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Crypto Minds at Risk: Ranking Cognitive Biases among Dutch Retail and Potential Investors

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Abstract

This thesis investigates how five key behavioral biases: herding, overconfidence, loss aversion, regret aversion, and anchoring shape cryptocurrency investment decisions among Dutch retail and potential investors. A mixed-methods design, consisting of the Fuzzy AHP, Likert-scale averages, and regression models, is used to distinguish between what investors believe influences them and what actually drives their investment behavior. The findings show that potential investors perceive herding and regret aversion as more influential, although they show no significant effect on investment propensity. For retail investors, anchoring and overconfidence are perceived as most important, with overconfidence also significantly affecting investment behavior. These findings emphasize the discrepancy between perceived importance and actual behavioral influence and highlight the differences between investor types. These insights contribute to behavioral finance literature and bring practical implications for tailored education and regulatory developments.

Key words: *behavioral biases, crypto investing, Fuzzy AHP, regression analysis*

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1 Introduction

On October 31, Nakamoto (2008) published a revolutionary white paper introducing Bitcoin. A decentralized digital currency that enables peer-to-peer payments through open-source software, without the involvement of financial authorities. The creation of this digital currency Bitcoin caused the emergence of several other cryptocurrencies such as Ethereum, Litecoin, Ripple, and many other altcoins. Although most were created as a means of payment, they experienced a rapid development into speculative investment assets in the global financial markets (Almeida & Gonçalves, 2023a; Blau, 2017). This new market along with the creation of accessible investment platforms, has brought the dream of high and easy profits closer to regular people without any financial knowledge. This has triggered a wave of new non-institutional investors seeking to make extremely high profits in a highly volatile market. Some managed to succeed, but others lost their entire investment capital. As a logical result, the cryptocurrency market has received significant attention from the media, regulators, institutional and non-institutional investors, and has become an important topic in different fields of academic research (Angerer et al., 2020).

Various studies (Mikhaylov, 2020; Mosteanu and Faccia, 2020; Abubakar et al., 2019) have shown that cryptocurrencies have established their position in today's digital world and will have a significant role in every investor's portfolio in the following years. The total value of cryptocurrency market capitalization has increased from \$1.2 billion in 2013 to over 3\$ trillion at the start of 2025, while Bitcoin alone already accounts for over \$2 trillion of this value (*Live Cryptocurrency Charts & Market Data | CoinMarketCap*, n.d.). Cryptocurrency has become a prominent investment vehicle besides conventional asset classes, such as stocks, bonds, and commodities. Research has even shown that cryptocurrency can be used as a diversification tool for an investor's portfolio as it exhibits a very weak correlation with traditional asset classes (Baur et al., 2017). While in these conventional markets, fundamental analysis is used to predict returns, this approach fails for the cryptocurrency market, leading to persistent mispricing, excessive volatility, and recurring speculative bubbles (Rubbianiy et al., 2021). As a result, price movements in the cryptocurrency market are largely driven by non-fundamental factors (Almeida & Gonçalves, 2023b).

Behavioral finance has gained a prominent role in modern economics. This shift emerged due to the inability of traditional rational theories, such as the Efficient Market Hypothesis (Fama, 1970), Expected Utility Theory (Von Neumann & Morgenstern, 1944), and Modern Portfolio Theory (Markowitz, 1952) to explain market anomalies, such as excessive volatility and speculative bubbles. In response, Baker and Nofsinger (2002) demonstrated that psychological biases have a severe impact on the decision-making process of investors. In the context of cryptocurrencies, which lack intrinsic valuation metrics, these psychological insights might help understand their extreme volatility and mispricing (Cheah & Fry, 2015; Gurdgiev & O'Loughlin, 2020). In recent years, several studies have already examined the impact of behavioral biases on crypto investors (Haryanto et al., 2019; Hasnain & Subhan, 2023; Sood et al., 2023). However, there is still no consensus regarding which bias has the strongest influence. While herding frequently appears as the most important bias, the order of the remaining biases is inconsistent. For example, Sood et al. (2023) identified herding and regret aversion as important drivers, whereas Hasnain and Subhan (2023) found overconfidence to be more influential.

Moreover, much of this research has been conducted on non-Western individuals, making it hard to generalize findings to the Dutch population. Cultural differences between populations can play a crucial role in behavioral finance, as shown by Rieger et al. (2014), who found a significant variation in risk preferences across countries. Additionally, Sood et al. (2023) proposed that future studies should investigate the effect of these biases among novel or less experienced crypto investors to understand if behavioral tendencies shift with investment experience.

Understanding the effect of these biases on crypto investors can contribute to better financial education and regulatory policies around the crypto market. This is especially relevant since the Dutch parliament has established the MiCA-wet, which is a European ordinance aiming to protect consumers (Ministerie van Financiën, 2024). Although the law has already come into effect and is currently being enforced, the government is still actively revising it. Knowing how retail and potential investors are influenced by cognitive biases around crypto investments can contribute to better-tailored and well-defined legislation.

According to Cornelli et al. (2023), the majority of retail investors lose money on their crypto investments, sometimes even in large amounts. Cheah and Fry, (2015) even found that these biases can be seen as drivers behind the speculative bubbles in the crypto market, which can lead to detrimental losses for investors. This highlights its social relevance as more individuals start investing in cryptocurrencies, without knowing the risks attached to it.

Given this empirical gap and its societal relevance, this thesis will aim to identify the rank and impact of the different biases among Dutch retail and potential cryptocurrency investors. These insights can be used to educate the Dutch population and protect them against their own irrationality, which influences decision-making, leading to mispricing of assets, systematic risks, and financial problems. Furthermore, it can be used to increase regulatory scrutiny and legislative developments, such as the MiCA framework. Additionally, this study seeks to explore how the biases differently affect the two investor groups, with the aim of more tailored educational interventions and policy measures. To better understand how these biases affect investor behavior, the key question this thesis aims to answer is:

Research question

Which behavioral biases have the largest and most significant impact on cryptocurrency investment decisions of Dutch retail and potential investors, and how do they rank in importance?

To answer this research question, a mixed-methods approach is used. First, the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) method is applied to determine the relative importance of each behavioral bias based on pairwise comparisons. Secondly, the average Likert scores are compared to create a second ranking of the biases. Then, a linear cross-sectional regression analysis is run to statistically test the relationship between the behavioral biases and the decision makers' investment propensity towards crypto. This serves as a complementary method, enabling distinction between the perceived importance of the biases and their actual impact on investment behavior. This mixed-methods approach makes the findings more robust and generalizable.

The data for both methods is collected by distributing an online Qualtrics questionnaire to Dutch retail and potential crypto investors. Its first section consists of demographic questions, which are used to measure the dependent variable and the control variables. In the second section of the survey data, participants are asked to evaluate different statements per bias based on a 7-point Likert scale. In the last section, participants are asked to make pairwise comparisons between the different biases based on linguistic terms that are later converted into triangular fuzzy numbers (Jain et al., 2019). A detailed description of these methods will follow in the methodology section of this thesis.

The results of the thesis provide several key insights. For Dutch retail investors, anchoring and overconfidence emerged as the most influential biases, with overconfidence also significantly increasing crypto investment allocations. Contrarily, herding and regret aversion were most prominent among potential investors, although they did not translate into actual investment behavior. Interestingly, regret and loss aversion were perceived as less important, but still showed significant negative effects on the investment propensity of retail investors. The findings suggest that there is a discrepancy between perceived importance and actual influence. Moreover, it reveals that biases influencing investors diverge across experience levels. This has important implications for developing tailored education and legislative frameworks.

2 Literature review

2.1 The value of cryptocurrency

Since the emergence of cryptocurrency in the financial markets, much research has been conducted to determine Bitcoins' true value. Cheah and Fry (2015) analyzed the value of Bitcoin using econometric modeling and found that Bitcoin has no intrinsic value. Instead of its underlying fundamentals, speculation is what drives the price. They even argued that in the long run, the value could go to zero, which implies the price only gets sustained by speculative trading. Baur et al. (2017) tried to determine if Bitcoin is a medium of exchange or a speculative asset. Despite that Bitcoin was originally developed as a means of exchange, it's barely used for everyday transactions. High price volatility, slow transaction speed, legal uncertainty, high transaction fees, and the lack of merchant adoption impede practical usability. Furthermore, they found evidence of bubble behavior by analyzing its price patterns. By examining the trading volume and price movements, they showed that Bitcoins' large price fluctuations often go along with news events, hype cycles, or herding behavior among traders, rather than changes in its intrinsic value or utility. Lastly, they found a very weak correlation of Bitcoin with other traditional assets, making it a potential tool for diversification benefits.

Following the literature, it is hard to tell what the fundamental value of cryptocurrency is specifically, making it interesting to discover why it gets traded so much. No fundamental value indicates that people might be driven by cognitive biases instead of rationality (Almeida & Gonçalves, 2023b). Currently, behavioral finance is one of the mainstream fields of economics, besides classic economics, which assumes investors behave rationally and make decisions to maximize their utility. Malkiel and Fama (1970) formulated this notion in the Efficient Market Hypothesis (EMH). They stated that financial markets should be efficient, implying that prices of assets immediately reflect all available information. Market anomalies cannot exist because mispricing would be exploited by rational investors, bringing back the market equilibrium. Furthermore, Von Neumann and Morgenstern (1944) formulated the Expected Utility Theory (EUT), which provides the foundation for rational decision-making under risk, suggesting that individuals evaluate alternatives based on expected payoffs and

risk tolerance. Markowitz (1952) developed a similar Modern Portfolio Theory (MPT), emphasizing the rational allocation of assets to obtain a minimum variance portfolio.

However, these rationality assumptions are currently being questioned due to persistent anomalies influencing the financial markets. Speculative bubbles, excessive volatility, and market crashes cannot be fully explained by these classic economic theories. Robert Shiller (2000) argued that asset prices often exhibit excessive volatility, which means that prices fluctuate way more than fundamental factors can justify, contradicting the Efficient Market Hypothesis. If investors are rational, the prices would only respond to real economic factors. However, Shiller observed that these prices often rose or crashed for no clear reason. Furthermore, he highlighted how speculative bubbles are formed by psychological factors such as investors' sentiment, media hype, and herding behavior rather than rational decision-making.

Additionally, studies have shown that investor behavior often deviates from the assumptions of traditional rationality theories. For instance, Kahneman and Tversky (1979), introduced the Prospect Theory, which revealed that people perceive gains and losses differently. Individuals often perceive a loss more intensively than an equivalent gain, a phenomenon called loss aversion. De Bondt and Thaler (1985), observed that investors tend to overreact to new information, causing price momentum followed by mean reversion. Banerjee (1992) demonstrated that investors often mimic the decisions of larger groups rather than relying on their own judgment. This herding behavior of investors leads to irrational and exaggerated price movements in financial markets. Moreover, Odean (1998), introduced the concept of overconfidence, implying that investors overestimate their knowledge and skill in predicting price movements. This leads to excessive trading, which is often detrimental to their overall returns. Together, these behavioral patterns have shown that financial markets are prone to systematic biases and that the decision-making process of investors is not purely rational.

As a response to the limitations of the traditional theories, behavioral finance emerged. It tries to explore the psychological insights of individuals to explain how their investment process deviates from rational decision-making. According to Baker and Nofsinger (2002), behavioral finance can be divided into two parts. One focuses more on the individual

investors' biases, such as overconfidence, loss aversion, and anchoring, while the other examines broader market anomalies, such as speculative bubbles and herding.

2.2 Behavioral biases in cryptocurrency trading

Cheah and Fry (2015) found that bitcoin trading is heavily influenced by psychological biases instead of their fundamentals. Because traditional valuation models fail to explain the extreme price volatility in cryptocurrencies, investigating which behavioral biases drive these extreme price movements becomes particularly relevant. Biases such as herding, overconfidence, anchoring, loss aversion, and regret aversion might play a crucial role in determining investment decisions.

Herding behavior is a well-known bias where investors tend to mimic others instead of making independent rational decisions, based on their own information. This phenomenon is particularly relevant in the crypto market due to various strong influences, including social media, influential figures, and news outlets promoting these digital assets (Sood et al. 2023). Hasnain and Subhan (2023) found that investment decisions regarding cryptocurrency are positively correlated with herding behavior. The authors conducted a regression analysis on the questionnaire responses of Pakistani investors, revealing that many participants based their decisions on the actions of other investors rather than on the analysis of the asset's fundamental value.

Furthermore, Hasnain and Subhan (2023) examined the impact of overconfidence on the investment decisions of Pakistani crypto investors. The results showed an even stronger, positive relationship between overconfidence and investors' decisions in cryptocurrency. This indicates that crypto investors are especially prone to overconfidence, even more so than to herding behavior. However, these results are not universal. Sood et al. (2023), for instance, showed that herding has the largest influence.

Another cognitive bias that influences cryptocurrency traders is loss aversion (Kaur et al. 2023). Kahneman and Tversky (1979) developed Prospect Theory, which included loss aversion. It states that investors feel the sting of losses harder than the joy of equivalent gains. During market bull runs, investors prefer conserving capital rather than focusing on increasing it (Jain et al. 2021). Consequently, investors tend to sell financial assets that have recently

acquired positive returns, while they hold on to losing assets. Haryanto et al. (2020) demonstrated the influence of loss aversion on the investment decisions of individual crypto investors during bearish periods. When investors lost money due to large price drops, they continue holding their losing cryptocurrency because they believe they will suffer greatly when they realize a loss. Hence, individuals will sell winning crypto's too early during bubble markets, while they hold on to losing crypto's during bearish periods (Haryanto et al., 2020).

Another closely related bias is regret aversion, which is the tendency of investors to avoid making decisions that could later result in regret. This is an emotional bias caused by an overreaction to sentiments of regret after realizing that alternative decisions appeared to have better outcomes (Sood et al., 2023). Research has shown the significant impact of regret aversion on the investment decisions of crypto investors in both bullish and bearish market trends. Investors often choose to spend more money than they can afford on very risky cryptocurrencies that have shown rapid growth because they fear the regret of not buying them (Sood et al., 2023). The root of this bias is the tendency of investors not wanting to acknowledge their own mistakes. Investors prone to this bias may avoid making certain decisions due to the fear of making a suboptimal decision. (Jain et al., 2019). In the highly speculative crypto market, this can lead to irrational and detrimental investment patterns where investors chase past winners and hold poor-performing cryptos out of fear of regretting their decision. Hence, regret aversion bias plays a role in explaining irrational behavior, especially among inexperienced retail investors.

Anchoring is also recognized as a relevant bias for crypto investors. This is a cognitive bias that causes investment decisions to heavily rely on initial information or specific reference points, such as past price levels. Gurdgiev and O'Loughlin (2020) found that crypto investors tend to anchor their expectations to previous price trends due to the crypto's high volatility and the lack of fundamental valuation metrics. Their analysis suggested that such anchoring behavior can significantly influence price dynamics in crypto markets because investment decisions are based on these arbitrary benchmarks.

2.3 Behavioral biases across investor experience levels

Literature has shown that investor experience plays an interesting role in the presence of behavioral biases. Empirical studies have shown that the influence of certain biases shifts significantly as investors gain experience in the financial markets (Feng & Seasholes, 2005; Mishra & Metilda, 2015; Raut & Kumar, 2018).

Raut and Kumar (2018) demonstrated that investors without experience exhibit more herding behavior. They are more likely to rely on signals from other decision-makers, thereby neglecting their own information about a financial product. In contrast, overconfidence appears more pronounced among experienced investors. The study of Mishra and Metilda (2015) found that more experienced investors scored significantly higher on the overconfidence bias than those with less experience. They argued that repeated exposure to markets and prior successful investment contribute to overestimating their own skills in predicting market movements.

However, the study of Raut and Kumar (2018) contradicted this and found overconfidence to be more pronounced among novice investors. They argued that a possible explanation might be biological predisposition. This is a neurological condition observed among new investors that increases their likelihood of irrational risk-taking and overestimating their own ability. Feng and Seasholes (2005) showed that after investors gained more experience, they become significantly less prone to the disposition effect, which is closely related to loss aversion and regret aversion. This indicates that investing experience promotes learning and can contribute to rationalizing investment decision-making. However, existing literature on these differences is very limited. Moreover, it is unclear whether this difference also holds for investors with no experience and in the context of the cryptocurrency market. Recognizing these differences is important in terms of practical applications. If retail and potential investors are systematically prone to different biases, then potential educational programs, risk disclosures, and regulatory interventions should be tailored accordingly. This aligns with the proposition of Sood et al. (2023), calling for future research targeting less experienced crypto investors.

2.4 Relevance of the cognitive biases

These biases influence the decision-making process of crypto investors, which may play a crucial role in declaring market anomalies. Lind (2009) defined a bubble as a: *“dramatic increase in prices followed by rapid falls in prices.”* According to Cheah and Fry (2015), these cognitive biases drive the speculative bubbles in the crypto market. Their study showed that bubbles arise from irrational investor behavior and market sentiment rather than from intrinsic economic factors. Particularly, irrational bubbles are formed when investors are driven by cognitive biases and simple heuristics rather than by fundamental analysis. This leads to rapidly increasing prices rising far beyond sustainable levels, fueled by investors’ optimism and herding behavior. As the bubbles develop, overconfidence among the investors further inflates prices because they believe they can continue profiting from the rising market. When the so-called “blow-off” phase starts and prices begin to fall, biases such as loss aversion, regret aversion, and anchoring, prevent investors from selling their assets, which delays corrections and worsens volatility (Cheah & Fry, 2015).

Given the potentially detrimental effects of bubbles on investors, it is of great importance to identify the biases involved. These understandings could be used as a foundation for investors’ protection through education and regulatory measures regarding the crypto markets. The relevance of studying the behavioral biases affecting crypto trading partly arises from the difference in the characteristics of the traditional stock market and the crypto market. Extreme volatility, lack of intrinsic valuation metrics, and influences from (social) media amplify the impact of cognitive biases on investors. (Baur et al., 2017; Cheah & Fry, 2015). Earlier studies have shown that biases such as herding, overconfidence, loss aversion, and anchoring are prominent biases that are particularly prevalent among crypto investors (Haryanto et al., 2019; Kaur et al., 2023; Sood et al., 2023; Subhan & Hasnain, 2023). However, the results across studies about the most influential biases are heterogeneous.

As the market capitalization of cryptocurrency has been growing rapidly, it has become increasingly more important to understand how and to what extent these biases influence investors. Many of these previous studies were conducted in non-western contexts. However, Rieger et al. (2014) found that cultural differences can significantly impact investment behavior. Dutch investors may respond differently to these cognitive biases, making it relevant

to conduct research that specifically focuses on Dutch investors. Hence, the questionnaire of this study is distributed across Dutch retail and potential investors, thereby offering new insights distinct from prior findings based on other populations.

2.5 Hypothesis

Prior research has shown that herding is one of the most substantial cognitive bias influencing crypto investors (Gurdgiev & O'Loughlin, 2020; Sood et al., 2023). The findings are consistent across various studies and different markets, where social influence drives the impulsive investment decisions of retail investors. Given that the crypto market has a speculative nature and high volatility, herding gets amplified through media channels and peer influences, as demonstrated by Hasnain and Subhan (2023) with Pakistani investors and by Haryanto et al. (2019) with Indonesian investors. Despite the literature's deviating results about the most influential bias, herding came out on top in several economic studies (Kaur et al., 2023; Sood et al., 2023).

Based on previous literature, overconfidence appears to be the second most influential bias among investors due to their strong beliefs in their own knowledge or trading skills, even though markets are highly unpredictable (Jain et al., 2019). The findings of Hasnain and Subhan (2023) confirm that crypto investors often display strong overconfidence, leading to impulsive trading decisions based on subjective convictions rather than on fundamental analysis. The pervasive and constant influence of social media's algorithms creates an environment where investors feel falsely reassured in their ability to predict the market. However, the results of Sood et al. (2023) showed a smaller influence of overconfidence on investment decisions.

Loss aversion emerges as crypto investors' third most influential cognitive bias, following herding and overconfidence. The high volatility of crypto imposes significant psychological discomfort when facing losses. Consequently, crypto investors tend to start making irrational decisions by holding on to losing positions, hoping prices will rebound and not having to feel the pain of realizing those losses (Haryanto et al., 2020). Jain et al. (2019) demonstrated the crucial role of loss aversion in the behavior of investors. Especially during

the blow-off phase, where the fear of losses prolongs holding on to losing assets, which is particularly detrimental in highly volatile crypto markets.

Regret aversion is expected to be the fourth most influential bias. This bias refers to the tendency of investors to avoid making decisions that could turn into regret. Due to crypto's high volatility and rapidly changing prices, investors often fear missing out on high returns. Consequently, they make impulsive purchases of risky assets instead of basing decisions on rational strategies (Sood et al., 2023). The results of this study showed that regret aversion is one of the biases with a large influence on investors' decision-making process. However, in the study of Jain et al. (2019), the influence of regret aversion was less prominent than herding, overconfidence, and loss aversion.

Lastly, anchoring is expected to have the lowest impact on crypto investors' investment decisions. Anchoring causes investors to rely heavily on initial price points or historical highs rather than looking at the current market data. This tendency gets amplified in the crypto market because there is a lack of intrinsic valuation metrics (Cheah & Fry, 2015). The study by Gurdgiev and O'Loughlin (2020) illustrated that investors often anchor their expectations on past price benchmarks. However, the study of Sood et al. (2023) showed that across the biases, anchoring had the least impact on the investment decisions of crypto investors. Based on the literature and to answer the research question, the following hypothesis is formulated:

H1: Among Dutch retail cryptocurrency investors and potential investors, herding behavior will have the largest impact on investment decision-making, followed by overconfidence, loss aversion, regret aversion, and anchoring in that order of influence.

While the previous section addresses how specific behavioral biases influence the investment behavior of retail and potential investors in general, it is equally important to explore if and how the influence of these biases differs across investor groups. Experience can play a critical role in shaping how individuals process information and make financial decisions. Research suggests that novice investors are often driven by herding due to their limited market knowledge (Raut & Kumar, 2018). Additionally, they are more likely to be influenced

by the disposition effect, indicating that loss aversion and regret aversion play a more crucial role in their investment decisions (Feng & Seasholes, 2005). In contrast, experienced investors are shown to be more prone to overconfidence, as repeated market exposure and successful investments can lead to overestimating their skill in predicting market movements (Mishra & Metilda, 2015). This shows that biases differ across investor experience, leading to the second hypothesis:

H2: The relative influence of behavioral biases on cryptocurrency investment decisions differs between Dutch retail and potential investors, both in terms of their perceived importance and their actual impact on investment behavior.

3 Methodology

This study will conduct a mixed-method approach by using the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) and regression analysis. Together, this will examine the impact of behavioral biases in cryptocurrency trading. The Fuzzy AHP method uses a pairwise comparison method to rank and prioritize behavioral biases based on perceived importance. Several other behavioral finance studies have already used the Fuzzy AHP method to prioritize cognitive biases affecting investment decisions (Jain et al., 2019 & Sood et al., 2023). Additionally, the regression analysis is applied to statistically measure the relationship between the biases and participants' investment decisions. Its complementary function enables distinction between perceived importance, as captured by the Fuzzy AHP, and the actual impact on investment propensity. Using both methods will enhance the robustness of the findings.

3.1 Data collection

The data for this study was collected through an online questionnaire in Qualtrics, which was distributed across Dutch retail and potential investors. The survey can be found in Appendix 7.1 and is divided into three sections including: the demographic questions, regression analysis statements, and pairwise comparisons. Its purpose is to find data on whether the participants are prone to the five behavioral biases: herding, overconfidence, loss aversion, regret aversion, and anchoring in the context of cryptocurrency investment decisions. The first section of the questionnaire is the demographic part, which is used for the control and dependent variables, including:

- Age
- Gender
- Retail or potential crypto investor (experience level), determined by the question: "Do you have experience investing in cryptocurrency, now or in the past?"
- Risk preference, measured by the question: "Risk preference How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?"

- Crypto Investment decision measured by the hypothetical question: “If you were given €10.000, to allocate between cryptocurrency and a completely risk-free savings account. How much of this amount would you choose to invest in cryptocurrency?”

Recent literature on the crypto market has shown that the investment decision is an appropriate proxy for the actual investment behavior of the participants (Kaur et al. 2023). This is especially the case in cross-sectional studies, where long-term tracking is not a feasible option. Moreover, the hypothetical question is used to measure the dependent variable separately from the other variables. This is a common approach in behavioral and experimental finance to capture investment decisions in a standardized and context-neutral manner (Dohmen et al., 2011). Additionally, the study found that such hypothetical questions correlate well with the actual behavior of participants, which supports their validity for financial decision-making experiments (Dohmen et al., 2011). The classification of potential investors specifically relates to their cryptocurrency exposure. Therefore, it is possible that participants labeled as “potential investors” may have experience with traditional investment products, such as stocks or bonds.

The second section includes three statements for each bias to collect data for the regression analysis. These statements are given in random order and are rated on the 7-point Likert scale (Finstad, 2010). Based on the collected data, composite index scores are calculated for each bias using the arithmetic mean (Joshi et al., 2015).

The third section includes pairwise comparisons between the indicators for the biases to conduct the Fuzzy AHP method. Each bias is compared to each other in random order, which leads to a total of ten comparisons. Participants evaluate which bias is more influential and to what degree by using linguistic terms ranging from equally important to very strongly more important. These terms are later converted into triangular fuzzy numbers for the analysis (Table 1) (Jain et al., 2019). This gets further explained in the Fuzzy AHP section of the methodology. Before distribution, the questionnaire is pre-tested by peer students to assess the clarity of the questions and to ensure that it does not exceed a completion time of 10 minutes. Research by Qualtrics shows that longer surveys tend to result in significantly lower completion rates (Qualtrics, n.d.).

3.2 The Fuzzy AHP method

The Fuzzy AHP method is a combination of the fuzzy set theory introduced by Zadeh (1965) and the traditional AHP framework introduced by Saaty (1980). The fuzzy set theory is a generalization of classical set theory to handle ambiguity and imprecision in human judgment. In traditional sets, certain elements belong fully or not at all to the membership, while fuzzy sets allow for gradual membership. For example, in a classical set, an investor is either prone to herding or not, while in a fuzzy set, this investor can belong to the herding group with a degree of 0.7. Zadeh (1965), argued that these fuzzy sets better capture how humans make decisions in real-world settings, where there are rarely strict boundaries between alternatives. Kaufmann and Gupta (1991) defined the membership function $\mu_{\tilde{a}}(x)$ (shown in figure 1) of triangular fuzzy numbers denoted in Equation 1. The membership function thus explains how triangular fuzzy numbers mathematically capture uncertainty in human judgment. A tilde (\sim) is placed above the symbols representing fuzzy sets (Jain et al., 2019).

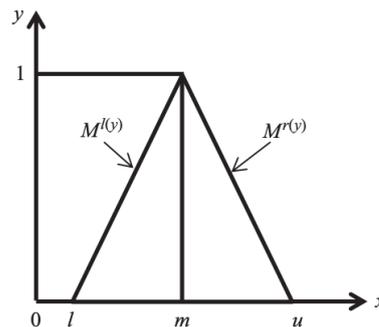


Figure 1: The membership function

$$\mu_{\tilde{a}}(x) = f(x) = \begin{cases} (m - l), & l \leq x \leq m \\ (u - m), & m \leq x \leq u \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

The Fuzzy AHP method incorporates fuzzy logic into the traditional AHP framework developed by Saaty (1980). The traditional AHP method is a structured technique to analyze complex decision-making processes, using a hierarchy of criteria and alternatives through pairwise comparisons. This traditional AHP method is also known as an eigenvector method. It indicates that the eigenvector corresponds to the largest eigenvalue of the pairwise comparison matrix,

giving the relative priorities of the different factors while preserving the ordinal preferences among the alternatives. So, if one alternative is preferred above another, its eigenvector will be larger. A vector of weights obtained from the comparison matrix reflects the relative performance of the factors (Ayağ & Özdemir, 2006).

The traditional AHP demands precise numerical input, which is often unrealistic in subjective or uncertain environments. The Fuzzy AHP resolves this limitation by allowing decision-makers to make comparisons expressed using linguistic terms, which are later converted into fuzzy numbers (Table 1). According to Wu et al. (2009), real-world decisions are inherently uncertain. Therefore, extending the AHP into the Fuzzy AHP provides a more nuanced evaluation of real complex decision-making problems. Gupta et al. (2018) stated that the mathematical structure of the traditional AHP is great for calculating the weights of different decision factors. However, a big limitation is that it is incapable of handling linguistic terms, leading to the development of the Fuzzy AHP. The Fuzzy AHP has become a great tool for handling inaccuracy or ambiguity, aiming at low-cost solutions for real-world problems (Gupta et al. 2018).

In the Fuzzy AHP framework, the biases are compared by using the linguistic terms: equally important, weakly more important, moderately more important, strongly more important and very strongly more important. These terms get converted into triangular fuzzy numbers (TFNs), represented by three values (l, m, u) indicating the lower, middle, and upper bounds of the judgment, respectively. For example, if a participant makes the comparison that the bias herding is moderately more important than overconfidence, then herding corresponds with the TFN (4, 5, 6) (Table 1). When the participant argues that overconfidence is moderately more important, herding gets the inverse fuzzy number (1/6, 1/5, 1/4) (Table 1). Jain et al. (2019) noted that when all these values are equal ($l = m = u$), there is no uncertainty and the TFN becomes a single fixed number. This gets called a crisp value, which is just a traditional exact number (e.g. 5 instead of (4, 5, 6)).

Table 1: The triangular fuzzy scale

Linguistic Term	Triangular fuzzy scale (l, m, u)	The inverse of the triangular Fuzzy scale
Equally important	(1, 1, 1)	(1, 1, 1)
Weakly more important	(2, 3, 4)	(1/4, 1/3, 1/2)
Moderately more important	(4, 5, 6)	(1/6, 1/5, 1/4)
Strongly more important	(6, 7, 8)	(1/8, 1/7, 1/6)
Very strongly more important	(9, 9, 9)	(1/9, 1/9, 1/9)

In this thesis, the fuzzy analytical process will mostly follow the steps outlined by Jain et al. (2019).

Step 1: Defining the criteria and sub-criteria

First, it needs to be evaluated, based on the literature, which behavioral biases are the most relevant in affecting the decision-making process of Dutch crypto investors. In this thesis, herding, overconfidence, loss aversion, regret aversion, and anchoring represent these criteria. The sub-criteria are represented by behaviorally driven statements that form the basis of the pairwise comparison of the Fuzzy AHP. These sub-criteria function as indicators of the chosen behavioral biases.

Step 2: Hierarchical structure

The most important behavioral biases are categorized into hierarchical structures, consisting of the main criteria (e.g. herding, overconfidence, etc.) and the sub-criteria (e.g. “I seek opinions from friends”). This structure consists of three levels: the biases affecting crypto investment decisions, the bias categories, and the specific behavioral statements (Appendix 7.2: Figure 2). So, while the Fuzzy AHP process is applied at the statement level, the resulting weights are compared and interpreted at the bias level, which is in line with the study of (Jain et al., 2019). In contrast to the related studies from (Jain et al., 2019; Sood et al., 2023), who conducted local consistency checks by comparing sub-criteria within each bias category, this study does not include such within pairwise comparisons. These studies applied local comparisons by comparing different statements from the same bias with each other. This allowed them to calculate local weights and assess the reliability of the responses of participants through statistical methods such as, the Consistency Ratio (CR). Due to time constraints in the survey design and to prevent low response rates, this thesis was limited to pairwise comparisons between the different biases. As a result, it is not possible to derive the local weights and implement consistency checks.

Step 3: Normal pairwise comparison matrix

A normal pairwise comparison matrix (NPCM) is developed based on Saaty's (1980) scale. Despite the final analysis relying on fuzzy numbers, the NPCM is included to illustrate the structure as in the paper of Jain et al. (2019).

Step 4: Fuzzy pairwise comparison matrix

Then, the fuzzy pairwise comparison matrix gets constructed based on the linguistic evaluation denoted in the triangular fuzzy numbers (TFNs) according to (Table 1 and Matrix 1), as proposed by Buckley et al. (1985). These TFNs represent the comparisons of the relative importance of the sub-criteria made by the participants of the questionnaire, which forms the basis for deriving the fuzzy weights.

Matrix 1: The Fuzzy pairwise comparison matrix

Bias	Anchoring	Herding	Loss aversion	Overconfidence	Regret aversion
Anchoring	(1, 1, 1)	(l, m, u)	(l, m, u)	(l, m, u)	(l, m, u)
Herding	(l, m, u)	(1, 1, 1)	(l, m, u)	(l, m, u)	(l, m, u)
Loss Aversion	(l, m, u)	(l, m, u)	(1, 1, 1)	(l, m, u)	(l, m, u)
Overconfidence	(l, m, u)	(l, m, u)	(l, m, u)	(1, 1, 1)	(l, m, u)
Regret aversion	(l, m, u)	(l, m, u)	(l, m, u)	(l, m, u)	(1, 1, 1)

Step 5: Aggregating the comparisons

Because multiple decision-makers are involved, their fuzzy pairwise comparison results must be aggregated into a single comparison matrix. This will ensure that the collective results are represented. Since all respondents provided their pairwise comparisons using linguistic terms that were directly translated into triangular fuzzy numbers (TFNs), the input consists of complete fuzzy comparison matrices. To combine these individual matrices in a consolidated matrix, the arithmetic mean aggregation method (AM) is applied, as proposed in the literature (Vinogradova-Zinkevič, 2023). For each comparison $\tilde{a}_{ij}^k = (l_{ij}^k, m_{ij}^k, u_{ij}^k)$, provided by respondents K, the aggregated group value $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is calculated by averaging each component across all the participants. This is conducted with Equation 2:

$$l_{ij} = \frac{1}{K} \sum_{k=1}^k l_{ij}^k, m_{ij} = \frac{1}{k} \sum_{k=1}^k m_{ij}^k, u_{ij} = \frac{1}{k} \sum_{k=1}^k u_{ij}^k, \quad (2)$$

This step will transform the respondents' multiple subjective inputs into a representative collective fuzzy comparison matrix, which is necessary before calculating the geometric means (Chang et al., 2008).

Step 6: The geometric mean of the fuzzy comparison values in the rows

After aggregating the individual responses of all respondents into a single fuzzy comparison matrix, the fuzzy geometric mean for each bias is calculated. The aggregated matrix from the previous step contains one triangular fuzzy number $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$, for each pair of criteria, which reflects the group's judgment. This means that all the answers for each comparison are reduced to only one lower (l), middle (m), and upper (u) value. To further derive each bias's relative importance from this aggregated matrix, the fuzzy geometric mean is computed for each row with Equation 3/4:

$$\tilde{r}_i = \left(\prod_{j=1}^n l_{ij} \right)^{1/n}, \left(\prod_{j=1}^n m_{ij} \right)^{1/n}, \left(\prod_{j=1}^n u_{ij} \right)^{1/n} \quad (3)$$

Where:

- l_{ij}, m_{ij}, u_{ij} are the lower, middle, and upper values of the aggregated triangular fuzzy numbers in row i , respectively.
- n represents the number of behaviorally driven statements.
- \tilde{r}_i represents the geometric mean for each bias.

Which can also be written in short as:

$$\tilde{r}_i = (r_i^l, r_i^m, r_i^u) \quad (4)$$

Where r_i^l, r_i^m, r_i^u are the geometric means of the lower, middle, and upper values of all comparisons in row i , respectively. This results in all comparisons across biases being combined into a single fuzzy number, giving one overall score that reflects the relative importance of that bias in comparison with the rest (Buckley et al., 1985; Jain et al., 2019). Hence, this step gives one fuzzy weight for each of the five behavioral biases. An important note is that one fuzzy number still consists out of three values (l, m, u).

Step 7: Find the fuzzy weights for each bias

When the fuzzy geometric means \tilde{r}_i for each bias are calculated, the next step is to determine the relative fuzzy weights by normalizing them. According to Buckley et al. (1985), the fuzzy weight \tilde{w}_i is obtained by multiplying each fuzzy geometric mean \tilde{r}_i by the inverse of the sum of all fuzzy geometric means. This ensures the fuzzy weights are proportional and that their total sum equals 1. This is conducted with the following Equation 5:

$$\tilde{w}_i = \tilde{r}_i \otimes \left(\sum_{j=1}^n \tilde{r}_j \right)^{-1} \quad (5)$$

Where:

- $\sum \tilde{r}_i = (l_{sum}, m_{sum}, u_{sum})$ is the sum of all fuzzy geometric means.
- $(\sum \tilde{r}_j)^{-1} = (\frac{1}{u_{sum}}, \frac{1}{m_{sum}}, \frac{1}{l_{sum}})$ is the inverse of the sum of the geometric means.
- \otimes indicates the fuzzy multiplication

Step 8: Defuzzify the TFNs by using the center of area approach (COA)

The fuzzy weights $\tilde{w}_i = (l_i, m_i, u_i)$ are calculated in the last step but are still in fuzzy form. To derive real insights and enable ranking, these weights need to be converted into crisp values. This defuzzification process is done by employing a widely used method, called the center-of-area approach (COA) (Liu et al., 2020). It takes the average of the three values (l_i, m_i, u_i) that gives the triangular fuzzy number. This provides one crisp value w_i that can be used to rank the different behavioral biases (Liu et al., 2020). This is conducted with Equation 6:

$$(w_i) = \frac{l\tilde{w}_i + m\tilde{w}_i + u\tilde{w}_i}{3} \quad (6)$$

Step 9 Normalizing the crisp value (w_i)

The last step is normalizing the crisp values to ensure that the sum of all weights equalizes 1, which allows for better comparability across biases. This is done with Equation 7:

$$(N_{wi}) = \frac{(W_i)}{\sum (wi)} \quad (7)$$

The resulting weights of these steps allow for prioritization and ranking of the different behavioral biases in terms of the impact on the investment decisions of retail and potential crypto investors. A radar chart is plotted to present the weights visually.

An important note is that the Fuzzy AHP produces a single crisp weight per bias, based on the aggregated group judgments. As a result, no standard errors or confidence intervals can be computed for these weights. Therefore, it is not possible to conduct conventional statistical significance tests.

3.3 Regression analysis

To complement the Fuzzy AHP and further empirically test the influence of each behavioral bias on investment decisions, the study will also conduct a linear regression analysis. This will help to analyze to what degree each bias independently influences the participant's crypto investments. Because a questionnaire was distributed to collect data at a single point in time, a cross-sectional linear regression is the most appropriate method (Wooldridge, 2016).

The dependent variable in this regression analysis is the investment decisions of retail and potential crypto investors. This is measured through a single question in the demographic part of the questionnaire. Respondents are asked: *"If you were given €10.000, how much of this would be invested in cryptocurrency?"* This will ensure that the dependent variable is measured independently of the other variables.

The different biases are included as independent variables and are measured through the responses of participants on the questionnaire. The different behavioral biases are each measured through three separate statements in random order. Their responses are captured using a 7-grade Likert scale (Scale: 1 = Strongly Disagree, 7 = Strongly Agree) (Appendix 7.2: Table 2). The study has chosen a 7-point scale rather than a 5-point scale because research has shown that this will offer better measurement precision and is more likely to reflect a participant's true subjective evaluation of a questionnaire (Finstad, 2010).

To convert the responses of the participants on the questionnaire into regression-ready variables, they need to be aggregated. This is done by computing the composite index scores by taking the arithmetic mean of the three statements from each bias. This gives an average Likert item representing the influence of each bias, which can be used in the regression analysis (Joshi et al., 2015). Before estimating the regression model, the average Likert scores are compared to indicate how participants perceive these biases influencing their investment decision. To test whether these differences are statistically significant, two non-parametric tests are conducted. First, a series of Wilcoxon signed-rank tests is employed to assess whether the differences in the average scores of the biases within groups is statistically significant (Harris & Hardin, 2013). Secondly, a series of Wilcoxon rank-sum tests is applied on the differences between groups to assess their significance (Harris & Hardin, 2013). These tests help with ranking the biases within groups based and making comparisons between groups. Given the use of survey data and the relatively small sample size, a significance level of 10 percent is accepted. This is particularly appropriate when analyzing human decision-making data such as self-reported investment behavior, where the cost of a Type I error is relatively low (Walters, 2021).

To test the second hypothesis, the regression model included a dummy interaction term between the investor type and each behavioral bias. This allowed the model to assess whether the effect of each bias deviates significantly across Dutch retail and potential investors. A binary variable is included to distinguish between retail and potential investors. This dummy variable gets a value of 1 for retail investors and a 0 for potential investors. Additionally, the model includes control variables for age, gender, and risk preferences, which all are surveyed in the demographic part of the questionnaire.

However, a VIF test on the interaction model revealed substantial multicollinearity, especially between the original bias and their interaction terms. This inflates the standard errors of the coefficients, reducing the statistical power to detect significant results. To overcome this statistical problem separate regressions were run on both investor types denoted in Equation 8.

$$\begin{aligned} INV = & \beta_0 + \beta_1HERD + \beta_2OC + \beta_3LOSS + \beta_4REG + \beta_5ANC + \beta_6AGE + \beta_7GEN \\ & + \beta_8PREF + \varepsilon \end{aligned} \quad (8)$$

To further assess whether being a retail investor influences the allocation towards crypto significantly, a regression is employed on the full sample, with a binary variable included for investor type, denoted in Equation 9.

$$\begin{aligned} INV = & \beta_0 + \beta_1HERD + \beta_2OC + \beta_3LOSS + \beta_4REG + \beta_5ANC + \beta_6AGE + \beta_7GEN \\ & + \beta_8PREF + \beta_9RET + \varepsilon \end{aligned} \quad (9)$$

To ensure the statistical validity of the OLS models, several tests were conducted: as noted, the VIF test is applied on the models to assess if there was multicollinearity among the predictor variables. Additionally, a pairwise Pearson correlation analysis examines the correlation between theoretically related biases. Furthermore, the Breusch-Pagan test is applied to assess potential heteroscedasticity, and the Durbin-Watson test is used to check for autocorrelation in the residuals. Lastly, residual plots are inspected to assess the linearity and overall model fit.

4 Results

This chapter presents and discusses the study's empirical findings. The purpose is to investigate the influence of cognitive biases on cryptocurrency investment decisions among Dutch retail and potential investors. By using two complementary methodological approaches, the study aims to find which behavioral biases are most prominent and how they statistically relate to the investment behavior of participants. First, the summary statistics of the survey responses are shown, providing an overview of the sample characteristics. Next, the results of the Fuzzy AHP are discussed, which provide a ranking of the perceived importance of the different biases under retail and potential crypto investors. This is followed by a comparison of the average Likert ratings per bias, offering additional insight into how individuals perceive the influence of the biases. Finally, the results of the regression models are discussed to assess how these biases affect the investment propensity of the participants for both groups.

4.1 Descriptive statistics

Table 3 provides the descriptive statistics for the participants, distinguishing between retail and potential crypto investors. It includes the variables age, gender, risk preference, and a hypothetical investment decision question (i.e., how much of a given €10.000 the respondent would allocate towards cryptocurrency). Table 3 shows that the retail investors ($\mu = 28.20$), on average, were younger than the potential investors ($\mu = 32.81$). A two-sample Welch t-test shows that this difference between the groups is statistically significant ($t = 2.01$, $df = 85.45$, $p = 0.048$). A more substantial difference is found in the risk preferences between groups. Retail investors reported a significantly higher average risk preference ($\mu = 6.46$) than the potential investors ($\mu = 4.31$). These findings are statistically significant ($t = -5.28$, $df = 89.42$, $p < 0.001$), indicating that people who invest in cryptocurrency are willing to take more risk. Another difference is found in the investment propensity between groups. Retail investors indicated a substantially higher allocation towards cryptocurrency ($\mu = 4364$) compared to potential crypto investors ($\mu = 2702$). This difference is statistically significant ($t = -3.70$, $df = 96.87$, $p < 0.001$) and consistent with expectations, since retail investors are already actively investing in

cryptocurrencies in real life, whereas potential investors have not started yet. The distribution can be found in Figure 3. It illustrates that retail investors tend to allocate higher amounts to crypto investments, with a wider and right-skewed distribution in comparison with potential investors. Potential investors have a frequency peak around €2700, while the frequency peak of retail investors is around €3750.

Table 3: Summary statistics

	N	Age (μ)	Male	Female	Risk preference (μ)	Investment propensity (μ)
Retail	56	28.2 (9.71)	44	12	6.46 (1.81)	4364 (2720.82)
Potential	48	32.8 (13.12)	31	17	4.31 (2.27)	2702 (1832.78)
Total	104	30.3	75	29	5.47	3597

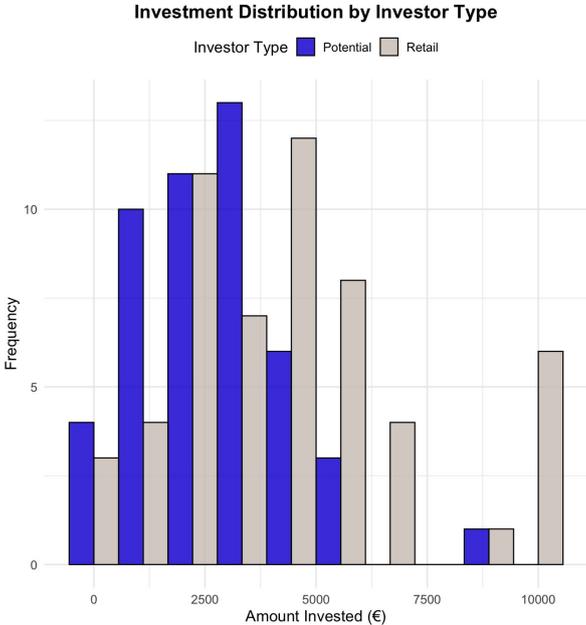


Figure 3: Distribution of crypto allocation

These descriptive findings show that there are several inherent differences between the two groups, justifying conducting the following analysis separately.

4.2 The Fuzzy AHP results

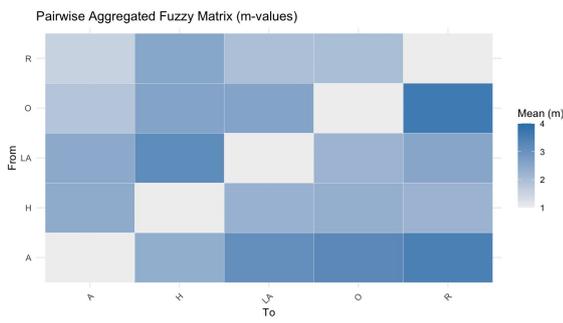


Figure 4: Heatmap retail investors

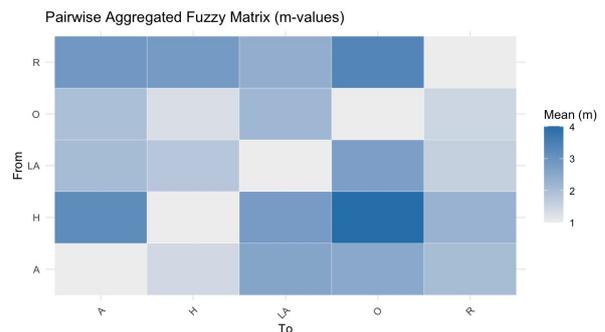


Figure 5: Heatmap potential investors

Before discussing the relative rankings and crisp weights resulting from the Fuzzy AHP, Figures 4 and 5 present heatmaps showing the average pairwise comparison values between the five biases. These descriptive statistics offer a visual summary of how often and to what extent one bias was preferred over another, based on the average middle values. In each pairwise comparison, the bias in the row (*from*) is compared to the bias in the column (*to*), meaning that the cell reflects the average middle value assigned in that directional comparison. Darker cells indicate higher average values, and therefore show stronger dominance of the row bias over the column bias.

An important note is that the heatmap is not symmetric. When participants tend to select extreme values, such as “strongly more important” for both directions of a comparison, both corresponding cells may appear relatively dark. To determine true dominance between two biases, it is important to compare the cells in both directions. Whichever cell is darker reflects the bias that was more dominant on average in that specific pairwise comparison.

Table 4: Global Rankings Fuzzy AHP Retail investors

Bias	Crisp Weight
Anchoring	0.233
Overconfidence	0.207
Loss Aversion	0.206
Herding	0.188
Regret Aversion	0.165

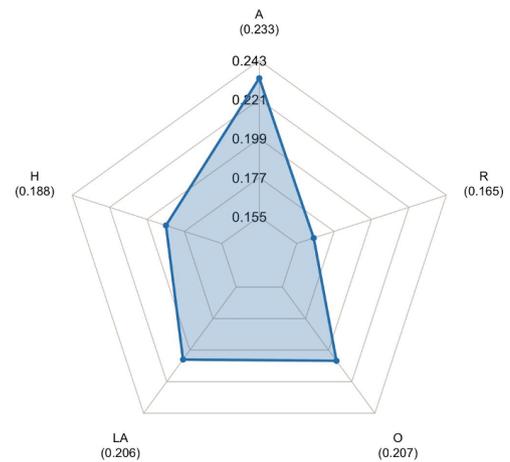
**Figure 6: Radar chart for retail investors**

Table 4 and Figure 6 present the global rankings of the behavioral biases among Dutch retail investors according to the Fuzzy AHP analysis. The use of Fuzzy AHP allowed participants to express nuanced preferences between biases, making the resulting rankings more robust and reflective of subjective judgment than simple rating scales. The results reveal that anchoring is perceived as the most influential bias with a crisp weight of 0.233, followed by overconfidence and loss aversion with crisp weights of 0.207 and 0.206, respectively. In contrast with previous literature, herding appears to be ranked as fourth with a crisp weight of 0.188, while regret aversion is ranked the lowest with a crisp weight of 0.165.

The results show that retail investors are particularly prone to anchoring, which makes them rely on prior price points or reference values when making investment decisions. This aligns with the literature that argues anchoring becomes more present in the crypto markets (Gurdgiev & O'Loughlin, 2020). Overconfidence and loss aversion both have relatively high weights, which aligns with prior literature, indicating that retail investors tend to overestimate their own skill in predicting market movements and are sensitive towards losses (Hasnain & Subhan, 2023; Jain et al., 2019). The high rankings of anchoring and overconfidence might be an indicator that these two biases reinforce each other. Overconfident investors might be more inclined to rely on past price levels and personal experiences because they think they can predict the market with those experiences (Hasnain & Subhan, 2023). While people are prone to anchoring become more overconfident in their belief of being able to predict market

trends. In this way, both biases may interact and amplify each other, leading to even stronger deviations from rational decision-making. Regret aversion is ranked lowest, suggesting that retail investors are less affected by the fear of making wrong decisions or missing out.

When comparing these results with those of Jain et al. (2019), who applied the Fuzzy AHP to rank behavioral biases among Indian retail equity investors, some notable differences emerge. Jain et al. (2019), found that herding was the most influential bias, followed by loss aversion, overconfidence, regret aversion, and anchoring. This divergence may partly arise from the differences between equity and crypto investors. The lack of intrinsic valuation methods in crypto markets may cause investors to rely more heavily on anchoring to past prices or reference points (Gurdgiev & O'Loughlin, 2020). Furthermore, Hasnain and Subhan (2023) showed that retail crypto investors often display strong overconfidence, reinforcing the role of internal heuristics. However, Sood et al. (2023), who applied Fuzzy AHP to Indian retail crypto investors, again found herding to be the most prominent bias, followed by regret aversion, anchoring, overconfidence, and loss aversion. These inconsistencies in results and literature may be attributed to cultural differences (Rieger et al., 2014) or to the fact that the cryptocurrency market is evolving so rapidly that the characteristics and decision-making patterns of its investor base are also undergoing continuous change. All in all, the findings partly contradict H1, which predicted herding to be the most dominant behavioral bias. For Dutch retail investors, herding ranks only fourth, while anchoring emerges as the most influential bias, suggesting that these investors rely more on personal reference points than on the behavior of others.

Table 5: Global Rankings Fuzzy AHP Potential investors

Bias	Crisp Weight
Herding	0.246
Regret Aversion	0.236
Anchoring	0.184
Loss Aversion	0.178
Overconfidence	0.156

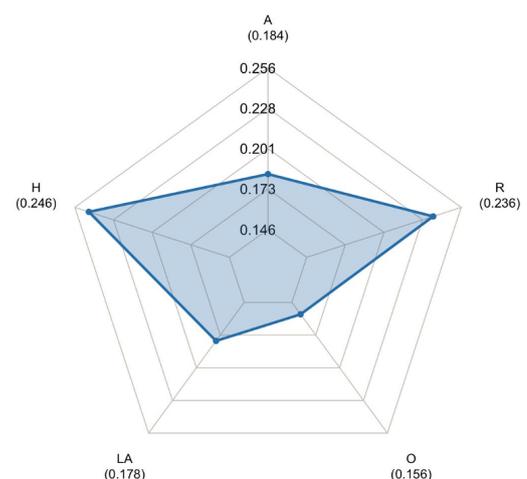


Figure 7: Radar chart for Potential investors

The results of the Fuzzy AHP rankings for potential investors, shown in Table 5 and Figure 7, are notably different from those of retail investors. Herding emerges as the most influential bias with a crisp weight of 0.246, followed by regret aversion (0.236). This pattern aligns with earlier findings that less experienced investors are more likely to rely on the actions or beliefs of others due to limited personal knowledge or confidence (Raut & Kumar, 2018). The studies of (Jain et al. 2019; & Sood et al. 2023) also identified herding as the most dominant bias. The heatmap in Figure 4 further shows that herding had consistent results and was dominant over all four other biases. Regret aversion becomes substantially more influential as it shifts from being the least to the second most dominant behavioral bias. This emotional bias, driven by the fear of making a wrong decision, may thus play a key role in people remaining hesitant to enter the crypto market. In contrast, overconfidence went from the second most influential bias to the least influential bias with a crisp weight of 0.156, which aligns with the expectations that these potential investors are less familiar with the market and therefore are less likely to overestimate their own predictive power (Mishra & Metilda, 2015). Furthermore, anchoring shifts from the most prominent bias among the retail investors to the third place among potential investors, suggesting that people who are not investing yet and therefore have less market exposure are less likely to base decisions on past prices and references.

Loss aversion is ranked lower among potential investors (0.178) than retail investors (0.206), which is somewhat unexpected given that the fear of losses could be a logical reason for not entering the crypto market. A possible explanation is that other biases, such as herding and regret aversion, are so important to this group, causing loss aversion to be perceived as less important in the pairwise comparisons. Another potential reason could be that retail investors may already have experience with financial losses, making them more aware that the pain of losing often outweighs the pleasure of winning, thereby increasing the impact of this bias. Interestingly, the ranking for potential investors closely aligns with the results found by Sood et al. (2023). In both studies, herding and regret aversion emerged as the top two biases, followed by anchoring in third place. The only difference lies in the ranking of the bottom two. In this study, loss aversion ranks fourth and overconfidence fifth, whereas Sood et al. (2023) found the opposite result. Overall, the results indicate that potential investors are more strongly influenced by biases with social dynamics and emotional considerations,

such as herding and regret aversion, while retail investors appear to rely on more internal behavioral biases, such as overconfidence and anchoring, when making investment decisions. The results offer partial support for H1, which predicted herding to be the most dominant behavioral bias. However, the remaining biases are in a different order, contradicting H1. The results fully support H2, which proposed that the influence of behavioral biases on investment decisions differs between retail and potential investors. The large contrast in the positions of all five biases between groups clearly illustrates this divergence.

4.3 Regression Statements

Before conducting the regression analysis, the behavioral bias statements are first reviewed by comparing the average Likert scores for each bias, based on the 7-point scale responses to the three statements per bias. This already gives insights into which biases are more strongly present in people's views before regressing it on the participants' investment decisions. Figure 8 visualizes the average scores per bias, separated for retail and potential investors. Among retail investors, the highest average scores were found for herding (4.75) and anchoring (4.44), closely followed by regret aversion (4.26) and overconfidence (4.09). Loss aversion (3.24) was rated considerably lower. For potential investors, herding (4.51), appeared to have the highest score, followed by regret aversion (4.44), and anchoring (4.42). Loss aversion (4.3) scored notably higher, while overconfidence (2.63) had a substantially lower score. The within-group ranking of the biases based on the statement scores does not fully match the ranking derived from the Fuzzy AHP for retail investors. In contrast, for potential investors, the rankings are exactly the same across both methods and almost the same as in the study of Sood et al. (2023), making the results more robust.

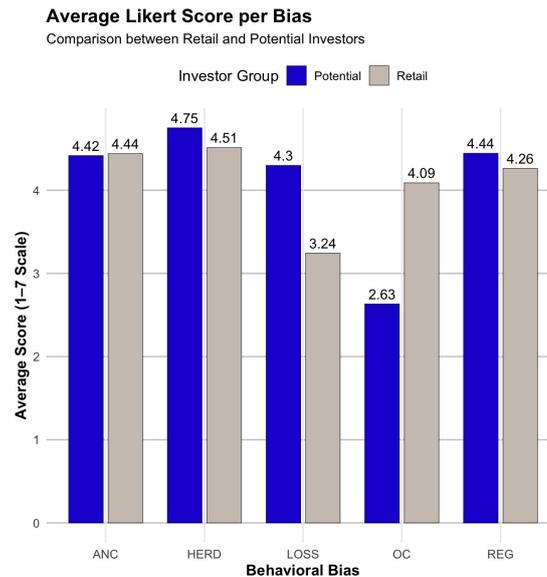


Figure 8: Average Likert scores for retail and potential investors

To further test whether the observed differences between biases within each group are statistically significant, a series of Wilcoxon signed-rank tests was run for both retail and potential investors. These non-parametric tests determine if there's a significant difference between the different biases within each group. The values in Table 6 represent the mean differences in the Likert scores between pairs of biases (e.g., herding – overconfidence = 1.27). The asterisks denote the statistical significance of these differences, as determined by the Wilcoxon test. Both matrices are symmetric, meaning that a negative difference in one cell corresponds to a positive difference in the reversed cell. The findings show that for retail investors, herding has scored significantly higher than loss aversion ($\Delta = 1.27$, $p < 0.01$) and overconfidence ($\Delta = 0.42$, $p < 0.01$), which aligns with the ranking from Jain et al. (2019) and Sood et al. (2023). Loss aversion was rated significantly lower than all four of the other biases, with all p-values smaller than 0.01. Anchoring had a small but statistically significant difference with overconfidence ($\Delta = 0.35$, $p < 0.1$), which corresponds with their difference in the Fuzzy AHP analysis. Among potential investors, herding was rated significantly higher than overconfidence ($\Delta = 2.12$, $p < 0.01$) and loss aversion ($\Delta = 0.45$, $p < 0.01$), but also than anchoring ($\Delta = 0.33$, $p < 0.05$). Overconfidence was rated considerably lower than all other biases in this group, with all p-values smaller than 0.01.

Additionally, a Wilcoxon rank-sum test was used to look for between-group differences. The results in Table 7 show that overconfidence was rated significantly higher by retail investors than potential investors ($\Delta = 1.46$, $p < 0.01$). This corresponds with the rankings of the Fuzzy AHP and the existing literature (Mishra & Metilda, 2015). In contrast, loss aversion was significantly lower for retail investors ($\Delta = -1.06$, $p < 0.01$), which does not correspond with the rankings derived from the Fuzzy AHP but is in line with Feng and Seasholes (2005). The remaining biases, anchoring, herding, and overconfidence, only showed minor differences that were not statistically significant.

Table 6: Wilcoxon signed-rank tests on the within group differences for retail and potential investors

Retail investors:	Anchoring	Herding	Loss Aversion	Overconfidence	Regret Aversion
Anchoring	-	-0.07	1.2***	0.35*	0.18
Herding	0.07	-	1.27***	0.42***	0.25
Loss Aversion	-1.2***	-1.27***	-	-0.85***	1.02***
Overconfidence	-0.35*	0.42**	0.85***	-	0.17
Regret Aversion	-0.18	-0.25	1.02***	0.17	-
Potential Investors:	Anchoring	Herding	Loss Aversion	Overconfidence	Regret Aversion
Anchoring	-	-0.33**	0.12	1.78***	-0.03
Herding	0.33**	-	0.45***	2.12***	0.31
Loss Aversion	-0.12	-0.45***	-	1.67***	-0.15
Overconfidence	-1.78***	-2.12***	-1.67***	-	-1.81***
Regret Aversion	0.03	-0.31	0.15	1.81***	-

Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Wilcoxon rank-sum test

Bias	Retail Investors (μ)	Potential investors (μ)	Difference in value (Retail (μ) – Potential (μ))
Anchoring	4.44	4.42	0.02
Herding	4.51	4.75	-0.20
Loss Aversion	3.24	4.30	-1.06***
Overconfidence	4.09	2.63	1.46***
Regret Aversion	4.26	4.44	-0.18

Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Interestingly, the rankings for retail investors based on the Likert averages only partly correspond with the results of the Fuzzy AHP results, which were based on the pairwise importance comparisons rather than direct agreement with the statements. While the ranking of herding for the potential investors corresponds with the ranking based on the Fuzzy AHP, it appears to be more prominent in the Likert averages for retail investors, where it is ranked

first instead of fourth. This may indicate that retail investors recognize herding behavior but perceive it as less important for their own decision-making when directly comparing it with other biases. Overconfidence, which ranked second in the Fuzzy AHP analysis for retail investors and fifth for potential investors, also received significantly higher average statement scores for the retail investors. This consistency across both methods further supports the idea that active crypto investors have a bigger tendency to overestimate their own ability to predict market movements, while potential investors recognize their lack of experience to make those kinds of predictions (Mishra & Metilda, 2015).

Anchoring appears to be a relatively stable bias across both groups, as there is no significant difference in average statement scores between retail and potential investors. However, when anchoring is compared to herding within each group, an interesting pattern emerges. For retail investors, the difference in the average Likert scores between herding and anchoring is not significantly different, while for potential investors, herding is rated significantly higher than anchoring. This aligns with the ranking of both biases in the Fuzzy AHP and further supports current literature that herding plays a more dominant role for less experienced investors (Raut & Kumar 2018). Anchoring remains consistent but loses its rank due to the preferences of potential investors for herding and regret aversion. Regret aversion is ranked higher for potential investors based on the Fuzzy AHP and has a slightly higher average Likert score, which is not significantly different.

The biggest inconsistency between methods is found in the rankings of loss aversion. While in the Fuzzy AHP, loss aversion is ranked higher for retail investors than for potential investors, the average Likert scores indicate a significantly larger score for potential investors. As noted before, one of the reasons might be that other biases are so important for potential investors that loss aversion is perceived as less important in the comparisons. The heatmap for retail investors (Figure 4), shows that loss aversion scores consistently against all four other biases, while the heatmap for potential investors shows very weak results against herding and regret aversion, which further supports this notion.

These findings again provide partial support for H1, as herding is ranked the highest for both groups. However, the remaining biases are ranked differently, contradicting H1. The

significant results of the between-group differences for overconfidence and loss aversion again support H2, confirming that the influence of cognitive biases differs between groups.

4.4 Regression results

Before including the different behavioral biases in the regression model, a separate regression was run with control variables to assess their explanatory power on the investment decision of participants. The variables included are age, gender, risk preference, and investment experience. The control variable, risk preference, shows positive and significant results for the whole sample and retail investors. This indicates that people who see themselves as more risk-seeking allocated more towards cryptocurrency. This result did not hold for potential investors ($\beta = 142.06$, $p > 0.1$) as they had a positive, insignificant result. This indicates that within this group, people who see themselves as risky are not necessarily allocating more towards crypto. For the whole sample, a binary variable is included to look at the effect of being a retail investor. The results ($\beta = 970.38$, $p < 0.1$) show that retail investors allocate significantly more funds towards cryptocurrency. As only men and women participated in the survey, one dummy is used to capture the difference between these groups. Variables age and gender did not show any significant effects in the model.

For all three models, a Durbin-Watson test was run, but there was no evidence of autocorrelation. The Breusch-Pagan test showed heteroscedasticity in the full sample model, but not in the separate models for both groups. The summary statistics revealed inherent differences between the groups, which likely contributed to unequal residual variances when both groups were combined into a single model, resulting in heteroscedasticity.

Table 8: Regression results of linear model on the control variables on investment decision

	All	Retail	Potential
(Intercept)	1484.27 (963.162)	154.15 (1768.02)	3084.44*** (967.64)
Age	-1.12 (20.427)	22.09 (36.87)	-19.90 (20.63)
Gender (Female)	-185.90 (557.99)	674.54 (936.56)	-964.94 (594.86)
Risk preference	306.71** (121.50)	532.48** (214.98)	142.06 (123.52)
Experience (Retail)	970.38* (528.01)	-	-
N	104	56	48
R ²	0.182	0.119	0.120
Adjusted R ²	0.149	0.068	0.060
Durbin-Watson	1.95	2.09	2.04
Breusch-Pagan	12.92**	5.02	3.33

Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To further empirically test how the cognitive biases influence the investment behavior, a linear regression was run using the control variables and the average composite scores for each bias as predictors. The initial regression model included interaction terms to distinguish between retail and potential investors, but a VIF test revealed multicollinearity between the biases across groups. Therefore, separate regressions were conducted for retail and potential investors, ensuring more reliable results.

Table 10 provides the findings of these separate regressions. In the model with both groups, overconfidence ($\beta = 635.50$, $p < 0.01$) and herding ($\beta = 507.27$, $p < 0.05$) have significant positive effects on allocation towards cryptocurrency. This indicates that individuals who agree with the statements of herding and overconfidence to a higher degree are more likely to invest larger amounts in cryptocurrencies. This mirrors the results from Hasnain and Subhan (2023), where both herding and overconfidence significantly influenced the crypto decisions of participants, with overconfidence demonstrating a larger effect.

However, the results are not the same once the model is split based on investment experience. The results for retail investors' overconfidence ($\beta = 635.50$, $p < 0.01$) show an even larger and significant effect on the allocation towards crypto, while for potential investors (β

= 2.03, $p > 0.1$), this effect becomes insignificant. This also explains why the coefficient for retail investors is larger than in the full sample, as the inclusion of potential investors dilutes the overall relationship. This is complementary to the rankings from the Fuzzy AHP, the average Likert scores, and the study of (Mishra & Metilda, 2015). Overconfidence is ranked higher for retail investors and positively affects the investment propensity towards crypto.

However, the effect of herding becomes insignificant for both groups. The remaining biases also have insignificant results for both investor groups. Remarkably, the coefficients for the biases in the regression models are relatively large, while they fail to become significant. This is likely due to the large standard errors, which can be caused by several reasons. For instance, the limited sample size, high variance within the estimates, or multicollinearity between related variables. As explained in the methodology, due to multicollinearity (Table 9) in the interaction model, separate regressions were conducted for both investor types (Table 10).

Table 9: VIF test for linear model with interaction term

Bias	Retail	Potential
Anchoring	49.52	5.58
Herding	23.00	4.02
Loss Aversion	23.05	5.80
Overconfidence	20.38	5.67
Regret Aversion	29.50	3.55

Table 10: Regression results of linear model on the control variables on investment decision

	All	Retail	Potential
(Intercept)	-360.14 (1889.83)	-296.80 (2559.27)	-1365.34 (2651.09)
Anchoring	136.19 (274.53)	129.55 (332.66)	535.28 (505.30)
Herding	507.27** (195.75)	346.6 (272.13)	438.40 (289.32)
Loss Aversion	-385.61 (264.09)	-525.241 (340.42)	-229.32 (407.28)
Overconfidence	635.50*** (195.75)	911.61*** (266.30)	-2.03 (327.87)
Regret Aversion	-131.58 (246.52)	-442.67 (342.83)	142.32 339.17

Age	1.42 (18.84)	30.09 (31.26)	-9.76 (21.40)
Gender (Female)	-450.04 (519.16)	8.706 (832.95)	-969.59 (595.95)
Risk preference	170.80 (119.91)	323.38* (197.74)	149.13 (136.20)
Experience (Retail)	-0.26 (581.28)	-	-
N	104	56	48
R ²	0.3598	0.4425	0.2666
Adjusted R ²	0.299	0.348	0.116
Durbin-Watson	1.80	2.40	1.88
Breusch-Pagan	12.32	6.99	7.97

Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Although a VIF test on the separate models did not indicate problematic multicollinearity, a pairwise Pearson correlation test on the variables regret and loss aversion revealed a moderate to strong correlation across these biases. This may partly explain some of the larger standard errors of these coefficients.

Table 11: Pearson correlation test on Loss aversion and Regret aversion

Group	All	Retail	Potential
Correlation	0.44***	0.37***	0.57***
T-statistic	4.88	2.94	4.66
Degrees of freedom	102	54	46

Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12 in Appendix 7.2 shows the results of the regression model without regret aversion. Loss aversion became significant for the full sample ($\beta = -443.59$, $p < 0.1$) and for retail investors ($\beta = -689.30$, $p < 0.05$), while for potential investors the effect remained insignificant. Interestingly, loss aversion showed contradicting results across methods: its rankings based on both the Fuzzy AHP and the average Likert scores were different but consistently low, suggesting that participants did not perceive it as one of the most influential biases. However, the high coefficient and large standard errors in the regression model indicate considerable variation in how this bias influences the investment decisions of individual retail investors. This suggests that while loss aversion may not be broadly perceived

as important, it can have a substantial negative effect on the investment propensity toward cryptocurrency for those investors who are particularly prone to it.

Table 13 in Appendix 7.2 shows the results of the model without loss aversion. Regret aversion had a significant effect on retail investors ($\beta = -640.09$, $p < 0.1$), while the findings for the full sample and potential investors stayed insignificant. Although regret aversion ranks relatively low among retail investors in both the Fuzzy AHP and the average Likert scale, it still significantly and substantially negatively impacts the investment propensity towards crypto. Similar to loss aversion, this suggests that regret aversion, although generally perceived as less important, can have a considerable impact on those retail investors who are particularly prone to it. The negative effect implies that affected individuals invest less due to the fear of making a wrong decision, rather than increasing investments out of the fear of missing potential gains. In this study, these biases did not significantly impact the investment behavior of potential investors, contradicting the findings of (Feng & Seasholes 2005) that these biases affected novice investors more than potential investors.

4.5 Insights from the Analysis

The applied methods in this study provided complementary insights to determine which biases are the most influential. The Fuzzy AHP revealed that anchoring and overconfidence are perceived as the most influential biases among retail investors, while herding and regret aversion dominate among potential investors. The average Likert scores confirmed the Fuzzy AHP rankings for potential investors, indicating a strong consistency in their perceived importance across both methods. In contrast, retail investors showed a mismatch between the rankings of both methods. Herding received the highest average Likert score but was ranked fourth in the Fuzzy AHP. This indicates that retail investors perceive herding as influential when asked directly, but not when they are forced to compare it against other biases. However, the regression models demonstrated that only overconfidence had a statistically significant positive effect on investment decisions for retail investors when all variables were included. This suggests that while other biases are perceived as more important, overconfidence is the most consequential bias for those already active in the crypto market.

H1 is only partially supported. Herding was the most dominant bias among potential investors, but this was not the case for retail investors. In the Fuzzy AHP, anchoring and overconfidence were rated higher, and only overconfidence significantly affected investment propensity. This highlights a broader pattern, that perceived importance does not always align with the actual behavioral influence. Biases like regret aversion and loss aversion were perceived as less important for retail investors, while they showed significant negative effects on their investment propensity, suggesting they may operate more subconsciously.

H2 is fully supported. The results consistently show that the influence of behavioral biases differs substantially and significantly between the two investor groups. This is evident in the Fuzzy AHP, the average Likert statements, and the regression analysis, especially for overconfidence and loss aversion.

5 Final Remarks

This thesis examined the impact of the five behavioral biases: herding, overconfidence, loss aversion, regret aversion, and anchoring on cryptocurrency investment decisions among Dutch retail and potential investors. These five biases were selected based on their theoretical relevance in the current literature. Their influence is particularly pronounced in the rapidly growing crypto market, characterized by its lack of valuation metrics, speculative nature, and high volatility (Cheah & Fry 2015; Gurdgiev & O’Loughlin 2020). Prior research has frequently identified herding and overconfidence as the more important drivers in such markets (Hasnain & Subhan 2023; Sood et al. 2023).

By applying a mixed-methods design consisting of the Fuzzy AHP, average Likert statements, and the regression analysis, this study provides a comprehensive overview of how these biases affect investors with different levels of investment experience. The regression analysis is complementary to the ranking, which allows to make a distinction between perceived importance and actual influence on investment behavior. While potential investors rated herding and regret aversion as most important, these biases did not show any significant effects on their investment behavior. Conversely, overconfidence was the only bias that demonstrated consistent results among retail investors, ranking relatively high in perceived importance (especially in the Fuzzy AHP) and showing a statistically significant effect on investment propensity.

Overall, the findings provided limited support for the first hypothesis. Although herding was indeed the most prominent bias among potential investors, the remaining biases did not follow the predicted order. In the ranking of biases among retail investors, only overconfidence aligned with expectations. The second hypothesis is fully supported, with clear differences between the importance of the behavioral biases among retail and potential investors.

5.1 Limitations

While this thesis provides valuable insights about how behavioral biases affect cryptocurrency investment decisions, several limitations should be acknowledged. Although the sample size was sufficient for explanatory results, a larger group could increase the statistical power of the regression analysis. This might reveal additional significant effects of other biases that remained undetected in the current analysis. Furthermore, all data were self-reported, introducing the possibility of response biases. For example, social desirability, misinterpretation, or misrepresentation of actual behavior. This may have contributed to the observed differences between the perceived importance of biases and their actual impact on investment behavior. Additionally, the dependent variable is based on a hypothetical investment scenario, which may deviate from their real-life financial decisions. Prior research has shown that people are less averse when dealing with hypothetical money, which could lead to more risk-seeking investment choices (Holt & Laury, 2002).

It is also worth noting that, although the study covers five fundamental biases based on previous literature, other biases are also relevant in the context of cryptocurrency. Their omission may leave relevant variance in the dependent variable unexplained, leading to a lower R^2 and Adjusted R^2 . Moreover, within-bias comparisons could not be included in the Fuzzy AHP section due to time constraints. Consequently, it was not possible to improve the statistical validity by conducting consistency checks, which may affect the reliability of the rankings. Additionally, since the Fuzzy AHP produces only a single crisp weight per bias, based on the aggregated judgments, no standard errors or confidence intervals can be calculated. This excludes the possibility for conventional significance testing. Lastly, the study focused only on Dutch retail and potential investors. Although this was necessary to better understand the behavior of this specific group, it limits the generalizability of the results.

5.2 Discussion and Future Research

The purpose of this thesis was to explore how different behavioral biases affect cryptocurrency investment decisions among Dutch retail and potential investors. By combining regression analysis with Fuzzy AHP rankings and Likert-based ratings, the study was able to distinguish between perceived importance and the actual impact of the different biases. This complementary structure is especially valuable in behavioral finance, where the beliefs and actions of decision-makers often diverge.

The observed discrepancies, regarding loss aversion and regret aversion, demonstrate that perceived importance did not align with actual impact. Both were often perceived as less important by retail investors but still exhibited a significant negative effect on their crypto allocation. These results imply that some biases subconsciously influence investment behavior. In contrast, overconfidence showed the clearest case of relative consistency, as it held a high perceived importance in the Fuzzy AHP and emerged as the bias with the most significant and substantial impact on the investment propensity of retail investors. However, it was not entirely consistent, as it was rated fourth based on the self-reported Likert scores.

From a practical standpoint, these findings could guide educational or policy measures. For instance, investor training programs for retail investors might focus on the reduction of overconfidence. This could reduce the problem of excessive trading, which is a consequence of overconfidence (Odean 1998). For individuals who have not yet entered the crypto market, education may particularly focus on the effects of herding and regret aversion and how to reduce them. Herding is a more systemic problem that contributes to exaggerated price movements (Banerjee, 1992), whereas regret aversion may have a direct impact on individual investor returns (Sood et al., 2023). For example, it can cause individuals to chase past winners while holding on to underperforming cryptos or discourage entering the market entirely out of fear of making wrong decisions. Moreover, the findings could help with improving legislative frameworks. The Dutch parliament has established the MiCA-wet, which is a European ordinance aiming to protect consumers (Ministerie van Financiën, 2024). Although the law is already in effect, the authorities are still working on adjusting it. As the results show that retail investors are particularly influenced by overconfidence, it can focus on increasing platform responsibilities. For example, obligating certain risk warnings and reminders when

people trade too much or do not diversify sufficiently. For potential investors, it may be more important to promote independent knowledge about the crypto market, as this would reduce social reliance, leading to herding. A practical implementation would be to mandate platforms to add entry assessments when individuals create an account. This assessment should additionally spread knowledge about other biases, such as anchoring and regret aversion, thereby helping investors to better recognize and manage the influence of these biases.

The results contribute to the current literature by looking at how the biases operate within the Dutch population. Moreover, it raises new theoretical questions about the distinction between perceiving biases and how they operate in actual decision-making contexts.

A limitation in the study is the assumption that the influence of these biases on investment decisions is stable across time and market conditions. Cheah and Fry (2015) showed that certain biases tend to be more active during the formation of bubbles, while others are more prominent during the blow-off phase. Due to time limitations, this study captured the decision-making process of participants at a single time point, therefore not accounting for market shifts, limiting the generalizability of the findings.

To overcome this limitation, future studies could develop a survey method that is distributed during both bubble formation and the blow-off phases. This allows researchers to assess whether, and to what extent the influence of biases varies across different market conditions. Knowing which biases contribute to the emergence and burst of bubbles could give valuable insights on how to mitigate their detrimental effects. Moreover, this study could be replicated across different European countries. Establishing similarities and differences in how biases operate across European countries would be highly valuable for a harmonized legislative framework. Lastly, an experimental design could be implemented, where participants are randomly assigned to two or more groups. The treatment groups would receive different types of educational methods. After the treatments, all groups complete a follow-up survey designed to assess to what extent they are influenced by behavioral biases. These insights could give practical insights for developing effective education programs.

6 References

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7 Appendix

7.1 Survey

Survey MT2025

Start of Block: Demographic Questions

Q46 This survey is part of a master's thesis at the Radboud University. The goal is to better understand investment decision-making. There are no right or wrong answers in this survey. All responses are anonymous and will be used for academic purposes only. Estimated completion time: 10 minutes. Thank you for your participation! By clicking the consent button below, you acknowledge that: - Your participation is voluntary. - You are 18 years or older. - You are aware that you may choose to withdraw your participation at any moment.

I consent (1)

I do not consent (2)

Gender What is your gender?

Male (1)

Female (2)

Non-binary / third gender (3)

Prefer not to say (4)

Age What is your age?

18 25 32 40 47 54 61 68 76 83 90

age ()	
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Experience in crypto Do you have experience investing in cryptocurrency, now or in the past?

Yes (1)

No (0)

Risk preference How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please place the slider on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'

0 1 2 3 4 5 6 7 8 9 10

Risk preference ()	
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Investment decision If you were given €10.000, to allocate between cryptocurrency and a completely risk-free savings account. How much of this amount would you choose to invest in cryptocurrency?

0 10002000300040005000600070008000900010000

Amount to be invested in cryptocurrency ()	
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End of Block: Demographic Questions

Start of Block: Regression Statements

Q47 On this page, you will find a series of statements related to decision-making in the context of cryptocurrency. Please indicate to what extent you agree or disagree with each statement. The order of the statements is randomized for each participant.

H1 I rely on other investors' decisions when investing in cryptocurrency.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

H2 When most investors buy a cryptocurrency, I feel more confident in investing in it.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

H3 I follow recommendations from family, friends, or experts before investing in crypto.

- Strongly disagree (1)
- Disagree (2)
- Partially disagree (3)
- Neutral (4)
- Partially agree (5)
- Agree (6)
- Strongly agree (7)

O1 I am confident about my own ability to do better than others when investing in cryptocurrencies.

Strongly disagree (1)

Disagree (2)

Partially disagree (3)

Neutral (4)

Partially agree (5)

Agree (6)

Strongly agree (7)

O2 I possess specific skills and experience for making crypto investments.

- Strongly disagree (1)
- Disagree (2)
- Partially disagree (3)
- Neutral (4)
- Partially agree (5)
- Agree (6)
- Strongly agree (7)

O3 I am confident about the time to enter in the crypto market and exit from the crypto market.

- Strongly disagree (1)
- Disagree (2)
- Partially disagree (3)
- Neutral (4)
- Partially agree (5)
- Agree (6)
- Strongly agree (7)

LA1 If I'm facing a loss in crypto, I tend to take more risk to try and recover it.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

LA2 When I've made a profit on crypto, I prefer to play it safe rather than risk losing it again.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

LA3 After losing money on a cryptocurrency, I tend to avoid risk with future investments.

- Strongly disagree (1)
- Disagree (2)
- Partially disagree (3)
- Neutral (4)
- Partially agree (5)
- Agree (6)
- Strongly agree (7)

R1 I feel more sorrow about holding losing cryptocurrencies too long than selling winning cryptocurrencies too soon.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

R2 I avoid selling cryptocurrencies that have decreased in value because I would regret realizing the loss.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

R3 I sell cryptocurrencies that have increased in value quickly because I don't want to regret not taking the profit.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

A1 I often rely on past experiences with similar cryptocurrency market situations when deciding how to invest now.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

A2 I usually buy those cryptocurrencies that have fallen considerably from their an all-time high.

- Strongly disagree (1)
 - Disagree (2)
 - Partially disagree (3)
 - Neutral (4)
 - Partially agree (5)
 - Agree (6)
 - Strongly agree (7)
-

A3 I usually consider the purchase price of cryptocurrencies as a reference point for trading.

- Strongly disagree (1)
- Disagree (2)
- Partially disagree (3)
- Neutral (4)
- Partially agree (5)
- Agree (6)
- Strongly agree (7)

Page Break

End of Block: Regression Statements

Start of Block: Fuzzy pairwise comparisons

R vs A Which of these statements influences your crypto investment decisions more, and to what degree? A. I make choices that I believe will minimize the chances of feeling regret later. B. I use prior price trends or experience as a baseline for new decisions.

▼ A is weakly more important ... B is very strongly more important

LA vs A Which of these statements influences your crypto investment decisions more, and to what degree? A. I usually keep investments that are doing poorly instead of selling at a loss. B. I compare current prices to past highs or lows when making investment decisions.

▼ A is weakly more important ... B is very strongly more important

LA vs R Which of these statements influences your crypto investment decisions more, and to what degree? A. I find it difficult to accept losses and tend to hold on to losing investments to avoid realizing them. B. I focus on avoiding decisions that could make me feel regretful in the future.

▼ A is weakly more important ... B is very strongly more important

O vs A Which of these statements influences your crypto investment decisions more, and to what degree? A. I rely on my market sense and intuition to make investment choices. B. I often use historical high or low prices to assess whether a cryptocurrency is worth buying or selling.

▼ A is weakly more important ... B is very strongly more important

O vs R Which of these statements influences your crypto investment decisions more, and to what degree? A. I trust my ability to time the market and make better decisions than the average investor. B. I am hesitant to act when I fear I may later regret my decision.

▼ A is weakly more important ... B is very strongly more important

O vs LA Which of these statements influences your crypto investment decisions more, and to what degree? A. I trust my ability to time the market and make better decisions than the average investor. B. I feel discomfort realizing losses and prefer to avoid them, even if it affects my portfolio performance.

▼ A is weakly more important ... B is very strongly more important

H vs A Which of these statements influences your crypto investment decisions more, and to what degree? A. I often take cues from the market behavior of others when deciding how to invest. B. I rely heavily on previous price points or personal past experiences when evaluating new investment opportunities.

▼ A is weakly more important ... B is very strongly more important

H vs R Which of these statements influences your crypto investment decisions more, and to what degree? A. My investment decisions are influenced by the opinions and actions of those around me. B. I try to avoid making investment choices that I might regret later, such as selling too early or holding too long.

▼ A is weakly more important ... B is very strongly more important

H vs LA Which of these statements influences your crypto investment decisions more, and to what degree? A: I often base my buy or sell decisions on the actions of other investors. B: I

tend to avoid selling at a loss, even if it means holding on to underperforming cryptocurrencies longer.

▼ A is weakly more important ... B is very strongly more important

H vs O Which of these statements influences your crypto investment decisions more, and to what degree? A: Basing decisions on the actions or recommendations of others such as other investors, friends, family, and analysts. B: Being confident in your own skills and market knowledge, E.g., timing entries/exits, outperforming others.

▼ A is weakly more important ... B is very strongly more important

End of Block: Fuzzy pairwise comparisons

7.2 Tables and Figures



Figure 2: The hierarchy along with the corresponding pairwise comparison

Table 2: The Likert scale

Likert Scale	Answer values of participants
Strongly disagree	1
Disagree	2
Partially disagree	3
Neutral	4
Partially agree	5
Agree	6
Strongly agree	7

Table 12: Regression results of linear model on the control variables on investment decision without regret aversion

	All	Retail	Potential
(Intercept)	-1400.63 (1798.57)	-836.08 (2420.83)	-1121.70 (2559.95)
Anchoring	106.30 (274.53)	-214.35 (328.37)	570.92 (492.95)
Herding	510.81** (194.90)	325.58 (273.53)	422.82 (283.96)
Loss Aversion	-443.59* (239.82)	-689.30** (318.00)	-139.70 (343.20)
Overconfidence	659.21*** (198.96)	996.94*** (259.76)	-28.34 (318.48)
Age	0.89 (18.74)	31.07 (31.47)	-8.23 (20.87)
Gender (Female)	-434.11 (516.35)	107.64 (835.16)	-967.47 (589.76)
Risk preference	176.50 (118.97)	300.53 (198.31)	134.90 (130.56)
Experience (Retail)	-84.34 (557.42)	-	-
N	104	56	48
R ²	0.3579	0.4228	0.2633
Adjusted R ²	0.3038	0.3386	0.1344
Durbin-Watson	1.81	2.49	1.85
Breusch-Pagan	12.84	8.86	6.49

Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13: Regression results of linear model on the control variables on investment decision without loss aversion

	All	Retail	Potential
(Intercept)	- 658.33 (1760.74)	-913.76 (2470.83)	-1841.23 (2491.21)
Anchoring	145.67 (275.91)	-111.39 (337.20)	531.66 (500.93)
Herding	468.92** (195.13)	339.84 (275.98)	404.31 (280.49)
Overconfidence	651.19*** (205.90)	930.30*** (269.83)	5.89 (324.76)
Regret version	-279.63 (226.05)	-640.09* (322.59)	-42.18 (286.31)
Age	5.25 (18.77)	32.34 (31.68)	-6.67 (20.50)
Gender (Female)	-484.76 (521.70)	179.41 (835.74)	-944.58 (589.20)
Risk preference	176.31 (120.56)	354.11* (199.55)	144.94 (134.84)
Experience (Retail)	346.65 (533.67)	-	-
N	104	56	48
R ²	0.3453	0.4143	0.2606
Adjusted R ²	0.2902	0.3289	0.1312
Durbin-Watson	1.85	2.41	1.84
Breusch-Pagan	11.66	5.06	7.16

Significance indicators: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

8 GenAI statements

Generative AI tools (e.g., ChatGPT, Copilot) were used to assist in coding, data analysis, and/or refining the language of this thesis. Appendix 2 of this thesis provides a detailed account of the use of Generative AI tools during the development of this thesis. By submitting this thesis I declare that I am fully responsible for the accuracy and completeness of its content.

8.1 Appendix 2

Statement purpose

This appendix provides a detailed account of the use of Generative AI tools during the development and writing of this thesis. These tools were used to support, refinement of language, ensuring clarity and precision in the presentation of findings. All outputs generated were critically evaluated and, where necessary, modified by myself to align with the objectives of this research.

Tools used

- Grammarly

Scope of use

- Tool: Grammarly
- Purpose: Grammarly is an online extension for my word application, which helps correct grammar mistakes and show refinements for language. There are no prompts for this tool.
- My Role: AI-generated suggestions were critically reviewed to see if the grammar suggestions did not change the meaning of the text.
- Applied: In the whole research proposal

A complete log of AI interactions

- No prompts are used for Grammarly

Tools used

- ChatGPT

Scope of use:

- Tool: Code Pilot
- Purpose: Generating the draft codes for analyzing my datasets.
- My Role: I asked Code Pilot to draft a code that aligned with my attached methodology. I checked all the codes first by analyzing all steps in the environment of R. I did not use all parts of the draft codes. I cleaned the data manually in Excel and put it in R through the workspace file option. Then I changed the names of my datasets in R with the "<->" function, so it aligned with the draft codes from the Code pilot. After checking the codes, I changed some of them manually. For instance, using color coding or different scalings for my plots.
- Applied: For coding purposes

AI interactions

First query for Fuzzy AHP:

The attached section is the methodology of my thesis. It applies the Fuzzy AHP. Write me a code for RStudio that implements this Fuzzy AHP on the attached Excel file. First, review the methodology very carefully and make sure to account for the reciprocal values in the pairwise comparisons.

First query for regression analysis:

Attached is the methodology section and dataset from my survey. Review them carefully and draft codes based on them. Make sure to aggregate the Likert-scale responses for each bias. Then set up the regression models based on the variables from the methodology and dataset.

In total, around 30 queries are used to refine and adjust the draft codes to the final codes.

