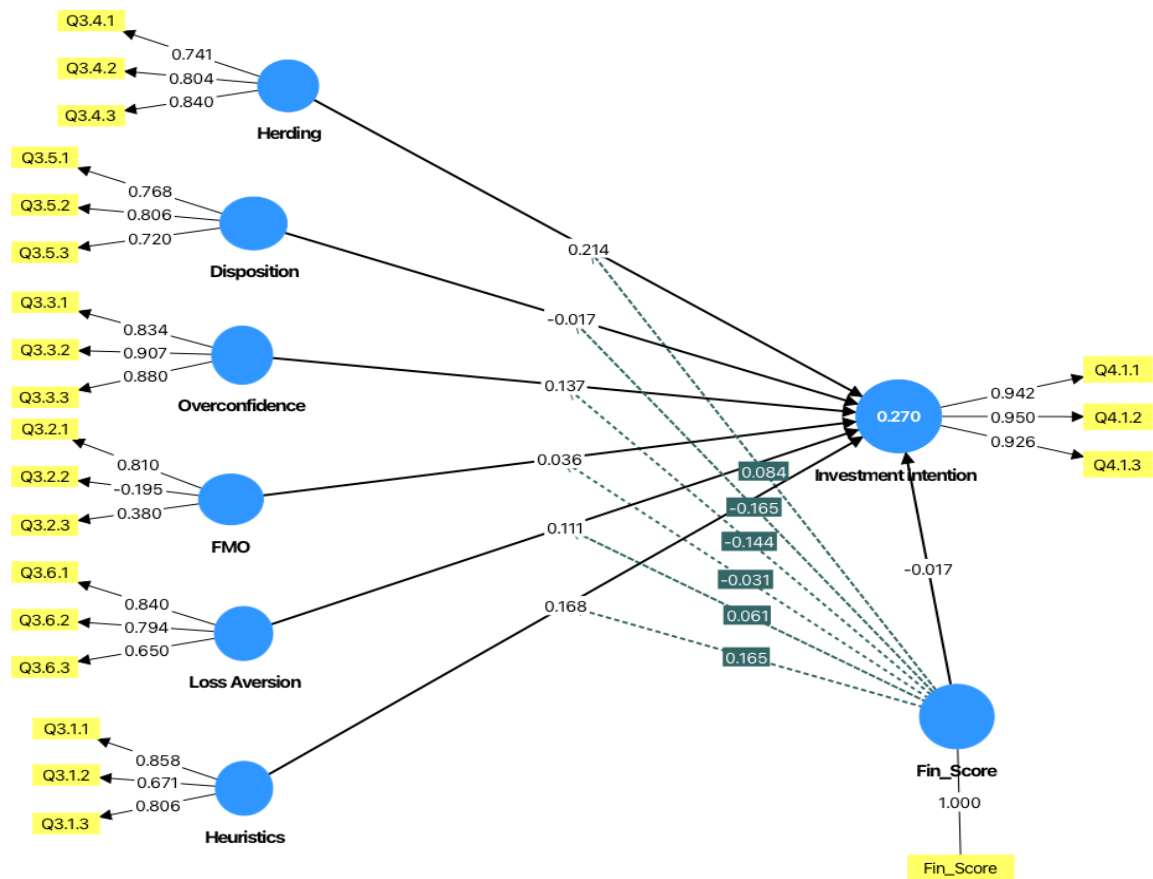


Figure 5.1: Original Model with FOMO

(Source: Author – PLS SEM Structural Model)

5.3. Descriptive Statistics: Demographics

The section details the descriptive characteristics of the valid responses of respondents, providing an overview of the sample's demographic attributes.

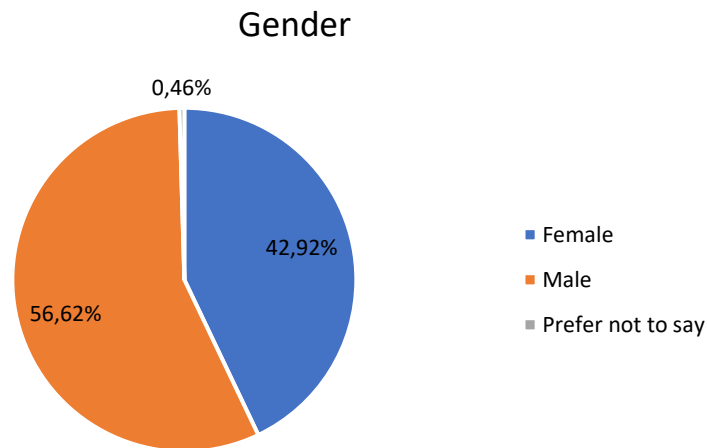


Figure 5.2: Gender Demographics

(Source: Author – raw data)

The demographic profile of the participants, as summarised above, reveals a sample composed of 56.62% males and 42.92% females. This is a fairly equitable representation of both genders.

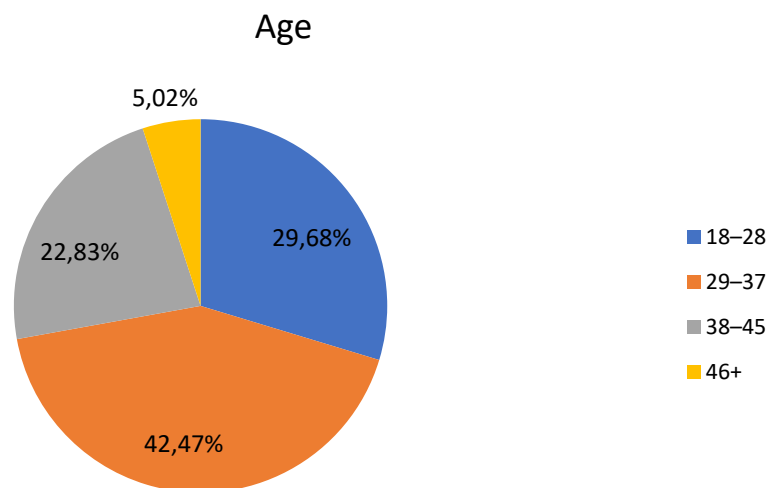


Figure 5.3: Age Demographics

(Source: Author – raw data)

The majority of respondents are between the ages of 29 and 37 years, representing 42.47% of the sample. This age range falls within the Millennial cohort. The next highest

cohort is 18–28, being Gen Z at 29.68%. The lowest representation sits in the 46 years and above bucket, which is the Gen X cohort.

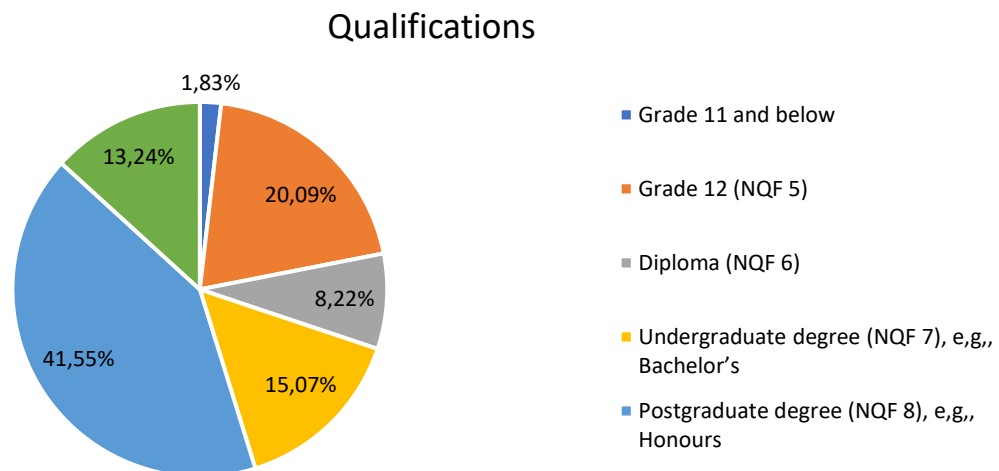


Figure 5.4: Qualification Demographics

(Source: Author – raw data)

The majority of the sample (41.55%) possess a postgraduate degree, followed by Grade 12 at 20.09% and then a Master's degree or higher with 13.24%

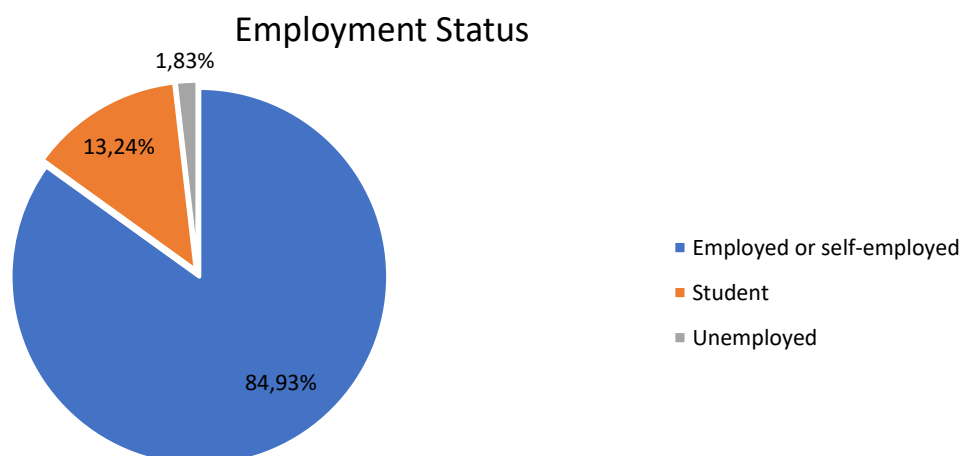


Figure 5.5: Employment Demographics

(Source: Author – raw data)

A substantial portion, 84.93%, are either employed or self-employed, and only 1.83% are unemployed, based on the sample group.

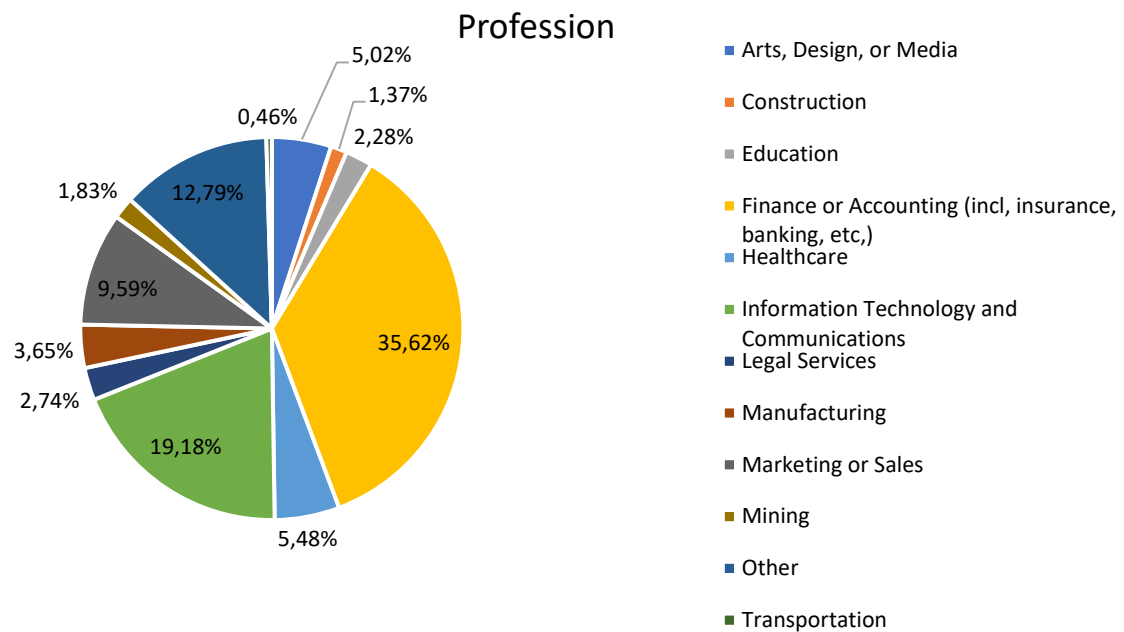


Figure 5.6: Professional Demographics

(Source: Author – raw data)

The highest concentration of respondents work in the Finance and Accounting field (35.62%), followed by 19.18% working in the Information Technology and Communications (ITC), respectively. This accounts for more than 50% of the sample, and the rest of the jobs are dispersed across the other fields.

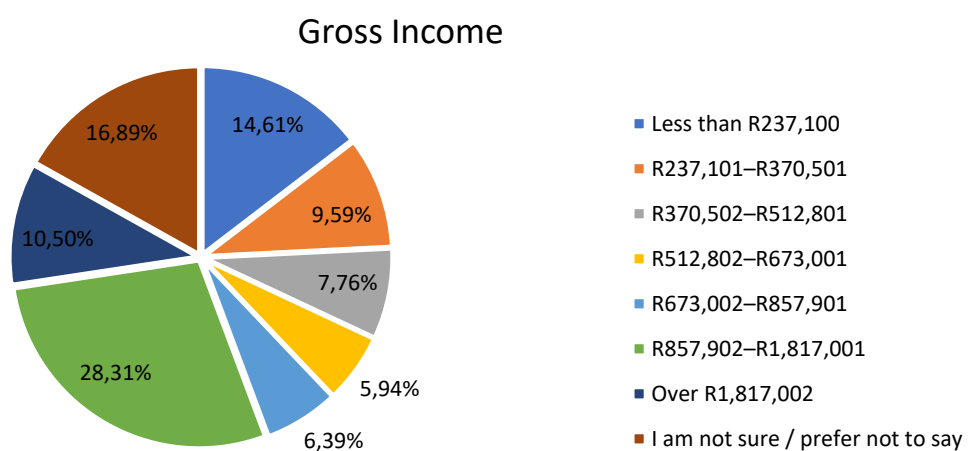


Figure 5.7: Income Demographics

(Source: Author – raw data)

The gross income brackets for the sample indicate a significant representation of individuals in higher-income brackets, with 38.81% earning over R857,902 and only 14.61% earning below R237,100.

5.4. Descriptive Statistics: Awareness, Usage and Adoption

Questions 2.1 to 2.4 pertained to participants' awareness, usage and uptake of cryptocurrency, which provides foundational insights into the prevalence of these activities within the sample.

2.1. Have you heard of Bitcoin or other cryptocurrencies?

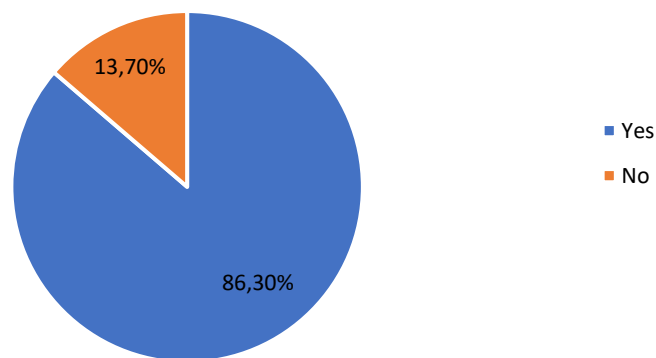


Figure 5.8: Awareness

(Source: Author – raw data)

Of the 219 respondents, 86.3% reported having heard of Bitcoin or other cryptocurrencies, while only 13.7% had not. This suggests a high level of general awareness regarding digital assets among South Africans based on the sample.

Q2.2. Which of the following statements most accurately applies to you?

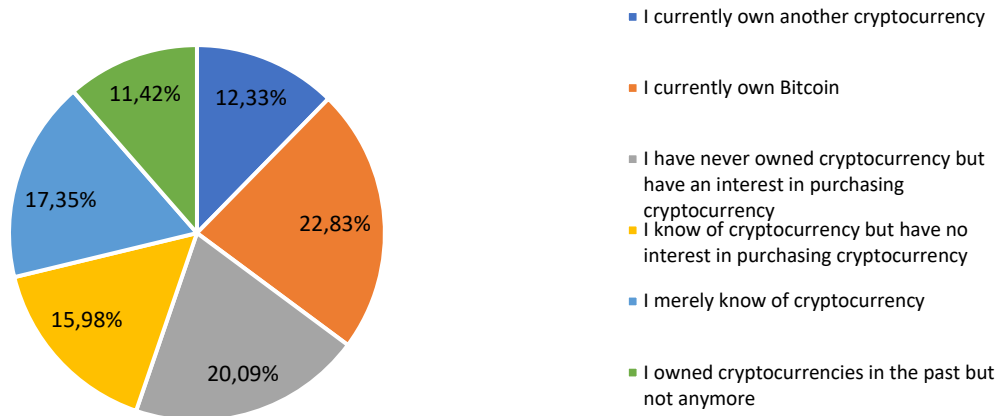


Figure 5.9: Ownership

(Source: Author – raw data)

Among the respondents, 22.8% currently own Bitcoin, and an additional 12.3% own other cryptocurrencies, resulting in a total cryptocurrency ownership rate of 35.1%. A further 11.4% are past owners; among non-owners, interest in purchasing is 20.1% while 17.4% merely know of cryptocurrency and 16.0% know of it but have no interest. Taken together, roughly 1 in 3 respondents is a cryptocurrency owner, and 1 in 5 non-owners expresses explicit purchase interest.

Q2.3. How likely are you to purchase cryptocurrency in the future?
(If respondent did not currently own crypto they were asked this question)

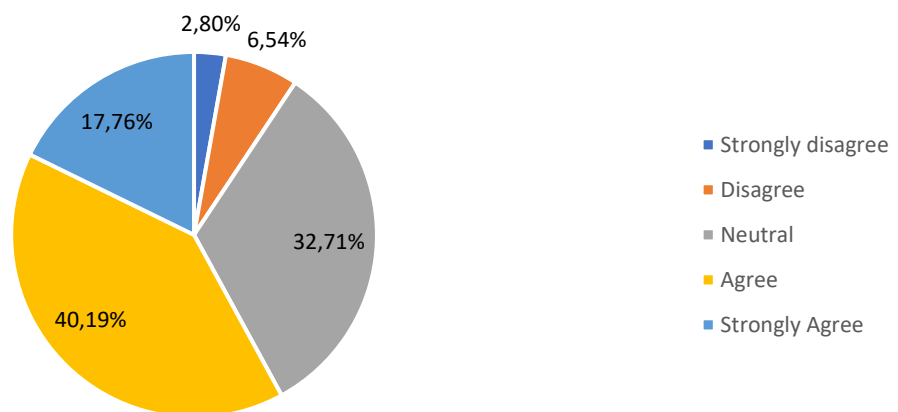


Figure 5.10: Intention to Invest

(Source: Author – raw data)

For respondents who do not currently own cryptocurrency (n = 107) and answered Q2.3, “How likely are you to purchase cryptocurrency in the future?”, the distribution suggests moderate-to-strong prospective demand with a mean of 3.64, where 58.0% selected Agree or Strongly Agree and 32.7% were Neutral. This pattern signals that the majority of non-owners are at least positively disposed towards future ownership, although a sizeable neutral group indicates ambivalence that could be shifted by information, education or incentives.

Q2.4. Please indicate your level of agreement with the following statements regarding your main use of cryptocurrency.

(If respondents own cryptocurrency, they were asked this question)

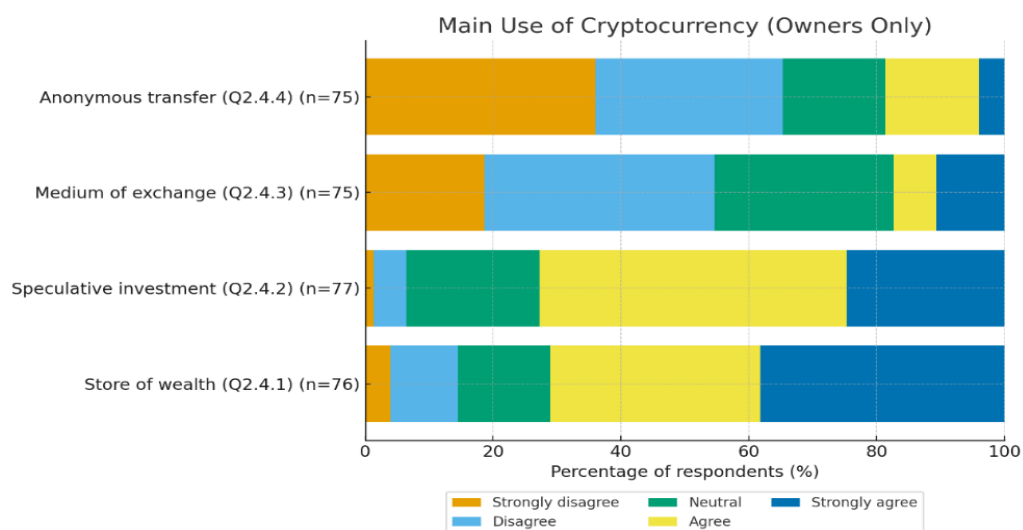


Figure 5.11: Main Usage of Cryptocurrency

(Source: Author – raw data)

Among current owners, the two primary use cases identified were as a store of wealth, with 71% of respondents agreeing or strongly agreeing, and as a speculative investment, with 73% agreeing or strongly agreeing. For cryptocurrency owners, practical transactional uses such as a medium of exchange or for anonymous transfers are uncommon, with only about 17% and 19% of respondents, respectively, endorsing these uses. This indicates that owners predominantly view cryptocurrency as an asset class rather than a payment technology or a privacy tool.

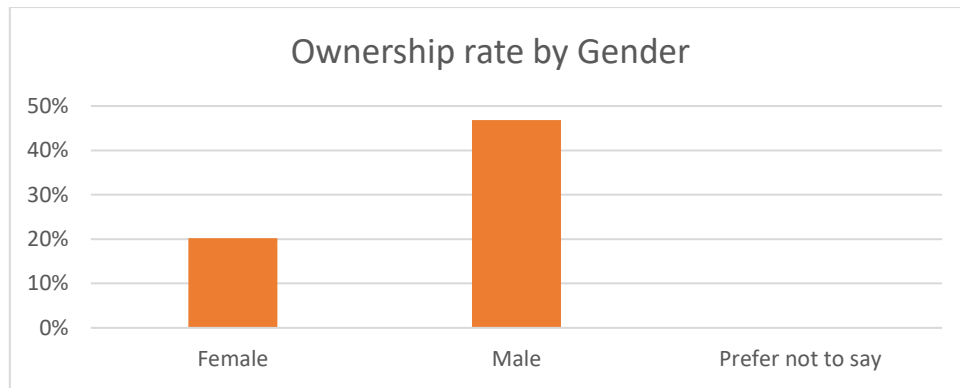


Figure 5.12: Ownership by Gender

(Source: Author – raw data)

There is a significant skew towards male ownership in cryptocurrency (46.80%) versus females (20.20%). The scale of ownership is more than double that of female ownership.

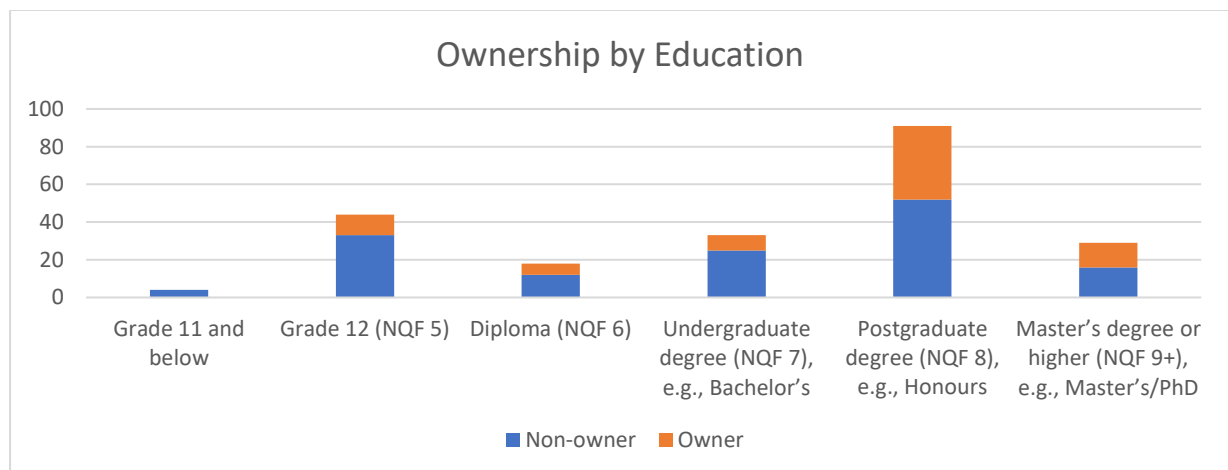


Figure 5.13: Ownership by Education

(Source: Author – raw data)

Postgraduates make up the largest share of ownership, followed by a Master's degree or higher and then Grade 12.

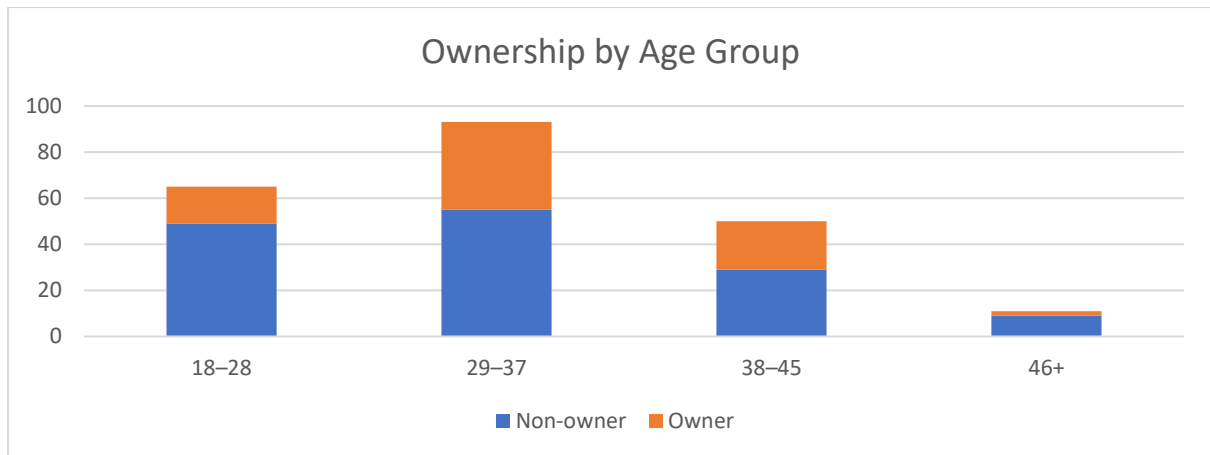


Figure 5.14: Ownership by Age Group

Ownership is the highest among the 29–37 years age group, followed by 38–45 and lastly 46+ years. Interestingly, ownership was the highest among Millennials compared to any other cohort.

5.5. Research Question One

Descriptive statistics: Bias factors

Table 5.1 below provides an overview of the descriptive statistics for the seven factors or constructs, financial literacy (*Fin_Score*), heuristics, overconfidence, herding, disposition, loss aversion and cryptocurrency adoption.

Table 5.1: Descriptive Statistics for Constructs

<i>Variables</i>	<i>n</i>	<i>mean</i>	<i>sd</i>	<i>median</i>	<i>min</i>	<i>max</i>	<i>skew</i>	<i>kurtosis</i>
<i>Fin_Score</i>	219	79,00	24,00	66,67	-	100,00	-0,90	0,24
<i>Heuristics</i>	219	3,07	0,91	3,33	1,00	5,00	-0,32	- 0,18
<i>Overconfidence</i>	219	2,58	1,00	2,67	1,00	5,00	0,30	- 0,38
<i>Herding</i>	217	2,70	0,87	2,67	1,00	5,00	-0,14	- 0,15
<i>Disposition</i>	218	2,93	0,81	3,00	1,00	5,00	-0,30	0,41
<i>Loss_aversion</i>	217	3,33	0,80	3,33	1,00	5,00	-0,50	0,77
<i>Adoption</i>	218	4,00	0,95	4,00	1,00	5,00	-0,95	0,79

(Source: Author – PLS SEM)

Financial literacy had 219 respondents, where 50% of the participants scored above 66.67%, indicating a moderate to high level of financial understanding within the sample. The mean financial literacy score of 78.99% further underscores a generally informed participant base, while the standard deviation of 24% is unusually large because only three questions were asked. This gives high weightings to each question, thus causing the high standard deviation (sd). Despite the high standard deviation, the skewness of -0.89 suggests that a larger proportion of respondents scored higher than the mean, reinforcing the notion of a financially literate sample, which could be implied by the high percentage of people working in finance and ICT. This skew is depicted in Figure 5.15, which highlights the distribution of financial literacy scores, with a pronounced clustering towards the upper end of the scale.

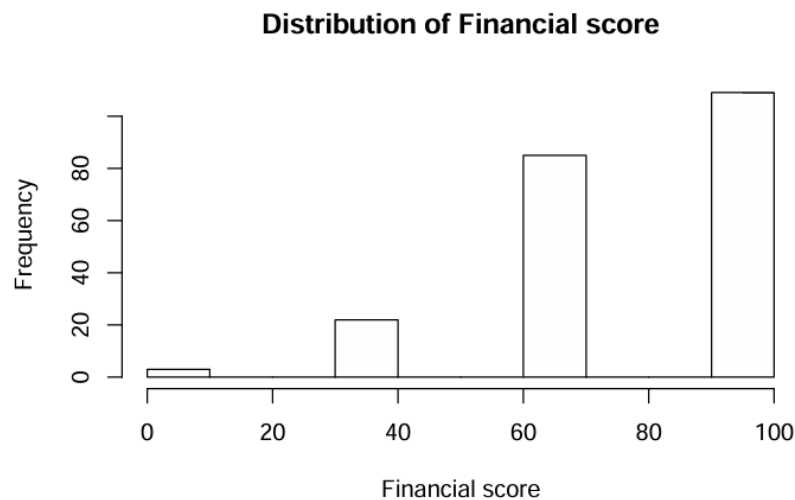


Figure 5.15: Financial Literacy Histogram

(Source: Author – PLS SEM)

The interaction plot (Figure 5.16) shows how financial literacy moderates the relationship between the disposition effect and cryptocurrency adoption. At low and average levels of financial literacy, the slope is positive, and individuals with stronger disposition tendencies display higher adoption intentions. However, at high financial literacy, this relationship flattens, indicating that knowledgeable investors are less swayed by the disposition bias when deciding to adopt cryptocurrency. This pattern aligns with the coefficient between the two variables ($\beta = -0.165$), implying that financial literacy weakens the behavioural

pull of disposition bias. Practically, it suggests that enhancing financial education could help investors make more rational adoption decisions by reducing bias-driven tendencies.

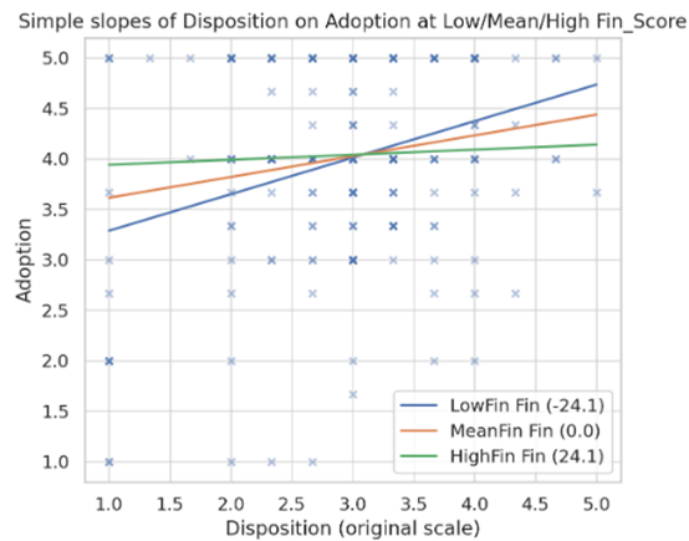


Figure 5.16: Disposition Effect on Cryptocurrency Adoption

(Source: Author – raw data)

The constructs (Figure 5.17) heuristics, overconfidence, herding, disposition and loss aversion exhibited means clustered around the neutral point of the Likert scale, ranging between 2.5 and 3.3 and the median between 2.6 and 3.3, suggesting no strong preference to either extreme of strongly agree or strongly disagree. The standard deviation was consistently below 1.0 and between 0.8 and 0.99. This indicates a relatively tight clustering of responses around their respective means, suggesting a general consensus and no extreme divergence in opinions regarding the factors.

Respondents who currently invest in cryptocurrency rely more on heuristic (rule-of-thumb) decision-making than those who do not. This is proven by cryptocurrency holders having a higher mean heuristic score.

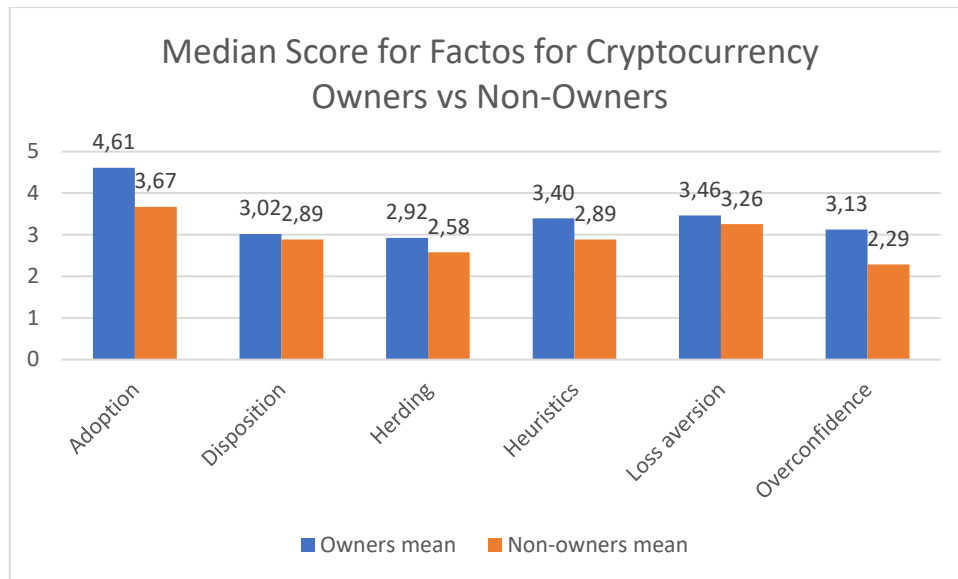
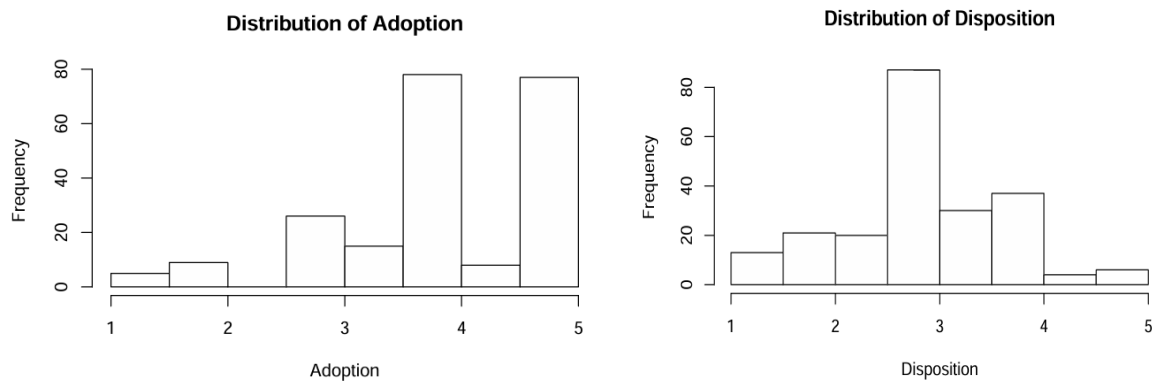


Figure 5.17: Median Score for Factors for Cryptocurrency Owners vs Non-Owners

(Source: Author – raw data)

Conversely, the adoption variable, with a mean and median of 4.00, indicated a notable inclination towards cryptocurrency adoption among the respondents, although the standard deviation of 0.95 suggests some variability in this trend. As for the remaining constructs, the histograms show a relatively standard clustering with no significant outliers.



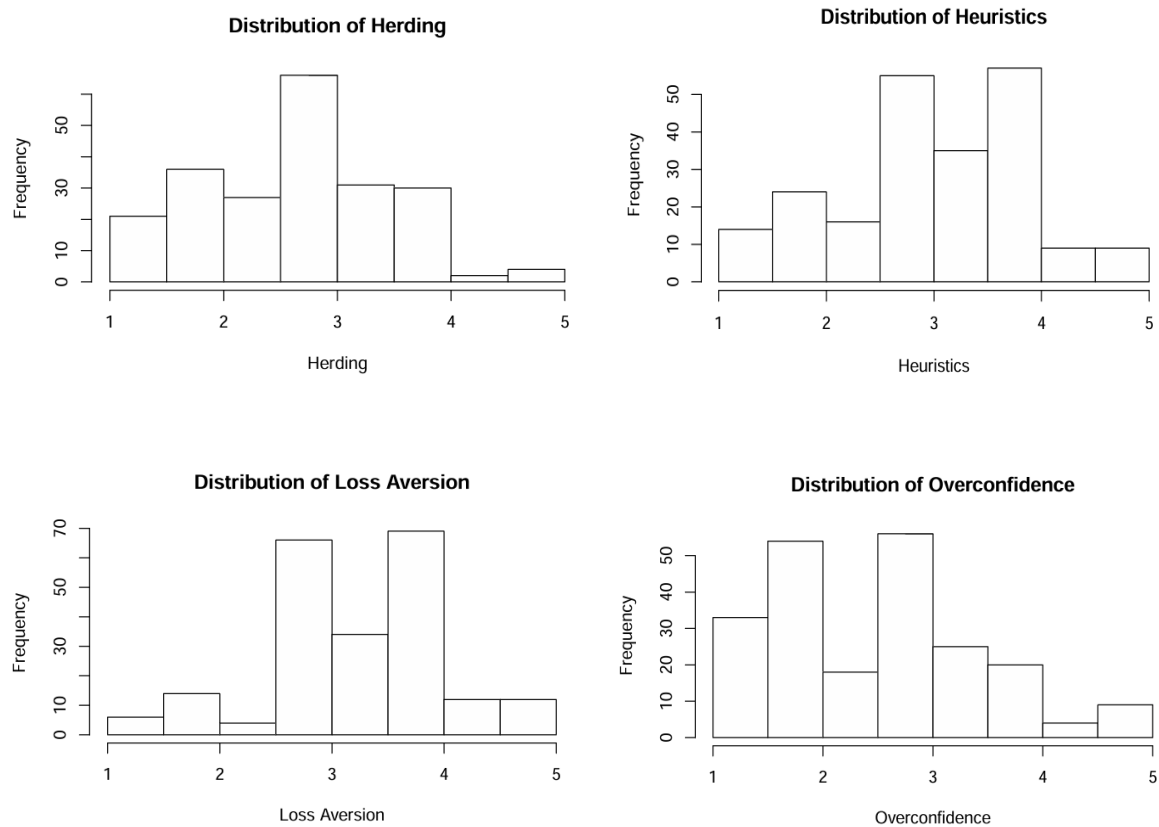


Figure 5.18: Construct Histograms

(Source: Author – PLS SEM)

5.5.1. Reliability and factor analysis

This section details the various tests of validity of the survey instrument through reliability assessments and exploratory factor analysis to ensure the robustness of the constructs measured (Table 5.2).

Table 5.2: Reliability and Validity Results

(Source: Author – PLS SEM)

Construct	Item	Loading	VIF	Cronbach's α	Composite reliability (ρ_a)	AVE
Disposition				0.675	0.665	0.586
	Q3.5.1	0.768	1.137			
	Q3.5.2	0.806	1.627			

Herding	Q3.5.3	0.720	1.697			
			—	0.717	0.747	0.634
	Q3.4.1	0.741	1.409			
Heuristics	Q3.4.2	0.804	1.448			
	Q3.4.3	0.840	1.368			
				0.700	0.761	0.612
	Q3.1.1	0.858	1.348			
	Q3.1.2	0.671	1.354			
Investment intention	Q3.1.3	0.806	1.394			
				0.933	0.937	0.883
	Q4.1.1	0.942	4.097			
	Q4.1.2	0.950	4.967			
	Q4.1.3	0.926	3.395			
Loss aversion				0.648	0.684	0.586
	Q3.6.1	0.840	1.351			
	Q3.6.2	0.794	1.353			
	Q3.6.3	0.650	1.177			
				0.846	0.859	0.764
Overconfidence	Q3.3.1	0.834	1.778			
	Q3.3.2	0.907	2.323			
	Q3.3.3	0.880	2.226			

5.5.1.1 Heterotrait-Monotrait Ratio

The HTMT (Heterotrait-Monotrait Ratio) ratio is used to evaluate discriminant validity, indicating whether two constructs are distinct from one another and not measuring the same thing (Ahmed et al., 2022). Values below 0.85 or 0.90 are acceptable, but values above 0.90 are considered unacceptable (Ahmed et al., 2022).

Table 5.3: HTMT Matrix with FOMO*(Source: Author – PLS SEM)*

<i>HTMT matrix</i>	Disposition	FMO	Fin_Score	Herding	Heuristics	Investment intention	Loss Aversion	Overconfidence
Disposition								
FMO	1.412							
Fin_Score	0.121	0.306						
Herding	0.645	1.399	0.270					
Heuristics	0.390	0.945	0.113	0.520				
Investment intention	0.256	0.174	0.072	0.454	0.438			
Loss Aversion	0.769	0.752	0.184	0.519	0.439	0.332		
Overconfidence	0.389	1.137	0.027	0.516	0.812	0.418	0.280	

The FOMO construct was removed from the model as it created discriminant validity problems, as shown in Table 5.3. The FOMO construct exhibits HTMT values exceeding 0.90 when compared with disposition (1.412), herding (1.399) and overconfidence (1.137), thereby failing the stringent discriminant validity criterion (Dabbous et al., 2022). The FOMO construct was removed from the model due to its high correlation with other constructs, such as disposition, herding and overconfidence, indicating a lack of discriminant validity. Furthermore, its negligible path coefficient (0.036) and low factor loading scores for two of the three questions (0.380 and -0.195) demonstrated minimal contribution to explaining investment intention, reinforcing the decision to exclude it for model integrity and theoretical coherence. This removal consequently enhances the model's predictive power and the interpretability of the remaining constructs by eliminating a confounding variable (Chauhan & Patel, 2024; Jariyapan et al., 2022). The new HTMT model without FOMO is presented in the table below. The removal of FOMO does not change the discriminant validity of the remaining constructs.

Table 5.4: HTMT Matrix without FOMO*(Source: Author – PLS SEM)*

	Dispo sition	Fin_Sc ore	Herding	Heuristi cs	Investme nt intention	Loss aversion	Overcon fidence
<i>Disposition</i>							
<i>Fin_Score</i>	0.121						
<i>Herding</i>	0.645	0.270					
<i>Heuristics</i>	0.390	0.113	0.520				
<i>Investment intention</i>	0.256	0.072	0.454	0.438			
<i>Loss aversion</i>	0.769	0.184	0.519	0.439	0.332		
<i>Overconfidence</i>	0.389	0.027	0.516	0.812	0.418	0.280	

5.5.1.2 Factor Loadings

The factor loadings (Table 5.2) show how well each survey question measures its underlying concept, where higher values mean the item reflects the construct more accurately (Altaf & Jan, 2023). This is considered the starting point for the quality of the constructs and then the construct reliability and validity (Dabbous et al., 2022). Loadings can range between +1 and -1, where a high absolute value indicates a strong relationship between the item and the underlying variable. Questions with a loading below 0.4 were excluded, which is why FOMO was removed. Loadings should be > 0.70; however, a loading of > 0.6 can be acceptable, provided that other indicators within the construct are robust and the study is exploratory in nature, which this study is (Hamid et al., 2017).

The squaring of a factor loading determines the variance in cryptocurrency adoption explained by a construct (Tubastuvi et al., 2024). For instance, Q3.1.1 has a loading of 0.858; when squared, it indicates that 73.6% of the variance in investment intention is accounted for by the question asked. Table 5.2 displays the loadings for all constructs, ranging from 0.65 to 0.95. Several indicators demonstrated particularly strong loadings, such as Q4.1.1 and Q4.1.2, explaining 88.7% and 90.0% of the variance, respectively.

The lowest loading, being Q3.6.3 still explains 65% of the variance. This consistency across all indicators affirms a strong relationship with cryptocurrency adoption, thus supporting the construct validity of the measurement model.

5.5.1.3 Multicollinearity of constructs

Multicollinearity occurs when two or more independent variables (constructs) in the regression model are highly correlated, which can lead to unreliable coefficient estimates and diminished statistical power (Kim, 2019). This study used the variance inflation factor (VIF) to test for multicollinearity (Hair et al., 2018). Hair et al. (2018) further added that a VIF score below 5 is acceptable, while values above 10 indicate problematic levels of multicollinearity that necessitate remedial action.

The VIF analysis (Table 5.2) for the constructs reveals no issues of multicollinearity, as all values are below the critical threshold of 5, thus confirming the independence of the predictor variables and the robustness of the regression model. It should be noted that Q4.1.2 is approaching this threshold, yet still within acceptable limits. This indicates that while there is some correlation with other variables, it is not severe enough to compromise the integrity of the model.

5.5.1.4 Cronbach's alpha and convergent validity

Cronbach's alpha and composite reliability were used to evaluate the internal reliability and consistency of the constructs to reflect how closely related they are as a group, while convergent validity assesses the extent to which these factors converge to explain the variance (Hair et al., 2018; Mouton, 2019; Raut, 2020). AVE is a standard metric for assessing convergent validity and is calculated as the mean of the squared loadings of factors measuring a construct. An AVE of 0.50 or higher is considered acceptable as it explains at least 50% of the variance (Gupta & Shrivastava, 2021; Hair et al., 2018). The acceptable thresholds for Cronbach's alpha are 0.7 or higher, although values between 0.6 and 0.7 are acceptable in exploratory research, which this study is (Hair et al., 2018).

The results (Table 5.2) indicated that herding, heuristics, investment intention and overconfidence exceed the acceptable threshold of Cronbach's alpha of 0.7 with a range of 0.70–0.93. Disposition and loss aversion fall slightly below the 0.70 threshold but exceed 0.60, which is still considered acceptable due to the exploratory nature of the study. All constructs had an AVE > 0.50 with a range of 0.58–0.88, supporting convergent validity. Overall, the study demonstrated satisfactory convergent validity and internal consistency, as evidenced by

the Cronbach's alpha coefficients, which confirmed that the items within each construct consistently measure the same underlying concept.

5.5.1.5 Discriminant Validity

Discriminant validity of the model was assessed using the Fornell-Larcker criterion (Table 5.5), which compares the square root of each construct's AVE, with its correlations with other constructs (Hair et al., 2018). A construct demonstrates discriminant validity when its value (example: Disposition =0.766; Fin_Score = 1.000 and Overconfidence = 0.874) exceeds all off-diagonal correlations in the same row and column, which is the case below (Amoa-Gyarteng & Dhiwayo, 2024; Gupta & Shrivastava, 2021; Hair et al., 2018).

Table 5.5: Fornell-Larcker Criterion Matrix

(Source: Author – PLS SEM)

	Dispositi on	Fin_Sco re	Herd ing	Heuristi cs	Investme nt intention	Loss Aversi on	Overconfide nce
Disposition	0.766						
Fin_Score	0.099	1.000					
Herding	0.450	0.243	0.796				
Heuristics	0.258	0.077	0.373	0.782			
Investment intention	0.232	0.071	0.385	0.386	0.939		
Loss Aversion	0.486	0.162	0.364	0.291	0.265	0.766	
Overconfide nce	0.301	-0.002	0.409	0.656	0.374	0.204	0.874

As shown in Table 5.2, the diagonal entries for disposition (0.766), herding (0.796), heuristics (0.782), investment intention (0.939), loss aversion (0.766) and overconfidence (0.874) all exceed their respective inter-construct correlations, indicating acceptable discriminant validity. Fin_Score is modelled as a single composite indicator (1.00), which does not provide the same AVE-based evidence as the other constructs and warrants cautious interpretation. To ensure robustness, the results were cross-validated with HTMT (Section 5.5.1.1) where values were below the threshold (0.90) and no cross-loading concerns emerged. Taken together, the Fornell-Larcker results and supplementary HTMT cross-loading checks support the distinctiveness of the constructs in the proposed model on cryptocurrency adoption.

5.5.2. Structural model

The assessment of the structural model provides critical insights into the proposed causal relationships and the predictive power of the constructs on cryptocurrency adoption.

Table 5.6: Structural Model Results

(Source: Author – PLS SEM)

Path		β (O)	SE	t	p	BCa 95% CI lower	BCa 95% CI upper	f ²	Interpretation
Herding	→	.224	.068	3.291	.001	.094	.359	.043	Significant, positive , small effect
Investment Intention									
Heuristics	→	.171	.081	2.112	.035	.001	.319	.020	Significant, positive , small effect
Investment Intention									
Loss Aversion	→	.111	.078	1.428	.153	-.034	.266	.011	Not significant
Investment Intention									

Overconfidence → Investment Intention		.130	.084	1.537	.124	-.031	.301	.012	Not significant
Disposition → Investment Intention		-.019	.074	0.253	.801	-.200	.104	~0.00	Not significant
Fin_Score → Investment Intention		-.017	.062	0.275	.783	-.137	.111	~0.00	Not significant
Interactions (moderation by Fin_Score)									
Fin_Score Disposition → Investment Intention	×	-.166	.088	1.896	.058	-.339	.001	.022	Trend (marginal): higher Fin_Score tends to attenuate the Disposition effect Not Significant
Fin_Score Heuristics → Investment Intention	×	.154	.097	1.587	.113	-.034	.347	.016	Not significant
Fin_Score Herding → Investment Intention	×	.079	.095	0.826	.409	-.094	.275	.005	Not significant
Fin_Score Loss Aversion →	×	.069	.082	0.838	.402	-.079	.247	.004	Not significant

<i>Investment Intention</i>							
<i>Fin_Score</i> ×	-.138	.102	1.356	.175	-.355	.050	.010
<i>Overconfidence</i> → <i>Investment Intention</i>							Not significant

Table 5.6 illustrates the direct relationships between the behavioural factors and cryptocurrency adoption, including the mediating effect of financial literacy at the 5% level of significance. It highlights the significance of each bias in influencing cryptocurrency adoption. Herding and heuristics demonstrate a statistically significant positive impact on cryptocurrency adoption, suggesting that individuals are more likely to adopt cryptocurrencies when influenced by peer or group behaviour and simplified decision-making rules.

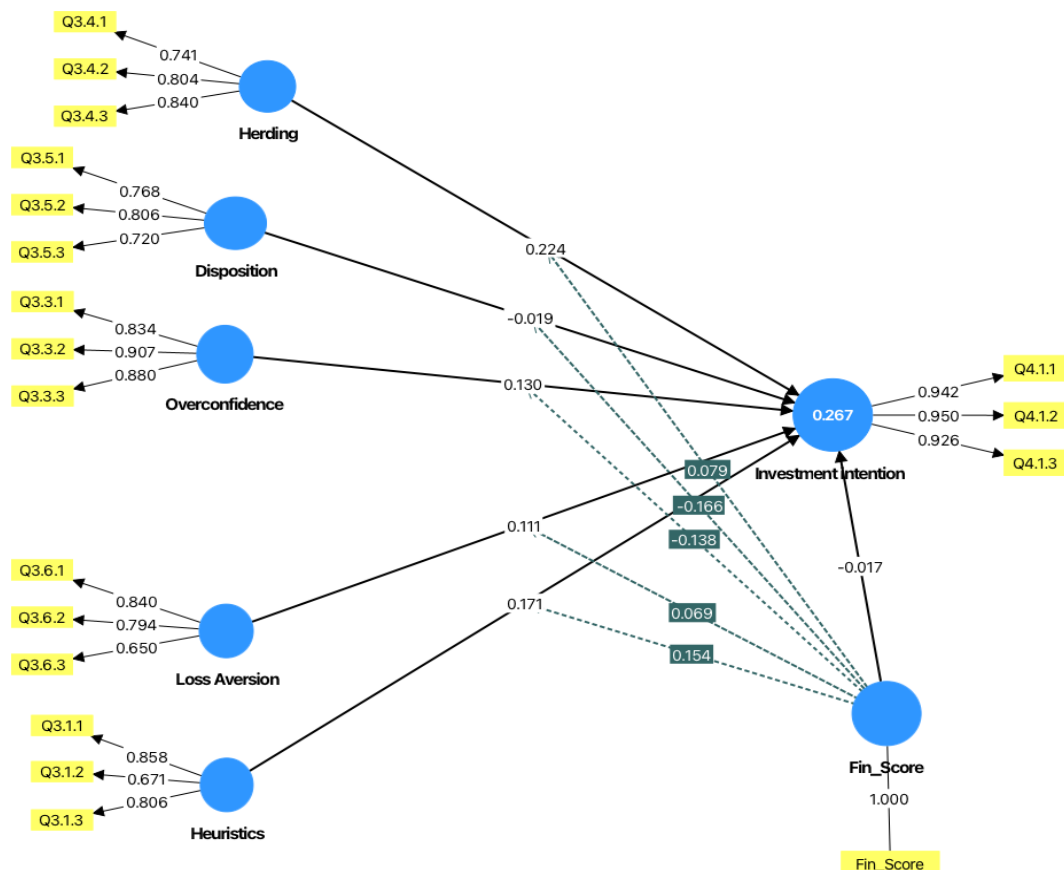


Figure 5.19: Final Structural Model without FOMO

(Source: Author – PLS SEM)

The final structural diagram (Figure 5.19) shows blue circles representing the behavioural constructs (herding, disposition, overconfidence, loss aversion, heuristics, investment intention and Fin_Score) while yellow labels on the left and right denote the survey questions related to each construct together with their factor loadings from the measurement model (0.65–0.95). Solid black arrows from the constructs to cryptocurrency adoption represent direct paths, with coefficients indicating their effects (Herding and cryptocurrency adoption, 0.214). Dashed teal lines, denoted with small green boxes and coefficients, depict the moderation effects of financial literacy (Fin_Score) on the relationships between each construct and cryptocurrency adoption (Heuristics×Fin_Score moderation is 0.154).

The R^2 value, representing the squared correlation between actual and predicted power, is located within the blue cryptocurrency adoption node. This value, ranging from 0 to 1, indicates that the independent variables or biases account for 26.7% of the variance in cryptocurrency adoption, which is considered a moderate level of explanation for behavioural intention models. The remaining variance, 74.3%, is unexplained by the variables, which implies there are other factors influencing investment intention. In addition, the adjusted R^2 value for cryptocurrency adoption is 22.8%, offering a similar level of explanation.

Table 5.7: Coefficient of Determination R^2

(Source: Author – PLS SEM)

	R-square	R-square adjusted
<i>Investment intention</i>	0.267	0.228

5.5.2.1 Model fit and predictive relevance (SRMR and Q^2)

The Standardised Root Mean Square Residual (SRMR) is a crucial metric for evaluating model fit, with values less than 0.08 generally indicating a good fit between the hypothesised model and the observed data (Budree & Nyathi, 2022; Jankeepsad & Tewari, 2022). Q^2 (Stone-Geisser's Q^2) is a measure of predictive relevance where a Q^2 value greater than 0 signifies that the model's prediction is smaller than that of the mean values, thus indicating better predictive performance in PLS-SEM (Hair et al., 2018).

Guideline thresholds often used are 0.02 (small), 0.15 (medium) and 0.35 (large) for substantive predictive relevance (Hair et al., 2018).

Table 5.8: Standardised Root Mean Squared Residual (SRMR)

(Source: Author – PLS SEM)

	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	0.076	0.053	0.060	0.077
Estimated model	0.076	0.053	0.060	0.077

Table 5.9: Predictive Relevance Values Q2

(Source: Author – PLS SEM)

	Q ² predict	RMSE	MAE
<i>Investment intention</i>	0.139	0.945	0.731

The SRMR for both the saturated and estimated models were 0.076, which was below 0.08, indicating a satisfactory model fit. Predictive relevance of the structural model was $Q^2 = 0.139$ (RMSE = 0.945; MAE = 0.731), indicating a moderate predictive power for investment intention. This suggests that while the model captures a notable portion of the variance, other latent factors likely contribute to the full spectrum of investment intention, which is further supported by the moderate R^2 value. This further reinforces the notion that additional psychological constructs, socio-economic factors or technological influences could be integrated into future iterations of the model to enhance its explanatory and predictive capabilities.

5.5.2.2 Effect Size

The effect size (f^2) is a measure of the impact of the behavioural biases on cryptocurrency adoption, with values of 0.02, 0.15 and 0.35 representing small, medium and large effects, respectively (Hair et al., 2018).

Herding ($f^2 = 0.043$) and heuristics ($f^2 = 0.020$) exhibit a small impact on cryptocurrency adoption, while the moderation of financial literacy $\times$ disposition interaction ($f^2 = 0.022$) lies at the lower bound of a small moderation effect. All other effects were below 0.02, indicating negligible contributions explaining cryptocurrency adoption. Although many bootstrapped confidence intervals for the f^2 metric spanned zero, indicating potential non-significance, these effect size estimates should be interpreted with caution. This caution is advised because the f^2 metric can be unstable, especially when predictors have minimal contributions, like the remaining constructs. The f^2 estimates in this study occasionally showed bias or instability, which is a recognised limitation of f^2 as an effect size measure in PLS-SEM, particularly when predictors have weak or overlapping influences on the cryptocurrency adoption (Steenkamp & Maydeu-Olivares, 2022).

Table 5.10: Effect Size of Constructs (f^2)

(Source: Author – PLS SEM)

	Original sample (O)	Sample mean (M)	Bias	2.5%	97.5%
Disposition -> Investment intention	0.000	0.006	0.006	-0.143	0.149
Fin_Score -> Investment intention	0.000	-0.021	-0.021	-0.101	0.145
Fin_Score x Disposition -> Investment intention	0.022	-0.165	-0.187	0.049	0.184
Fin_Score x Herding -> Investment intention	0.005	0.081	0.076	-0.225	0.115
Fin_Score x Heuristics -> Investment intention	0.016	0.148	0.132	-0.266	0.076
Fin_Score x Loss Aversion -> Investment intention	0.004	0.061	0.056	-0.201	0.111
Fin_Score x Overconfidence -> Investment intention	0.010	-0.129	-0.139	-0.053	0.236
Herding -> Investment intention	0.043	0.217	0.174	-0.153	0.007

Heuristics	->	0.020	0.179	0.159	-0.109	0.021
Investment intention						
Loss Aversion	->	0.011	0.107	0.096	-0.233	0.067
Investment intention						
Overconfidence	->	0.012	0.122	0.111	-0.235	0.067
Investment intention						

5.5.2.3 Hypothesis testing

This section presents the results of the hypothesis tests, evaluating the significance and direction of the relationship established in the structural model. The path coefficients quantify the strength and direction of relationships between constructs within the structural model (range: -1 to +1), similar to regression coefficients. These coefficients, along with their associated p-values and confidence intervals, determine the statistical significance of each path and provide a basis for accepting or rejecting the proposed hypothesis (Gupta & Shrivastava, 2021).

5.5.2.4 Direct and moderation effects

Path coefficient significance was determined using bias-corrected bootstrap confidence intervals (95%) (Table 5.12) with 10,000 resamples, a method chosen to accommodate the data's non-normal distribution and ensure reliable estimates (Ekarani & Artini, 2025; Gupta & Shrivastava, 2021). The bias values for all paths are minimal, suggesting that the bootstrap sample mean closely approximates the original estimate with little systematic bias from resampling. This minimal bias, coupled with the bias-corrected method, reinforces confidence in the bootstrap intervals. The bias-corrected bootstrap intervals are preferred as they account for skewness and bias in the bootstrap distribution. These intervals align with the findings from the earlier results, indicating that herding and heuristics are marginally significant predictors. The moderation of $\text{fin_score} \times \text{disposition}$ interaction, which was near-significant in the t-test, remains non-significant when using the bias-corrected interval. Therefore, it should be considered a trend rather than a confirmed moderator.

Table 5.11: Bootstrap Results Mean, Std Dev, t-values, p-values – Direct Effects

(Source: Author – PLS SEM)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Disposition -> Investment intention	-0.019	0.006	0.074	0.253	0.801
Fin_Score -> Investment intention	-0.017	-0.021	0.062	0.275	0.783
Fin_Score x Disposition -> Investment intention	-0.166	-0.165	0.088	1.896	0.058
Fin_Score x Herding -> Investment intention	0.079	0.081	0.095	0.826	0.409
Fin_Score x Heuristics -> Investment intention	0.154	0.148	0.097	1.587	0.113
Fin_Score x Loss Aversion -> Investment intention	0.069	0.061	0.082	0.838	0.402
Fin_Score x Overconfidence -> Investment intention	-0.138	-0.129	0.102	1.356	0.175
Herding -> Investment intention	0.224	0.217	0.068	3.291	0.001
Heuristics -> Investment intention	0.171	0.179	0.081	2.112	0.035

Loss Aversion	->	0.111	0.107	0.078	1.428	0.153
Investment intention						
Overconfidence	->	0.130	0.122	0.084	1.537	0.124
Investment intention						

5.5.2.5 Direct Effects

The impact of herding on cryptocurrency adoption was statistically significant (Table 5.13) with a coefficient (β) of 0.224 (bias-corrected 95% bootstrap CI [.094, .359], $t = 3.291$, $p = .001$). The CI excludes zero, and the bootstrap sample mean ($M = 0.217$; bias = -0.007) closely matches the original estimate, indicating a reliable positive effect. Likewise, heuristics positively predicted cryptocurrency adoption ($\beta = 0.171$; bias-corrected 95% bootstrap CI [.001, .319], $t = 2.112$, $p = .035$); the CI barely excludes zero and the bootstrap mean ($M = 0.179$; bias = 0.008) aligns with the observed coefficient, supporting a modest but significant influence. The effects of disposition ($\beta = -0.019$, $p = .801$) and financial score ($\beta = -0.017$, $p = .783$) on cryptocurrency adoption were not statistically significant. Likewise, the effects of loss aversion ($\beta = 0.111$, $p = .153$) and overconfidence ($\beta = 0.130$, $p = .124$) were not significant, as their confidence intervals included zero.

Table 5.12: Bootstrap Results for Direct Effects (bias-corrected and accelerated confidence intervals)

(Source: Author – PLS SEM)

	Original sample (O)	Sample mean (M)	Bias	2.5%	97.5%
Disposition -> Investment intention	-0.019	0.006	0.025	-0.200	0.104
Fin_Score -> Investment intention	-0.017	-0.021	-0.003	-0.137	0.111
Fin_Score x Disposition -> Investment intention	-0.166	-0.165	0.002	-0.339	0.001

Fin_Score x Herding -> Investment intention	0.079	0.081	0.002	-0.094	0.275
Fin_Score x Heuristics -> Investment intention	0.154	0.148	-0.005	-0.034	0.347
Fin_Score x Loss Aversion -> Investment intention	0.069	0.061	-0.008	-0.079	0.247
Fin_Score x Overconfidence -> Investment intention	-0.138	-0.129	0.009	-0.355	0.050
Herding -> Investment intention	0.224	0.217	-0.007	0.094	0.359
Heuristics -> Investment intention	0.171	0.179	0.008	0.001	0.319
Loss Aversion -> Investment intention	0.111	0.107	-0.004	-0.034	0.266
Overconfidence -> Investment intention	0.130	0.122	-0.008	-0.031	0.301

5.5.2.6 Moderation Effects

The interaction between financial score x disposition on cryptocurrency adoption (Table 5.13) was negative and approached significance ($\beta = -0.166$; bias-corrected 95% CI $[-0.339, 0.001]$; $t = 1.896$, $p = .058$). However, the confidence interval narrowly includes zero and therefore is statistically insignificant. With more conviction, the moderation effects of financial score on the other constructs were not significant: financial score $\times$ herding ($\beta = 0.079$, $p = .409$), financial score $\times$ heuristics ($\beta = 0.154$, $p = .113$), financial score $\times$ loss aversion ($\beta = 0.069$, $p = .402$), and financial score $\times$ overconfidence ($\beta = -0.138$, $p = .175$) all produced confidence intervals that include zero. These results indicate no reliable evidence that financial literacy meaningfully moderates these relationships in the current sample population.

5.6. Research Question Two

Research question two aims to identify if there are differences in the behavioural factors influencing cryptocurrency adoption across various age groups in South Africa.

Descriptive analysis was performed, including a one-way ANOVA to test for the significance of constructs between age groups.

5.6.1. Descriptive statistics

Table 5.14 summarises age group means for the various constructs and cryptocurrency adoption based on a 5-point Likert scale (financial literacy is a percentage). Adoption is the highest among 18- to 28-year-old participants (4.04) and decreases slightly with age to 3.88 in the 46+ cohort. Heuristic use rises steadily across cohorts (3.00 to 3.48), while herding shows the opposite pattern, declining modestly with age (2.80 to 2.60), which is consistent with younger respondents' reporting greater peer influence and older respondents relying more on rules of thumb. Disposition is flat from 18–45 (2.90–2.95) but higher in 46+ (3.15), whereas overconfidence is broadly similar across groups (2.5–2.7) and the lowest in 46+. Loss aversion varies little (3.18 to 3.40), peaking slightly in the 29–37 group, and financial literacy is uniformly high and comparable (76–80%). These observations suggest a nuanced interplay between age and behavioural biases in cryptocurrency adoption, where younger demographics exhibit higher propensities for adoption and susceptibility to herding, while older groups, despite similar financial literacy levels, demonstrate increased reliance on heuristics and differing dispositional effects.

Table 5.13: Age Group Means for Adoption

(Source: Author – PLS SEM)

Bias	18–28 Mean	29–37 Mean	38–45 Mean	46+ Mean	Pattern across age
Adoption Bias	4.04	4.01	3.97	3.88	Decreasing
Disposition Effect	2.90	2.90	2.95	3.15	Increasing
Financial Literacy	75.9	80.0	80.0	79.0	No trend
Herding Behaviour	2.80	2.70	2.60	2.60	Decreasing

Heuristics Usage	3.00	3.20	3.30	3.48	Increasing
Loss Aversion	3.30	3.40	3.30	3.18	No trend
Overconfidence	2.60	2.70	2.70	2.50	No trend

5.6.2. ANOVA results – age group comparison

To address research question two, “Is there a difference between the behavioural factors of cryptocurrency adoption among different age groups in South Africa?”, a one-way ANOVA was performed to determine if significant variations exist in cryptocurrency adoption behaviours across diverse age demographics within South Africa. These results are presented in Table 5.15.

Table 5.14: ANOVA Results

Outcome	df (grp, res)	F	p	Result
<i>Adoption</i>	3, 214	0.116	0.951	Not sig
<i>Heuristics</i>	3, 215	0.930	0.427	Not sig
<i>Disposition</i>	3, 214	0.298	0.827	Not sig
<i>Loss aversion</i>	3, 213	0.527	0.665	Not sig
<i>Fin score</i>	3, 215	0.528	0.663	Not sig
<i>Overconfidence</i>	3, 215	0.249	0.862	Not sig
<i>Herding</i>	3, 213	0.693	0.557	Not sig

Table 5.15: Effect Sizes for Behavioural Drivers*(Source: Author – PLS SEM)*

Variable	Eta²	% Variance Explained
<i>Adoption</i>	0.001621	0.1621%
<i>Heuristics</i>	0.012807	1.2807%
<i>Disposition</i>	0.004154	0.4154%
<i>Loss aversion</i>	0.007360	0.7360%
<i>Fin score</i>	0.007317	0.7317%
<i>Overconfidence</i>	0.003467	0.3467%
<i>Herding</i>	0.009662	0.9662%

The ANOVA results (Table 5.15) did not indicate any statistically significant differences in behavioural factors of cryptocurrency adoption across the various age groups. This is validated by all p-value results for each construct greater than the conventional significance level of 5%. This suggests that factors beyond age may play a more prominent role in influencing cryptocurrency adoption patterns among South Africans. This is further supported by the effect size (Table 5.16), which demonstrates that the proportion of variance in the behavioural constructs was small to negligible, ranging between 0.16% and 1.28%, for adoption and heuristics, respectively. In the South African context, these results suggest that age, a variable frequently considered significant, does not substantially differentiate the behavioural precursors to cryptocurrency adoption (Jankeeparsad & Tewari, 2022).

Although there may be observable trends in the data at face value, the results indicate that these differences are not significant enough to be reliably generalised to the broader population of South Africa. This implies that while certain age-related tendencies, such as reduced cryptocurrency adoption in older groups and increased disposition and heuristics with age, might be present within the sample, they do not hold statistical significance for predicting adoption behaviour across the different age cohorts in South Africa.

5.7. Conclusion

The results of the study show that there was adequate representation from both genders; however, there was a notable skew towards an educated sample and the majority of participants were working in the ICT and finance sectors. The awareness of cryptocurrencies was high at 86.3%, while ownership was moderate at 35.1%. Participants primarily used cryptocurrency as a speculative investment and wealth storage rather than transactional use.

The results for RQ1 found that herding behaviour and heuristics were the only statistically significant positive predictors of cryptocurrency adoption. This suggests that in the South African context, investors are more influenced by observing others' actions and utilising mental shortcuts, aligning with behavioural finance theories in uncertain markets. Notably, other commonly cited biases such as disposition effect, loss aversion and overconfidence did not demonstrate significant direct impacts on investment intention in this sample. This absence of significance for widely recognised biases warrants further investigation, and so does FOMO, as this was removed due to the low reliability statistics of the construct. Furthermore, financial literacy exhibited no direct significant effect on cryptocurrency adoption and largely failed to moderate the relationships between behavioural biases and adoption. This challenges conventional assumptions that financial literacy mitigates biases, which suggests a more complex interplay not fully captured by the model.

RQ2 found that the ANOVA analysis comparing age groups yielded no statistically significant differences across any behavioural constructs or adoption measures. While descriptive trends existed in the sample, these were not robust enough to generalise across the population, challenging assumptions about age-related variations in cryptocurrency adoption behaviour in South Africa. This implies that factors beyond age might play a more dominant role or that methodological limitations, such as sample size in older cohorts, may have impacted statistical power. The model's moderate explanatory power of 26.7% further indicates that additional psychological, socio-economic or technological factors likely contribute to investment intention.

Chapter 6: Discussion of Findings

6.1. Introduction

This chapter discusses the key findings of the study on the behavioural drivers of cryptocurrency adoption in South Africa, interpreting the results in light of the theoretical framework and prior literature. The study aimed to identify which behavioural biases significantly influence the intention to adopt cryptocurrencies (RQ1) and to examine whether these influences differ across generational or life-stage groups (RQ2). The findings are critically examined against the Theory of Behavioural Finance, building a deeper conceptual understanding of how and why certain biases drive cryptocurrency adoption.

The study found that herding and heuristics were the primary behavioural drivers of cryptocurrency adoption in this study. In contrast, life-stage cohorts have no significance; however, there was a noticeable trend between financial literacy and the disposition effect, suggesting that the more educated one is, the lower the disposition effect. The structural model shows that the constructs explain only 26.7% of the variance in cryptocurrency adoption, leaving a considerable balance that can be addressed by macroeconomic or other behavioural factors.

6.2. RQ1: Behavioural Drivers of Cryptocurrency Adoption

Herding and heuristics had a statistically significant influence on cryptocurrency adoption at the 5% level of significance. In contrast, disposition effect, overconfidence and loss aversion did not show significant direct effects on adoption. This means that respondents who exhibited stronger herd behaviour or who relied more on heuristic thinking, like mental shortcuts or rules of thumb, were more likely to express interest in investing in cryptocurrencies. Conversely, the remaining biases did not significantly predict cryptocurrency adoption in the model. It can be suggested that not all biases that affect traditional assets necessarily translate to other asset classes like cryptocurrency.

6.2.1. Structural Model

The structural model findings demonstrated a moderate explanatory power for cryptocurrency adoption, with the coefficient of determination (R^2) of 26.7%. While not extremely high, this result is respectable for a behavioural model in a maturing research

area and indicates that the biases analysed provide meaningful predictive insight into cryptocurrency adoption. Herding and heuristics show small-to-medium effects on adoption, with $f^2 = 0.043$ and $f^2 = 0.020$, respectively, whereas all other effects were below 0.20. This indicates that herding exerts a comparatively stronger influence on cryptocurrency adoption in South Africa. The findings, therefore, suggest that the South African adoption margin appears driven more by social influence and cognitive simplification than by classical risk-preference or personality-related biases. At the same time, the moderate R^2 underscores the inherent complexity and novelty of cryptocurrency adoption, implying that additional determinants beyond those tested in this study are also at work.

The explanatory power observed here is consistent with, and sits within, the range reported in comparable literature on behavioural finance regarding novel asset classes. It confirms the results of Mahmood et al. (2024), Raut (2020), and Kaur et al. (2023), who reported explanatory power of 20.5%, 36%, and 47.9%, respectively. This suggests that an R^2 within this range is typical in this stream of research. At the upper end, Handoko et al. (2024) reported an R^2 of 68.6% for behavioural factors impacting cryptocurrency trading decisions, demonstrating that higher explanatory models are possible under certain contexts and specifications. Turning to effect sizes, the comparatively stronger role of herding in this study converges with the literature, identifying herding behaviour as a significant determinant in cryptocurrency markets, especially among Millennials and Gen Z cohorts (Almeida & Gonçalves, 2023; Gupta & Shrivastava, 2021; Handoko et al., 2024). Notably, Gupta and Shrivastava (2021) reported an effect size of 0.015 for herding on investment intention, which is directionally consistent with the current study's small but meaningful effect. The small effect recorded for heuristics in this model also resonates with findings by Handoko et al. (2024), but their analysis found the bias to contribute a larger effect. Such disparities are plausibly rooted in differences in methodological approaches, cultural contexts or the particular heuristics examined.

This finding of the structural model carries significant implications for predicting behaviour, suggesting that while specific behavioural biases can moderately forecast intentions to adopt cryptocurrencies, not all biases are equally influential. The moderate R^2 value also underscores the inherent complexity and novelty of cryptocurrency-related decisions, implying that factors beyond this study may also shape cryptocurrency adoption, unlike traditional stock market investments. Overall, the South African adoption of cryptocurrency

is driven more by social influence and cognitive simplification than by classical risk-preference or personality-related biases.

6.2.2. Demographics and Awareness

Beyond behavioural biases, the demographic and awareness evidence frames how cryptocurrency adoption manifests in this study. Confirmed in the findings, gender patterns skew towards male ownership, and the youngest adults exhibit a slightly higher intention to adopt cryptocurrency. In the South African context, the general demographic profile (section 5.1) reflects a younger, predominantly male cohort with higher education and income, though the precise influence of these factors on crypto currency adoption intention varies according to literature. Awareness was high across all groups at 86.3%, yet this did not translate directly into participation as actual ownership was 37% (i.e. less than half of those aware). This finding indicates that high familiarity alone is insufficient for equal uptake. Notably, 73% and 71% of respondents reported investing for speculative reasons and as a store of wealth, respectively.

The observed male skew in ownership is consistent with evidence in the literature that cryptocurrency investors are predominantly male and inclined toward early adoption of financial and technological innovations (Gerrans et al., 2023; Steinmetz et al., 2021). Age-related intent in this study aligns directionally with these patterns, although regional variations caution against overgeneralisation. A study by Carbó-Valverde et al. (2024) reported a much smaller gender gap and, in Vietnam, females showed a greater propensity to invest, underscoring the value of cultural nuances (Nyhus et al., 2023). The high awareness identified in this study affirms Shahzad et al. (2024), who found that adoption rises with awareness. However, the persistence of barriers such as perceived risk and complexity noted by Walton and Johnston (2018) helps explain why ownership lags awareness. The prominence of financially inclined respondents is consistent with literature by Carbó-Valverde et al. (2024), Fujiki (2021) and Mazambani & Mutambara (2019). The strength of speculation and diversification in this study confirms findings by Stix (2021) and Auer and Tercero-Lucas (2022), while Steinmetz et al. (2021) reaffirm the importance of socio-economic considerations. Broader macro-environmental interpretations are compatible with Bhimani et al. (2022), who argued that development levels, regulatory quality, corruption and economic freedom shape ownership. At the same time, Saiedi et al. (2020) emphasised that shortcomings in conventional financial systems

and a lack of confidence in banks can drive adoption, an effect that may be attenuated in South Africa's context, where robust banking coexists with speculative and diversification motives (Auer & Tercero-Lucas, 2022; Sergio & Wedemeier, 2025). This suggests that speculation and diversification are stronger motives than distrust in the banking sector within South Africa's robust financial context.

6.3. Hypotheses Discussion

6.3.1. *Does herding behaviour have a positive influence on the adoption of cryptocurrency?*

This study found herding to be significant and to positively influence cryptocurrency adoption. It suggests that individuals are influenced by the actions of others in their decision to engage with cryptocurrency, aligning with social proof and conformity biases (Shahzad et al., 2024). Cryptocurrency adoption appears to be linked to network effects, individual convictions and social learning processes. Considering the socio-economic dynamics of South Africa, where financial literacy varies and access to traditional financial services can be uneven, herd behaviour may be particularly pronounced as individuals look to peers for guidance in navigating novel and new financial investments (de Almeida & Gonçalves, 2023).

The findings corroborate existing literature indicating that social influence plays a critical role in encouraging cryptocurrency participation. This conclusion is supported by Balutel et al. (2022) and Gupta et al. (2020), who both identify social influence as the most significant factor affecting cryptocurrency adoption. Hackethal et al. (2021) additionally highlighted the importance of media sentiment as a contributing driver. The role of social dynamics and the speed of information dissemination in shaping investment decisions, and in increasing the propensity to invest during bull markets is consistent with Kaiser and Stöckl (2019), Silva et al. (2019) and Ullah et al. (2022). Herding behaviour can accelerate adoption during periods of market exuberance but also introduces a susceptibility to rapid market corrections and speculative bubbles as investors feed off each other's actions, thus extending the findings of Kyriazis (2020). This resonates with Kallinterakis et al. (2010), who identified herding as being the strongest in rising markets with high trading volumes. The mechanism whereby perceived social validation reduces uncertainty is captured by Shahzad et al. (2024) and is also supported by findings from Youssef (2020) and Bouri et al. (2018), who identified herding as a significant contributor to cryptocurrency

adoption, However, Handoko et al. (2024) found the contrary to be true, where herding was not a significant factor. Bouri et al. (2018) also reported conflicting results as herding was not significant overall, but when uncertainty increases, the phenomenon turns significant and vice versa. This confirms findings by Carbó-Valverde et al. (2024), who found investors might be more prone to following trends rather than conducting independent due diligence in volatile emerging markets where the intensification of herding relative to traditional equity markets remains salient.

In summary, herding behaviour significantly drives cryptocurrency adoption, particularly in emerging markets like South Africa, yet it also exposes investors to heightened market volatility and speculative risks due to collective irrationality (Bouri et al., 2018; de Almeida & Gonçalves, 2023). However, these findings are nuanced by the fact that investors often herd more intensely in the cryptocurrency market compared to traditional equity markets, potentially due to the asset class's characteristics and inherent uncertainty.

6.3.2. Does disposition behaviour have a positive influence on the adoption of cryptocurrency?

The findings are that the disposition effect did not significantly predict cryptocurrency adoption. This indicates that initial entry decisions in this context may be driven by considerations other than the immediate realisation of gains or avoidance of losses. While the disposition effect typically captures investors' tendency to sell profitable assets too early and hold onto losing assets too long, its non-significance at the adoption stage suggests that respondents' choices may reflect dynamics distinct from those of investors who have passed the initial investment stage. Another reason for the non-significance of the disposition effect in the findings is that it is often most visible in post-adoption investing rather than as the entry decision (de Almeida & Gonçalves, 2023). Interpreted through this lens, the result is compatible with the possibility that many respondents were in an intent or early ownership phase where disposition is latent and the bias emerges later, once positions move materially in or out of the money. Within South Africa, Shandu and Alagidede (2022) observed that direct evidence on cryptocurrency-specific disposition is scarce but prevalent and that the intensity of the effect is higher with men compared to women. The findings extend this local gap by showing that, at the adoption stage, disposition is not a primary driver.

The results of this study contrast with prior literature that has identified a significant disposition effect in similar contexts, as documented by An et al. (2018), Haryanto et al. (2019), Schatzmann and Haslhofer (2023), Shandu and Alagidede (2022) and Shefrin and Statman (1985). Haryanto et al. (2019) demonstrated that cryptocurrency investors held assets even through significant drawdowns, anticipating continued price increases based on past performance, while Schatzmann and Haslhofer (2023) showed that the effect varies in intensity over time. Specifically, the negative disposition effect manifests during rising Bitcoin prices, while a positive disposition effect is observed during declining Bitcoin prices as per findings by Kaur et al. (2023), which then confirms Haryanto et al. (2019) on the inverse nature of the effect during the boom-and-bust years of the cryptocurrency market.

More broadly, the disposition effect and loss aversion generate asymmetric evaluations of gains versus losses, encouraging premature profit taking and the deferral of losses. Furthermore, these patterns intensify return swings through synchronised selling on upswings and entrench risk-seeking in downturns among riskier investors (Bui & Sällberg, 2022; Dickason-Koekemoer & Ferreira-Schenk, 2018). Dickason-Koekemoer and Ferreira-Schenk (2018) and Son et al. (2025) addressed mental accounting as a reinforcing mechanism that compartmentalises gains and losses, while Prospect Theory posits risk-seeking in losses and risk-aversion in gains, prompting investors to hold losers and sell winners prematurely (Ratanabanchuen et al., 2024).

In this study, however, the absence of a significant adoption-stage effect is compatible with the view that disposition primarily manifests in selling and holding behaviour rather than in initial uptake. The near-significant moderation by financial literacy in the findings aligns with work indicating that knowledge and experience can temper biased responses (Adil et al., 2021; Baker et al., 2018; Raut, 2020). Taken together, the literature situates disposition as a pervasive bias, but its manifestation and impact on cryptocurrency adoption, particularly in emerging economies like South Africa, appear contingent on investment stage and on moderating influences such as financial literacy (Schatzmann & Haslhofer, 2023).

6.3.3. *Does overconfident behaviour have a positive influence on the adoption of cryptocurrency?*

The absence of overconfidence as a significant factor in the findings suggests that individuals confident in their financial abilities were not more inclined to invest in cryptocurrency. This finding deviates from the literature, as overconfidence did not notably predict cryptocurrency adoption when it should have (Altaf & Jan, 2023; Sabir et al., 2019; Zhao & Zhang, 2021). Furthermore, Kim et al. (2021) and Kaur et al. (2023) found overconfidence to be significant, which warrants further exploration. The way overconfidence presents itself can also be shaped by cultural norms and market exposure, as highlighted by Ooi (2022) and Yates et al. (1996), who emphasised that expressing confidence is dependent on culture and context. Individuals from more collectivist backgrounds often report less overconfidence, meaning the same underlying knowledge can result in varied external displays of assurance (Ooi, 2022). This confirms the findings in this study, which showed relatively high and consistent financial literacy scores and a concentration of ITC and finance professionals, likely leading to a convergence of perceived and actual knowledge and diminishing the behavioural impact of overconfidence (Sabir et al., 2019).

A recent study by Iamin (2025) found that overconfidence is a key characteristic distinguishing cryptocurrency investor from non-investors, contradicting the findings of this study. Iamin (2025) also identified a correlation between market experience and overconfidence but found financial knowledge to be an insignificant predictor of cryptocurrency adoption, which contrasts with other studies by Zhao and Zhang, (2021). However, Sabir et al. (2019) indicated that higher financial literacy can moderate the influence of overconfidence on investment decisions by aligning perceived and actual knowledge. This assertion is further substantiated by Xiao et al. (2022), who noted that this trend is particularly evident among wealthy male demographics in Chinese markets, and similar research by Nyhus et al. (2023) further explained the gender gaps. The present study's findings align with these observations, revealing similar characteristics. Furthermore, research by Altaf and Jan (2023) and Park et al. (2010) shows that investors' tendency to overestimate their knowledge and control leads to excessive trading with lower returns. This broad characterisation is corroborated by foundational behavioural finance literature such as Barber and Odean (2001), who documented that overconfident traders transact more frequently, and Kahneman and Tversky (1977) established the

cognitive roots of such miscalibration (Sathya & Gayathiri, 2024). Ahmad (2022) explained that this is due to the “Dunning-Kruger” effect, which states that investors with limited knowledge often overestimate their investment competence.

South Africa has a history of socio-economic issues, while the salience of community consultation may explain the non-significance of overconfidence. Walton and Johnston (2018) stated that perceived complexity and education are central to cryptocurrency adoption due to access and education inequality. These social and cognitive shortcuts absorbed the variance that might otherwise have been attributed to overconfidence at the entry decision. In corroborating the literature and findings of this study, overconfidence may be more nuanced than a first-order effect (Walton & Johnston, 2018).

6.3.4. *Does loss aversion behaviour have a positive influence on the adoption of cryptocurrency?*

The study did not find loss aversion to be a significant predictor of cryptocurrency adoption, a result that contrasts with Prospect Theory’s expectation and evidence supported by Shandu and Alagidede (2022). The results of the study propose a stage-dependent and context-sensitive view of loss aversion. A recent study by Fahlin and Gustafsson (2024) similarly found no significant disposition effect, confirming the results of the study. This could be attributed to cryptocurrency holders’ elevated risk tolerance and willingness to absorb investment losses in anticipation of above-average profits, as explained by Carbó-Valverde et al. (2024) and Stix (2021). Practically, one should not assume a uniformly loss-averse public but anticipate a self-selected, risk-tolerant sample whose loss-averse tendencies may become consequential after market entry and country context specific.

In high volatility settings such as cryptocurrency markets, this bias is expected to be especially salient, with rapid drawdowns triggering panic selling and prolonged holding of depreciating assets (Almansour, 2020; Schatzmann & Haslhofer, 2023). Consistent with that view, Kaur et al. (2023) found loss aversion to shape cryptocurrency investment decisions and highlighted that FOMO served as a mediating variable and whereby even loss-averse investors may still purchase when FOMO is strong. To support this view, the findings suggest that selection bias and limited range are highly probable, where those most averse to losses may simply avoid the cryptocurrency sector, resulting in a pool of respondents who are relatively tolerant of risk, which could be the case with the sample

of this study. This self-selection mechanism could explain the observed non-significance of loss aversion as a direct predictor of cryptocurrency adoption within the sampled population (Mazambani & Mutambara, 2019). This finding aligns with Prospect Theory, which underscores the characteristics of individuals nearing adoption (Guenther & Lordan, 2023).

Research by Stix (2021), Steinmetz et al. (2021), Hackethal et al. (2021) and Fujiki (2021) posited that cryptocurrency holders typically exhibit higher risk tolerance than non-holders and, in particular, Fujiki (2021) showed that holders are more impatient, more risk-seeking and have less self-control than non-holders. The view by Schatzmann and Haslhofer (2023) and Almansour (2020) is that mental accounting and framing can blunt loss aversion at entry, as some respondents may have framed cryptocurrency as “speculative capital”, quarantining potential losses and tolerating drawdowns while seeking rebound opportunities. In addition, the literature shows that across multiple geographies, market experience can catalyse active information search and learning about cryptocurrency risks and mechanics, where early losses may initially deter some, but for others, they prompt knowledge acquisition that reframes subsequent participation and risk management (Auer & Tercero-Lucas, 2022; Balutel et al., 2022; Carbó-Valverde et al., 2024; Fujiki, 2021).

The results from the study could mute the negative association between loss aversion and adoption. Auer and Tercero-Lucas (2022) indicated that context matters, especially in developing countries, where macroeconomic instability caused by inflation and limited financial access leads to higher tolerance of volatility relative to local opportunity costs (Gupta & Shrivastava, 2021; Kaur et al., 2023). Within South Africa’s socio-economic realities, prospective adopters may accept cryptocurrency’s downside risk for potential upside. It is further substantiated that cryptocurrency adoption may be dominated by risk-tolerant investors, which is suggested by the findings that, in the context of this study, are influenced by socio-economic factors that can reshape behaviour (Carbó-Valverde et al., 2024).

6.3.5. *Does heuristics behaviour have a positive influence on the adoption of cryptocurrency?*

Heuristics significantly and positively predicted cryptocurrency adoption, and current holders of cryptocurrency scored higher on heuristics than non-holders. This pattern indicates that, in a technical, volatile and often opaque setting, fast, intuitive rules

substitute for costly analysis when information is noisy and time is scarce, as suggested by Baker et al 2018, Sathya & Gayathiri (2024) and Almansour (2020). Consistent with the literature, the findings of this study also found herding to be significant in explaining cryptocurrency adoption, suggesting that when markets are premature and ambiguous, investors compress complexity into a handful of cues and participation rises hence confirming Handoko et al. (2024) and Hackethal et al. (2021). Taken together, the positive association between heuristics and adoption, coupled with higher heuristic scores among current holders, implies that simple decision rules are actively employed at the entry point of investing.

The direction of heuristics in findings aligns with prior literature that availability, representativeness and anchoring guide choices under information scarcity (Baker et al., 2018; Sathya & Gayathiri, 2024). Mulyadi et al. (2025) identified availability and related shortcuts as strong predictors of cryptocurrency decisions, reinforcing Almansour's (2020) view that heuristics shape mental accounting and can feed into other biases such as the disposition effect. Handoko et al. (2024) further argued that herding and heuristics are closely related and capture much of the psychology driving investor participation. However, they also observe that heuristics were not significant for investors with less than two years of experience but became so thereafter, implying that these shortcuts can be acquired, practised and applied with greater assurance as familiarity increases. At the same time, other studies temper the strength of heuristics. Jain et al. (2019) highlighted herding as the most significant factor, while heuristics carry minimal weight, which is supported by Piotrowski and Bünnings (2022). Similarly, Handoko et al. (2024) noted that availability bias does not always directly influence investment decisions. Disaggregated findings echoed these nuances in the literature. Mardiana et al. (2025) reported confirmation bias as significantly negative and representativeness as significantly positive, whereas anchoring and availability are insignificant, further underscoring the heterogeneous operation of sub-biases across scenarios (Handoko et al., 2024).

In an emerging market such as South Africa, where information can be scarce, heuristics act as a cognitive accelerant of adoption, aiding participation yet predisposing investors to overlook critical information or rely on superficial cues, as suggested by Ahmad (2022), Asbaruna (2023) and Handoko et al. (2024). This duality motivates context-specific literacy and evidence-based client-centric designs to harness the efficiency of simple rules without allowing them to dominate judgment.

6.3.6. *Is financial literacy a moderating variable between behavioural factors and cryptocurrency adoption?*

The study's structural model indicates that financial literacy did not significantly moderate the relationships between the behavioural biases and cryptocurrency adoption (herding, heuristics, overconfidence, loss aversion and disposition). A marginal, negative moderation was observed for disposition ($p \approx .058$), which would be significant at a 10% level, corroborating the direction of disposition in the literature while contradicting the expectation of broad-based significance. Given the demographic profile of the study's sample, which is skewed towards younger individuals with higher educational levels, as 70% possess an undergraduate degree or higher, it is reasonable to infer that respondents have adequate financial literacy to engage with complex instruments. Nevertheless, respondents may continue to demonstrate biases that are not entirely mitigated by their knowledge. In the South African context, uneven access to education and persistent perceptions of technological complexity mean that investors with varying literacy levels may continue to rely on heuristics to cope with ambiguity and speed. The result that financial literacy did not moderate the influence of heuristics reinforces the notion that even knowledgeable individuals depend on "rules of thumb" when faced with uncertainty, consistent with the view that System 1 processing can be adaptive gateways to participation while raising tail risks as suggested in literature (Baker et al., 2018; Handoko et al., 2024; Tversky & Kahneman, 1974)

The literature positions financial literacy as a corrective force that tempers cognitive errors (Adil et al., 2021; Baker et al., 2018). Sabir et al. (2019), Baker et al. (2018) and Adil et al. (2021) found that higher literacy weakens overconfidence, while Raut (2020) reported that more knowledgeable investors make more deliberate choices (Carbó-Valverde et al., 2024). Yet Baker et al. (2018) described literacy as a double-edged sword that can attenuate informational cascades but amplify tendencies such as overconfidence in novel markets. Similarly, Zhao and Zhang (2021), Kim et al. (2021), Hayashi and Routh (2025) and Carbó-Valverde et al. (2024) showed that perceived knowledge may spur speculative participation, whereas actual knowledge often tempers it. Against this backdrop, the non-significance of all moderation paths in this study aligns with a nuanced view where formal education may provide a foundation without fully mitigating psychological drivers in a volatile market. Walton and Johnston (2018) and Adil et al. (2021) further suggested that access and complexity issues sustain heuristic use even among the literate, and the near-

significant literacy $\times$ disposition interaction is consistent with evidence that knowledge and experience can dampen dispositional tendencies (Raut, 2020; Adil et al., 2021; Baker et al., 2018).

Finally, the results contradict assumptions that literacy will offset herding and heuristic biases across the board (Baker et al., 2018; Carbó-Valverde et al., 2024; Kim et al., 2021), instead converging with findings that objective literacy can be negatively associated with participation. Conversely, subjective literacy may be positive or null, implying that context and socio-economic factors as with other factors in the study can be more predictive and that, in speculative, socially charged markets, heuristics and herd dynamics remain powerful even among the well-informed (Baker et al., 2018; Handoko et al., 2024; Mulyadi et al., 2025).

6.4. RQ2: Life-Stage Differences

6.4.1. Introduction

RQ2 tested whether South Africans' behavioural drivers of cryptocurrency adoption differ by life stage (18–28; 29–37; 38–45 and 46+ years). A one-way ANOVA between bias factors and age cohorts showed no significant age group differences in overall cryptocurrency adoption. Descriptively, the youngest cohort exhibited marginally higher adoption intention and slightly greater herding; the oldest cohort reported somewhat greater reliance on heuristics, with a small uptick in disposition. Overconfidence and loss aversion showed no clear age gradient. In short, age alone did not materially alter or show material behavioural propensities in this sample.

6.4.2. The Life-Stage Hypothesis

The results only partially echo age-based expectations. Descriptively, adoption and herding tilt slightly higher among the youngest group but the absence of statistically significant age differences contradicts the notion that cohort identity, by itself, robustly predicts cryptocurrency adoption. This pattern implies that income, period and cohort effects are intrinsically confounded and that generational labels rarely add predictive power beyond life-stage indicators, hence confirming NASEM (2020), Pokharel & Maharjan (2024) and Rudolph et al. (2020).

The consistently high levels of awareness and robust financial literacy observed across all age demographics further clarify the findings, reconciling them with literature that the highly educated nature of investors who hold cryptocurrency for speculative or store-of-wealth purposes may compress behavioural variation (Hayashi and Routh, 2025). Accordingly, cryptocurrency in South Africa appears to have progressed beyond novelty towards broader acceptance driven by diversification, experimentation, social influence and opportunistic hedging and returns consistent with the literature (Gupta et al., 2020; Mazambani & Mutambara, 2019). The findings also highlight a minor decrease in cryptocurrency adoption with increasing age, aligning with life-stage risk-taking (Auer and Tercero-Lucas, 2022; Bui & Sällberg, 2022). Further to the findings was a slight rise in heuristic application among older participants, which is consistent with reliance on cognitive shortcuts in unknown or nascent areas (Baker et al., 2018).

A common view in literature is that risk tolerance declines with age and that younger investors more readily embrace novel, volatile assets such as cryptocurrency, whereas older investors prefer safer allocations (Bhilawadikar & Garg, 2020; Bui & Sällberg, 2022; Rauvola et al., 2019). Generational Theory likewise predicts cohort differences, especially among Millennials and Gen Z, shaped by digital nativity and macro shocks such as the 2008–2009 crisis that catalysed Bitcoin (Altaf & Jan, 2023; Bharadwaj & Deka, 2021; Rosdiana, 2020). In addition, the literature also states that younger generations are more open while older groups are more sceptical of unregulated digital instruments (Osakwe et al., 2024; Auer and Tercero-Lucas, 2022; Hackethal et al., 2021).

Against this backdrop, the study's non-significant age differences suggest that cohort identity is a weak standalone predictor once life-stage factors have been considered, aligning with arguments from literature that income, horizon and experience better explain behaviour (NASEM, 2020; Pokharel & Maharjan, 2024; Rudolph et al., 2020). Rudolph et al. (2020) proposed moving beyond generational stereotypes via social constructionist and lifespan perspectives. The present pattern identified in these findings relates more strongly to the latter, with no differences in bias factors across age groups and indications that age effects are mediated by other influences (Honold & Oh, 2025; Osakwe et al., 2024; Pokharel & Maharjan, 2024; Rudolph et al., 2020). Consistent awareness and literacy across ages, confirming Hayashi and Routh (2025) help explain reduced variance and the finding that older respondents' intentions were not dramatically lower, challenging stereotypes of senior disengagement (Altaf & Jan, 2023; Osakwe et al., 2024).

Life-stage theories in literature suggest that individuals' optimal engagement in risky behaviour is influenced by factors such as investment horizon, income uncertainty and personal preferences, as human capital gradually transitions to financial assets. Meanwhile, experience-based learning connects significant macroeconomic events to individual risk attitudes and portfolio decisions, while financial literacy and behavioural characteristics contribute to the overall sophistication of these choices (Antwi & Naanwaab, 2022; Parker et al., 2025; Baker et al., 2018; Lusardi & Mitchell, 2007; Malmendier, 2021).

In an emerging market characterised by expanding fintech access and media exposure, behavioural biases are prevalent across cohorts, market dynamics and pervasive digital influence appear to homogenise responses. The small trends and non-significant age differences in biases, together with uniformly high literacy, confirm that age explains little. However, life-stage resources and experience appear to matter more than cohort identity for whether South Africans intend to adopt cryptocurrency.

6.5. Conclusion

This study demonstrates that herding and heuristic biases are the most significant behavioural drivers of cryptocurrency adoption among South African investors, while other biases were not statistically significant. The ANOVA results reveal that these behavioural drivers are remarkably consistent across age groups, although minor descriptive differences exist, such as younger individuals' showing slightly higher herding and adoption, and older participants exhibiting greater heuristic reliance; however, these were not statistically significant. This challenges traditional generational assumptions and supports a life stage and experience-based perspective, as highlighted in recent literature (Altaf & Jan, 2023; NASEM, 2020; Parker et al., 2025).

Importantly, financial literacy did not moderate these relationships, suggesting that psychological biases and social influence outweigh demographic factors. Given the rapid evolution of fintech and the competitive pressures outlined in Chapter 1, these insights are urgent for policymakers and financial institutions aiming to foster responsible adoption and develop targeted interventions in South Africa's emerging cryptocurrency market. Therefore, understanding who adopts crypto relies less on demographic labels and more on underlying mechanisms such as knowledge, available resources, risk management strategies, digital exposure and social influence. For both scholars and practitioners, this

implies a crucial shift towards a client-centred understanding, emphasising psychological biases over broad generational categories.

Chapter 7: Conclusion

7.1. Introduction

This study aimed to identify the significance of various behavioural drivers influencing cryptocurrency adoption in South Africa and determine whether this differs by age group. The insights gleaned from this research have profound implications for understanding the nuanced interplay between psychological factors and technological assimilation within South Africa. This chapter synthesises the study's principal findings, contextualises them within the existing theoretical framework of behavioural finance and empirical literature, articulates contributions to theory and practice, and identifies limitations with directions for future research. The structure provides a comprehensive integration of insights from Chapters 1 to 6, culminating in actionable recommendations for stakeholders in South Africa's cryptocurrency and financial ecosystem.

7.2. Research Context and Relevance

South Africa has participated in the global growth of cryptocurrency, experiencing rising awareness and increased use in recent years (Mofokeng et al., 2024; Cai & Zhao, 2023). With inflows to the tune of \$20–30 billion in cryptocurrency annually flowing into South Africa, this underscores substantial local engagement necessitating the understanding of the behavioural drivers of adoption (Gerrans et al., 2023; Rzayev et al., 2024). This study identified 86.3% public awareness of cryptocurrency and 35.1% of which are cryptocurrency owners, signalling that cryptocurrency has moved from a speculative niche into a material component of South African retail portfolios. Simultaneously, regulatory frameworks remain nascent, although maturing and financial literacy levels vary widely, heightening the relevance of exploring the behavioural mechanisms behind adoption decisions in this context.

The explanatory model explained 26.7% of the variance in cryptocurrency adoption, indicating a moderate level of explanatory power where roughly three-quarters of the variation is due to factors outside this model. Although herding and heuristics contribute significantly, a large portion of the decision is driven by other determinants not captured (Shahzad et al., 2024). Mazambani and Mutambara's (2019) findings in South Africa highlighted the importance of perceived usefulness, ease of use and social influence on

attitudes toward cryptocurrency. This supports the suggestion that behavioural biases are just one piece of the puzzle.

The importance of this research lies in bridging that knowledge gap by identifying the behavioural biases of cryptocurrency adoption among South African retail investors and examining how these may vary across different life-stage cohorts. Beyond academic interest, the topic has practical significance. The rise of fintech platforms and cryptocurrency exchanges poses competitive and regulatory challenges to traditional financial institutions. Understanding investor behaviour in this domain can inform banks, investment platforms and policymakers as they adapt to an ecosystem increasingly influenced by decentralised finance and alternative investments underpinned by unique socio-economic dynamics and a growing base of digital asset users. Gaining insight into these behavioural drivers is crucial for designing effective investor education, appropriate regulation and strategies that harness the benefits of cryptocurrency while mitigating its risk to the investor.

7.3. Addressing the gaps in Knowledge

Drawing from the problems and gaps in the literature, this lead to the research questions which the study addressed in two primary research questions:

RQ1: What are the key behavioural biases that significantly influence the adoption of cryptocurrency among South African adults, and to what extent does financial literacy moderate these effects?

RQ2: Do the behavioural influences on cryptocurrency adoption differ across various age groups (life-stage cohorts) in South Africa?

These questions were designed to examine both the direct impact of specific cognitive biases on cryptocurrency adoption and the potential moderating effect of financial literacy, as well as to investigate whether generational differences play a role in these relationships. To answer RQ1, seven hypotheses (H1–H7) were proposed based on Behavioural Finance Theory: H1–H6 considered that each bias (herding, disposition effect, overconfidence, FOMO, loss aversion and heuristics, respectively) would have a positive influence on cryptocurrency adoption, and H7 posited that financial literacy would moderate these bias-adoption relationships (mitigating or accentuating their effects). RQ2 was addressed with an exploratory hypothesis that the influence of these behavioural

factors might differ across age cohorts. To achieve this, a quantitative approach was pursued.

7.3.1. Methodology Utilised

A positivist, quantitative, cross-sectional research design was employed. The data were collected via a structured online survey, yielding 219 valid responses. Respondents were South African retail investors identified through non-probability purposive and snowball sampling. The data were analysed by performing a reliability and validity check, testing the structural model with PLS-SEM and doing an ANOVA analysis. In this process, FOMO was excluded as it was found to exhibit a low factor loading and insufficient reliability, indicating it did not adequately measure its intended construct. The model fit was deemed acceptable (SRMR = 0.076, below the 0.08 threshold; Stone-Geisser Q^2 = 0.139), indicating moderate predictive relevance. The one-way ANOVA compared mean bias scores and adoption across the four age cohorts to test for generational differences. No statistically significant findings were found to support this. The relevance of these findings is contextualised below.

7.4. The importance of the findings

7.4.1. Herding

Herding behaviour was the strongest single predictor in the model with a positive effect on cryptocurrency adoption (β = 0.224, p = 0.001). Bouri et al. (2018) and Ballis and Verousis (2022) found the same during market booms and busts, and Almeida and Gonçalves (2023) reported pronounced herd behaviour among emerging market cryptocurrency investors. The present finding confirms that South African investors, when faced with an uncertain and information-scarce environment, are swayed by others' actions. In the local context, social media and peer activity on investment platforms have been noted to correlate with surges in cryptocurrency trading (Bogdan et al., 2023; Almeida & Gonçalves, 2023). Lower institutional trust and unclear regulations in South Africa may further encourage reliance on social proof, consistent with Balutel et al. (2022), who found that lower trust in institutions correlates with a greater propensity to follow crowd behaviour.

However, herd effects are not uniform across all scenarios and can be tempered under certain circumstances. Coskun et al. (2020) noted that overconfident investors might

exhibit contrarian behaviour in some situations of uncertainty. The modest effect size ($f^2 \approx 0.04$) suggests that educated investors are somewhat less prone to blindly follow the crowd. The significant herding effect highlights the vulnerability of South African retail investors to collectively driven decision-making, reinforcing the importance that behavioural finance literature places on herd psychology in speculative asset classes.

7.4.2. Heuristics

Heuristics was the only other significant relationship which had a positive relationship with cryptocurrency adoption ($\beta = 0.171$, $p = 0.035$). This finding supports the view that cognitive shortcuts or “rules of thumb” are influential in crypto-related decisions. The result is consistent with prior studies by Almansour (2020) and Mulyadi et al. (2025), who found that heuristic-driven thinking significantly correlates with crypto investment propensity. Handoko et al. (2024) also emphasised that heuristics, alongside herding, capture key psychological dynamics behind crypto investments. This implies that South African investors rely on mental shortcuts when evaluating cryptocurrencies. This is theoretically in line with the heuristic and biases perspective, whereunder conditions of uncertainty and information overload, people use intuitive judgments under System 1 thinking (Tversky & Kahneman, 1974). The findings in this study mirror those of Mulyadi et al. (2025), who identified availability bias as one of the strongest predictors of crypto investment decisions, and suggest that in South Africa, as elsewhere, heuristic simplifications encourage entry into the crypto market by glossing over detailed risk analysis.

7.4.3. Non-Significant Findings: Disposition Effect, Loss Aversion and Overconfidence

In contrast to herding and heuristics, the other behavioural biases, disposition effect, loss aversion and overconfidence did not show statistically significant effects on cryptocurrency adoption. This outcome diverges from some expectations based on classical behavioural finance but can be rationalised by considering the context and scope of the research, as this is fundamental.

Disposition – The non-significance is not entirely surprising because this bias primarily manifests after an asset is owned and the study measured cryptocurrency adoption intention (the initial decision to enter the market), so the disposition effect may simply be irrelevant at this entry stage (Haryanto et al., 2019). The psychological pressures

underlying the disposition effect do not come into play. The finding contributes to the literature suggesting that biases like the disposition effect might be stage-specific, relevant to post-adoption trading behaviour but not to the initial adoption decision. Additionally, individuals who are strongly disposition-prone avoid cryptocurrency altogether; therefore, those who do consider investing in cryptocurrency have a higher risk tolerance diluting the disposition effect (Mazambani & Mutambara, 2019).

Loss Aversion – The results did not show a significant impact of loss aversion on adoption. A likely explanation is similar to that of the disposition effect. Those with extreme loss aversion may simply opt out of cryptocurrencies entirely, meaning the sample of potential adopters is skewed toward people with higher risk tolerance. To solidify this view, investors may engage in mental accounting by treating cryptocurrency as a separate portfolio where they are more willing to tolerate potential losses, thus mitigating the traditional influence of loss aversion (Kaur et al., 2023; Almansour, 2020; Thompson et al., 2022). Furthermore, in the South African context, investors might view crypto's potential upside as worth the downside risk, thereby overriding loss-aversion impulses (Stix, 2021; Carbó-Valverde et al., 2024). These considerations help explain why, at the adoption stage, loss aversion was not a differentiator among respondents inclined to invest in crypto.

Overconfidence – The results found no significant effect of overconfidence on cryptocurrency adoption. A key reason may be the sample's characteristics. The average financial literacy in the study was relatively high. This suggests that respondents' confidence was at least somewhat grounded in real knowledge, leaving less room for the kind of overconfidence that drives risky behaviour; therefore, the "Dunning-Kruger" effect may have been less prevalent here (Ahmad, 2022). Another consideration is that overconfidence might influence how people invest in cryptocurrency more than whether they adopt it in the first place, as per the previous two biases. Overconfident investors might dive deeper, or trade more aggressively once involved, but the initial decision to enter the market could be driven by other factors (Auer & Tercero-Lucas, 2022; Hackethal et al., 2021). A more refined measure versus what was used in this study might capture overconfidence effects more clearly. In a relatively informed population, simply being confident in one's financial knowledge did not strongly distinguish cryptocurrency adopters from non-adopters.

FOMO – Although FOMO was originally included as a construct with a high degree of anticipation of being significant, it was excluded from the final analysis due to measurement reliability issues. This resulted in an unreliable construct that had to be dropped during factor analysis. However, it is likely that FOMO-like motivations were indirectly captured under the umbrella of herding behaviour. One reason people “follow the crowd” is precisely the fear of missing out on profits that others are apparently gaining. Kaur et al. (2023) found that FOMO tendencies amplify herd-driven trading in crypto markets. The fact that herding was significant in our results suggests that many respondents were influenced by social media and a sense of urgency to join in, which is essentially FOMO. Future studies should attempt to measure FOMO with improved survey instruments or capture it via qualitative means as the study leaves a gap in fully understanding the emotional drivers of crypto adoption.

7.4.4. Non-significance of Financial Literacy as a Moderator

Financial literacy did not directly predict cryptocurrency adoption, nor did it significantly moderate any of the bias adoption relationships. However, there was a notable trend and if the study considered a 10% level of significance, the interaction of financial literacy on disposition effect would have been significant ($\beta = -0.166$, $p = 0.058$). In essence, higher or lower financial literacy on its own made no significant difference in willingness to adopt cryptocurrency, and it did not substantially alter the impact of other psychological biases on adoption. This finding challenges a common assumption that more financially knowledgeable individuals will behave differently (Adil et al., 2021; Sabir et al., 2019; Hasan et al., 2021). The results propose a more nuanced theme alluding to a “financial literacy paradox”. This paradox suggests that financial expertise may actually make investors more cautious and less likely to jump into speculative assets (Kim and Hanna, 2021; Carbó-Valverde et al., 2024). Therefore, knowledge alone does not act as a reasoning tool against the bias factors or as a driver of cryptocurrency adoption. Even individuals with high financial literacy were influenced by herd and heuristic factors, indicating that situational factors and psychological impulses can level the playing field between more and less educated investors (Gerrans et al., 2023; Kaur et al., 2023).

Given the homogenous sample of highly educated respondents, there were not enough individuals with genuinely low financial literacy to adequately observe how a lack of knowledge might impact the biases. The novelty and excitement around cryptocurrencies

might trigger intuitive, emotion-driven decisions from novices to experts. The overarching message is that knowledge alone is not a safeguard in the cryptocurrency context. The finding that financial literacy did not moderate bias impacts implies that more knowledgeable individuals were just as susceptible to herd mentality or heuristic thinking in this context as their less knowledgeable peers (Mulyadi et al., 2025). Further, alluding to the fact that financial institutions should not rely solely on boosting financial education but should be complemented with strategies that directly address behavioural impulses. The result adds to a growing recognition in behavioural finance that informed investors are not immune to market euphoria or panic, and that the psychological ideology of a new asset class can transcend levels of formal knowledge.

7.4.5. *Non-significance of biases between age groups*

The one-way ANOVA tests revealed no statistically significant differences in any behavioural bias results or in cryptocurrency adoption across the four age cohorts (18–28, 29–37, 38–45, 46+). This finding is notable as it contradicts prevalent generational assumptions in technology and investment, which suggest that younger investors are more amenable to cryptocurrencies, influenced by online trends, while older investors are typically portrayed as more conservative, wary of unregulated assets, and potentially more susceptible to biases like loss aversion (Altaf & Jan, 2023; Antwi & Naanwaab, 2022; Auer & Tercero-Lucas, 2022; Osakwe et al., 2024; Rauvola et al., 2019). Minor descriptive trends exist, such as the youngest group having the highest average cryptocurrency adoption herding scores and the oldest group having the lowest adoption intention and slightly higher disposition tendencies, but these differences were not statistically significant.

This challenges current literature and the usefulness of broad generational cohort labels such as Gen Z, Millennials, Gen X, for predicting behaviour in this domain. It aligns with an emerging critique in social science that generational categories are often too crude, conflating age with other factors like socio-economic status, technological exposure and life stage, which may be more influential in shaping investment decisions (Handoko et al., 2024; NASEM, 2020; Rudolph et al., 2020). This aligns with the Diffusion of Innovations Theory, which proposes that early adopters of any new technology share certain traits. Therefore, one's birth cohort is not a significant contributor, but other variables that can cut across age groups. This could explain why the older participants in our survey who

were interested in crypto behaved more like younger investors. The sampling bias toward educated, tech-savvy individuals likely created a group of respondents who, across all ages, were relatively homogeneous in attitude, probably washing out the traditional age differences.

The non-significant findings align with those of Gupta et al. (2020) and Mazambani and Mutambara (2019), who similarly observed that in certain emerging market settings, variations in fintech product adoption were better attributed to socioeconomic exposure and access to information rather than solely to age. The widespread adoption of the internet and social media may have eliminated information disparities between generations, implying that a middle-aged investor on Twitter receives much of the same cryptocurrency hype as a teenager on TikTok.

Within this sample group, evidence suggests that psychological drivers of crypto adoption are broadly shared across ages. This cautions against stereotyping investors based on generation. It supports the idea that one should focus on life-stage and situational segments (such as investment experience, professional background or tech exposure) rather than age brackets when assessing behaviour, especially with the introduction of newer technology.

7.5. Contribution to Theory

7.5.1. An extension of Behavioural Finance Theory – Cryptocurrency in an emerging-market context

This study extends the application of Behavioural Finance Theory, traditionally applied to stock markets in developed nations, by examining cryptocurrency adoption in an emerging market such as South Africa. It reveals that social (herding) and cognitive (heuristics) shortcuts primarily influence cryptocurrency adoption, while typical risk-aversion biases and overconfidence are less prominent at this initial adoption stage. Researchers and practitioners should not consider only the existence of a particular bias, but more critically, the specific contexts that amplify its influence. This finding extends existing theory by identifying specific conditions or stages under which certain biases become more salient. In environments characterised by high information asymmetry, limited regulatory oversight and new technology, which are common features of cryptocurrency markets in many emerging economies (Almansour, 2020; Walton & Johnston, 2018). Essentially, the

research suggests that behavioural finance models need to consider the context-specific importance of biases in the country of origin. For initial engagement with a speculative new asset, factors like social proof and cognitive ease can outweigh personal risk tolerance or confidence levels (Ahmad, 2022; Baker et al., 2018). This extends theoretical understanding by showing that the hierarchy of impactful biases is not universal but depends on market maturity and macro-specific context.

7.5.2. The financial literacy paradox in investment behaviour

This study contributes to the academic discussion on financial literacy and investor behaviour. It challenges the common economic assumption that increased knowledge automatically leads to more rational decision-making (Adil et al., 2021; Baker et al., 2018; Sabir et al., 2019). The non-significant findings regarding financial literacy as a moderating variable further substantiate recent empirical evidence, suggesting that even investors with financial expertise can be susceptible to biases, especially within emerging markets. This supports research that highlights a paradoxical effect, where greater financial literacy does not consistently prevent biased behaviour and may even foster overconfidence (Adil et al., 2021; Baker et al., 2018; Iamin, 2025; Sabir et al., 2019). This is particularly relevant in the nascent and volatile cryptocurrency markets, where traditional financial models and rational decision-making are frequently challenged by emotional and cognitive heuristics (Kaur et al., 2023).

This implies that investors may possess the knowledge for rational decisions, but whether they apply an analytical approach or rely on intuition is context-dependent and rather influenced by factors such as excitement, peer influence or novelty. This study provides evidence that education alone does not sufficiently counteract behavioural biases. This finding underscores the complex nature of Behavioural Finance Theory, which is shaped by both contextual elements and specific biases.

7.5.3. Life-stage over generational cohorts in adoption behaviour

The findings of this study challenge the utility of rigid generational labels, suggesting instead a greater emphasis on life-stage and other factors that transcend age categories. The narrative of “younger people are more likely to adopt cryptocurrency because they are more digitally native” was not supported. The lack of age effects in bias susceptibility

suggests that theoretical models should reconsider age as an explanatory variable for behaviour in contexts of the sample demographics and rather life-cycle stages.

The study suggests that life stage is more influential, considering factors like time horizon, family responsibilities and income stability, which evolve with age but are not strictly tied to generational identity. This implies that a technologically adept and risk-tolerant older investor can share significant similarities with a younger investor possessing the same traits, thereby indicating that age alone is a weak predictor. The theoretical contribution here serves as a reminder that broad demographic labels can be misleading in behavioural research, particularly within the diverse socio-economic landscapes of emerging countries such as South Africa. More specific constructs such as risk appetite, technology exposure and peer group influence may offer superior explanatory power (Altaf & Jan, 2023).

7.5.4. Integrative conceptual models for crypto adoption

Finally, the research extends the concept by testing an integrative model that combines behavioural biases with financial literacy and demographic segmentation to explain cryptocurrency adoption. This study forces the consideration of a multi-theoretical approach. Constructs from theoretical frameworks such as the information systems field (perceived usefulness/ease of use), social influence theories (network effects, peer pressure) and even macroeconomic theories (hedging against inflation or currency risk) might all need to be intertwined to conceptually explain cryptocurrency adoption. The amalgamation of these diverse theoretical perspectives can offer a more robust and nuanced understanding of the complex factors driving cryptocurrency adoption in varied socioeconomic contexts (Mazambani & Mutambara, 2019; Bhilawadikar & Garg, 2020). This approach recognises the interplay of individual psychology, social dynamics, technological and broader economic conditions in shaping adoption patterns (Mazambani & Mutambara, 2019).

The proposed approach extends academic knowledge by illustrating how both established and modern theories can be applied to explain the rapidly developing financial landscape of cryptocurrency adoption within emerging markets. This allows for a comprehensive analytical framework that accounts for the multifaceted nature of this novel asset class and its diffusion across diverse populations, such as those found in South Africa (Kellerman et al., 2020).

7.6. Practical Implications for Management

The insights from this research carry practical implications for a range of stakeholders in the financial ecosystem. The theoretical contributions of this study establish that financial literacy does not mitigate against behavioural biases. In addition, it highlights that an individual's life-stage, rather than their generational cohort, is a potentially more influential determinant of cryptocurrency adoption. The research also indicates that specific biases hold significance within a given contextual environment.

Understanding why South African investors decide to adopt or avoid cryptocurrencies can guide interventions to promote healthy, informed investment practices and inform strategic decisions by industry players. Below are key stakeholder-specific recommendations outlined, which translate the findings into actionable guidance.

7.6.1. Client centric experience-redesigned platform

Platform businesses have been on a drive to entice and keep clients on their platform longer to improve the chances of facilitating a transaction. This is done through gamification, rewards, social features and personalised content, aiming to foster deeper engagement and loyalty among users (Mazambani & Mutambara, 2019; Pereira et al., 2025; Sharma et al., 2023). These platforms, unfortunately, capitalise on people's biases, raising ethical considerations when these engagement strategies exploit cognitive biases, potentially leading to suboptimal decision-making or compulsive behaviour rather than genuine financial well-being, which can lead to earlier attrition of the client base.

The aim is for this research to be utilised to diminish such exploitation and to reduce the emphasis on activity feeds that could trigger cascade effects. Stakeholders can design platforms that encourage financial literacy and mitigate the adverse impacts of cognitive biases, rather than leveraging them (Carbó-Valverde et al., 2024; Ahmad & Shah, 2020). Platforms should instead prioritise clear communication and provide educational tools that empower users to make well-informed decisions, thereby adhering to ethical design principles and cultivating sustainable financial practices (Gupta & Shrivastava, 2021; Ballis & Verousis, 2022; Bouri et al., 2018; Almeida & Gonçalves, 2023). The intended outcome and benefit of this recommendation are that investment platforms can anticipate a slight decrease in impulsive trading volume, offset by an increase in the quality of decisions, user trust and retention.

7.6.2. Pre-screening of bias behaviour and implementation of structured journeys

Identifying and addressing biases through pre-screening mechanisms can facilitate the implementation of structured investment journeys, guiding users towards more rational and evidence-based decision-making. This proactive approach can mitigate the impact of cognitive shortcuts, such as heuristics and herding, which often lead to suboptimal investment outcomes in volatile markets like cryptocurrency (Ahmad & Shah, 2020; Susana et al., 2020; Kaur et al., 2023). This strategy also fosters a deeper understanding among investors regarding the inherent risks and opportunities within the cryptocurrency landscape, moving beyond superficial engagement (Handoko et al., 2024). Platforms can use simple, visual risk cues or short confirmations (“I understand the risk”), which will nudge clients towards more prudent investment behaviours (Ahmad, 2022). This will reduce regret trades, prompt more diversified allocations, lower complaint rates and improve regulatory posture for proactive investor protection (Almansour, 2020; Handoko et al., 2024). Platforms can offer an opt-down path for experienced users to avoid unnecessary burden.

7.6.3. Targeted financial education

Educators can leverage these findings within financial literacy programs in secondary and tertiary institutions to enrich their curriculum on investments and the influence of biases on decision-making, particularly in emerging markets. This educational strategy aims to prepare future investors to identify and counter prevalent cognitive biases, such as herding behaviour and heuristics, which frequently impact cryptocurrency investment decisions (Handoko et al., 2024; Iamin, 2025). This would involve integrating specialised modules designed to address cognitive biases.

7.6.4. Financial institution readiness

Based on the results of awareness and adoption, it validates the demand and rationale for investors wanting to invest in cryptocurrency. This understanding allows financial institutions and FinTech companies to develop more robust, ethically sound and user-centric products and services that cater to this evolving demand, while simultaneously safeguarding investors from the pitfalls of behavioural biases (Iamin, 2025). It was established that clients are investing for wealth generation and speculation. Knowing this, institutions can build detailed journeys, products and educational resources tailored to

these motivations, thereby fostering more responsible engagement with digital assets (Carbó-Valverde et al., 2024; Handoko et al., 2024).

These modules should be contextualised with case studies relevant to cryptocurrency in South Africa. Delivery channels can be expanded to Non-Governmental Organisations, employer-sponsored programmes and in-app education. The greatest impact of this education is likely when combined with supportive platform design and regulatory incentives. This holistic approach, integrating education with practical application and regulatory frameworks, offers a robust defence against speculative investments and excessive risk-taking (Osakwe et al., 2024).

7.7. Limitations

While this study provides insights into cryptocurrency adoption behaviour in South Africa, it is not without limitations. It is important to acknowledge these limitations for contextualising the findings and identifying avenues for future research to build upon this work. Key limitations as identified throughout the study are as follows.

The primary constraint of this study stems from its cross-sectional survey design, which captures respondents' attitudes at a single moment in time. This methodology inherently prevents the establishment of causal inferences and limits the capacity to observe shifts in behaviour or perceptions over an extended duration. Given the rapid evolution and regulatory changes within the cryptocurrency market, respondents' attitudes can dramatically change with environmental context. While a cross-sectional study provides a snapshot, a more dynamic understanding of evolving investor motivations and the efficacy of interventions would be better achieved through a mixed-methods approach (Ahmad, 2022).

The generalisability of these findings to other emerging markets might be limited due to the unique local socio-economic and regulatory landscape experienced by the respondents in this study. Additionally, purposive and snowball sampling yielded a sample skewed to younger, urban, highly educated demographics employed in the finance and IT field. This is an underrepresentation of the true demographics of South Africa, which is characterised by lower education levels with a diverse job market. Over and above, the reliance on self-reported data introduces potential biases, such as social desirability bias, which could affect the accuracy and reliability of the responses (Adil et al., 2021).

The study also experienced some weak validity and reliability scores with disposition and loss-aversion ($\alpha \approx 0.68$ and 0.65), which fell below conventional thresholds ($\alpha = 0.70$), and the FOMO construct was dropped for low loadings considering the significant findings in other studies (Choudhary et al., 2024; Friederich et al., 2023; Kaur et al., 2023). Consequently, the model explained only 26.7% variance in cryptocurrency adoption. This emphasises the need to measure other constructs that could explain more of the variance in adoption and relook at FOMO as a reliable construct.

A notable limitation was in RQ2 where the age-group 46+ years contained only 11 respondents. This small sample size within an older demographic could skew findings, highlighting the necessity for future research to include a more robust representation of older investors to accurately gauge their adoption patterns and motivation.

In summary, the study's findings should be interpreted considering its limitations to properly contextualise the results and inform researchers about its applicability. The subsequent section will outline potential areas for future research to expand upon this field of study, either confirming or refuting these findings within a similar context.

7.8. Future Research

Building on the above limitations and findings, several avenues for future research is explored below.

Future research could employ longitudinal studies to capture the dynamic shifts in consumer attitudes and behaviours toward cryptocurrency adoption over time, moving beyond the cross-sectional limitations of the current study. Such studies could also integrate qualitative methodologies as a mixed methods approach, which provides in-depth interviews or focus groups, to provide a richer understanding of underlying motivations and perceptions that quantitative data alone might not fully capture (Barroga et al., 2023).

Expanding the geographical scope to include diverse emerging markets would enhance the generalisability of findings, while also enabling comparative analyses of regulatory impacts and socio-economic influences on adoption rates. In addition, the investigations should consider a broader and more representative sample across various demographics and geographical locations within South Africa, as the current study experienced a limitation in this context.

The consideration of additional constructs grounded in theoretical frameworks such as Theory of Planned Behaviour, Technology Acceptance Model and Unified Theory of Acceptance and Use of Technology models offer a promising direction for future research on cryptocurrency adoption behaviour (Islam et al., 2023; Shahzad et al., 2024; Venkatesh, 2021). Constructs such as perceived risk, trust, usefulness, perceived ease of use and FOMO can further elucidate the drivers of cryptocurrency adoption.

By pursuing these and other rigorously conducted research directions, this study endeavours to enrich the existing literature, address identified gaps and ultimately foster a more comprehensive and practically relevant understanding of cryptocurrency adoption in an emerging market context.

7.9. Conclusion

The research examined how behavioural biases influence cryptocurrency adoption among South African retail investors and financial literacy, acting as the moderating variable. Furthermore, it was tested whether these effects differ across age groups. This matters for banks, investment platforms and policymakers seeking to design responsible products, investor education and regulation in a fast-evolving digital asset environment where fintechs are increasingly agile and traditional institutions face pressure to remain relevant.

The study addressed gaps in emerging-market evidence by testing multiple behavioural drivers and the possible moderating role of financial literacy. The key findings are first, herding behaviour and heuristic-driven thinking significantly and positively predict intention to adopt cryptocurrency. Investors appear to follow perceived collective sentiment and rely on mental shortcuts under uncertainty. Second, other well-known behavioural biases – such as loss aversion, disposition effect and overconfidence – did not significantly predict initial adoption. This suggests that some classic behavioural finance effects may become more important after entry (e.g. in holding or selling decisions) rather than at the point of first investing. Third, financial literacy neither directly predicted adoption nor significantly moderated the effect of biases. Notably, awareness of cryptocurrency was high (86%), and adoption was substantial (33%), indicating both mainstream visibility and a willingness to engage in speculation and perceived wealth creation. Finally, no meaningful age-group differences were detected: younger and older respondents in this sample appeared to be motivated by similar psychological factors.

These results deepen the understanding of retail investor psychology in digital finance. It shows that social influence and cognitive shortcuts are central to cryptocurrency adoption, while assumptions such as “younger investors are inherently more pro-crypto” or “more literate investors behave more rationally” were not strongly supported (Ballis & Verousis, 2022). As cryptocurrencies continue to diffuse, outcomes for both investors and institutions will depend not only on technology, but also on how these human drivers are recognised, guided and, where necessary, safeguarded against.

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Appendix A: Questionnaire

Section 1: Sociodemographic Information

1.1. Are you a SA citizen

[If no end survey]

Please select:

- Yes
- No

1.2. Gender of the participant

Please select one:

- Male
- Female
- Prefer not to say

1.3. Age of the participant

Please select one:

- 18 – 28
- 29 – 37
- 38 – 45

1.4. Highest qualification obtained

Please select one:

- Grade 11 and below
- Grade 12m (NQF5)
- Diploma (NQF6)
- Undergraduate Degree (NQF7)
- Postgraduate Degree (NQF 8)
- Masters Degree and Higher (NQF 9)

1.5. Employment status

Please select one:

- I am currently employed or self-employed

- I am currently unemployed
- I am a student
- I am retired

1.7. Net income Earned per month

Please select one:

- Income less than R237 100
- Income between R237 101 and R370 501
- Income between R370 502 and R512 801
- Income between R512 802 and R673 001
- Income between R673 002 and R857 901
- Income between R857 902 and R1 817 001
- Income over R1 817 002
- I am not sure or prefer not to say

1.8. Area of professional expertise

Please select one:

- Finance (including banking)
- Education
- Health
- Information and communications technology
- Legal
- Science and engineering (including actuarial)
- Manufacturing
- Mining
- Transport
- Construction
- Other

Section 2: Cryptocurrency Awareness & Usage

Please note: Below is a list of the top 10 cryptocurrencies (by market capitalisation) for your reference:

1. Bitcoin (BTC)
2. Ethereum (ETH)
3. Ripple (XRP)
4. Tether (USDT)
5. Binance Coin (BND)
6. Solano (Sol)
7. USD Coin (USDC)
8. Doge Coin (Doge)
9. Cardono (ADA)
10. Tron (TRX)

2.1. Have you heard of Bitcoin or other cryptocurrencies?

- Yes
- No

2.2. Which of the following statements most accurately applies to you?

Please select one:

- I currently own Bitcoin
- I currently own another cryptocurrency
- I owned cryptocurrencies in the past but not anymore
- I have never owned cryptocurrency but have an interest in purchasing cryptocurrency
- I merely know of cryptocurrency
- I know of cryptocurrency but have no interest in purchasing cryptocurrency

[If respondent does NOT currently own crypto]

2.3. How likely are you to purchase cryptocurrency in the future?

- Strongly agree
- Agree

- Neutral
- Disagree
- Strongly disagree

[If respondent currently owns crypto]

2.4. Please indicate your level of agreement with the following statements regarding your main use of cryptocurrency.

2.4.1. I mainly use cryptocurrency as a store of wealth

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

2.4.2. I mainly use cryptocurrency as a speculative investment

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

2.4.3. I mainly use cryptocurrency as a medium of exchange

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

2.4.4. I mainly use cryptocurrency to transfer funds anonymously

- Strongly agree
- Agree

- Neutral
- Disagree
- Strongly disagree

Section 3: Behavioural Factors

Please indicate your level of agreement with the following statements:

3.1 Heuristics

3.1.1. I believe that my skills and knowledge of the cryptocurrency market can help me to outperform the market.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.1.2. I rely on my previous experiences in the market for my next investment.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.1.3. I forecast the changes in cryptocurrency prices in the future based on recent cryptocurrency price movements.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.2 Fear of Missing Out (FMO)

3.2.1 I fear my friends have more rewarding experiences of cryptocurrency investing than me.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.2.2 I get worried when my friends invest in cryptocurrency without my knowledge.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.2.3. When I earn a good return from cryptocurrency, it is important for me to share the details online.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.3. Overconfidence (OCF)

3.3.1. I have complete knowledge of various types of cryptocurrency investments.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**

- **Strongly disagree**

3.3.2 I believe that my investing skills help me to outperform the cryptocurrency market.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.3.3 I can predict the future prices of my cryptocurrency investments better than others.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.4. Herding

3.4.1. I follow others in all my cryptocurrency investment decisions.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.4.2. I prefer to invest in the cryptocurrencies that other investors are buying.

- **Strongly agree**
- **Agree**
- **Neutral**

- **Disagree**
- **Strongly disagree**

3.4.3. I follow social blogs and forums before making a cryptocurrency investment decision.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.5. Disposition Effect (DSP)

3.5.1. I am often reluctant to realize losses in cryptocurrency investments.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.5.2. I prefer to sell cryptocurrencies whose prices have recently increased.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.5.3. I sell profitable cryptocurrencies because I am afraid that their price would fall again.

- **Strongly agree**
- **Agree**

- **Neutral**
- **Disagree**
- **Strongly disagree**

3.6. Loss aversion (LA)

3.6.1. Your prior loss experience highly affects your risk-taking ability.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.6.2. You usually have the tendency to avoid selling shares that have attained a lower value.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

3.6.3. You usually sell shares that have attained higher values.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

Section 4: Investment Intention

4.1. Investment Intention (INT)

4.1.1. I may invest in cryptocurrency in the future.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

4.1.2. I would most probably invest in cryptocurrency.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

4.1.3. I am quite willing to invest in cryptocurrency.

- **Strongly agree**
- **Agree**
- **Neutral**
- **Disagree**
- **Strongly disagree**

Section 5: Financial literacy

5.1. Financial Literacy (FL)

5.1.1. The stock market helps to predict stock prices and earning?

- **Yes**
- **No**

5.1.2. Considering a long-term period (e.g. 10–20 years) stocks normally generate inflation beating returns

- Yes
- No

5.1.3. If you spread your money among different assets, does the risk of losing money increase?

- Yes
- No