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Essays on cryptomarket individual investors' behavior

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In loving memory of my parents, Ambrosio and Olga, whose legacy of unconditional love and dedication continues to inspire me to pursue my dreams.

"Anyone who stops learning is old, whether at twenty or eighty. Anyone who keeps learning stays young. The greatest thing in life is to keep your mind young."

Henry Ford

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Abstract

Cryptocurrencies have garnered significant attention from investors, media, and scholars due to their innovative nature. Emerging from a 2008 white paper, these digital assets revolutionized finance. However, the cryptomarket is still in an early stage, remaining highly volatile and unpredictable. Despite warnings, the influx of retail investors has grown exponentially, and they seem to trade mostly based on sentiments and apparently neglecting risks, having expectations of extreme outcomes. In this context, the elements that drive individual investment decisions are still unclear, leaving the crypto market a largely unexplored domain.

This thesis is dedicated to unravel the intriguing realm of cryptocurrencies, particularly investigating the nature of individual investors in this market and the behavioral factors that might be driving them to buy cryptocurrencies. The main goal is to answer the following research question: What are the key behavioral, demographic, and psychological factors shaping the personal intention to invest in cryptocurrencies, and how do they interact to influence actual behavior? The research unfolds through four interconnected studies.

The first study (Chapter 2) systematically reviews the academic literature on cryptocurrencies to provide a structured and comprehensive understanding of investor attitudes. Analyzing 507 peer-reviewed articles, our work highlights the inefficiencies of the cryptocurrency market, the challenges of price prediction, and the uncertain diversification benefits associated with crypto-assets. Furthermore, it identifies a significant research gap regarding individual investor behavior in the cryptomarket,

underscoring the necessity of empirical investigations into the psychological and demographic characteristics shaping investment attitude toward cryptocurrencies.

The subsequent three chapters employ survey-based research, gathering 826 responses through an online questionnaire. The first empirical study (Chapter 3) examines the role of overconfidence in distinguishing cryptocurrency investors from non-investors. Utilizing SPSS and logit regression modeling, the findings confirm that overconfidence significantly predicts investment in cryptocurrencies. While overconfidence and risk propensity are closely linked, they stem from distinct personality traits. Age and market experience correlate positively with overconfidence but negatively with risk propensity, while financial knowledge does not significantly impact investment decisions. These results indicate that psychological biases rather than financial literacy may be key drivers of investment behavior in the cryptomarket.

We also examine how personality traits influence investment intentions (chapter 4). Employing Partial Least Squares Structural Equation Modeling (PLS-SEM), we find that agreeableness, conscientiousness, and neuroticism negatively affect investment intentions, while higher risk propensity increases the likelihood of investment and mediates the link between conscientiousness and attitudes toward cryptocurrencies. Additionally, this research highlights the significant role of overconfidence in shaping both investment intentions and actual behavior (chapter 5). Results confirm that behavioral intention mediates the link between personal characteristics and investment actions. Furthermore, a comparative analysis with online banking adoption suggests that familiarity with digital financial platforms may facilitate cryptocurrency engagement.

Synthesizing insights from the systematic review and empirical studies, this thesis advances the literature on behavioral finance by integrating psychological and technological dimensions into the analysis of cryptocurrency investment. The findings contribute to theoretical frameworks on overconfidence and risk propensity, contextualizing them within the volatile and speculative nature of the cryptomarket. By examining personality traits alongside behavioral biases, this research offers a more holistic perspective on investment decision-making.

From a practical standpoint, the findings have implications for policymakers, financial institutions, and investors. Regulatory bodies can leverage these insights to design investor education programs that account for psychological biases and demographic variations. Financial advisors may also incorporate personality-based insights to offer personalized investment strategies that align with client risk profile. For retail investors, this research highlights the importance of self-awareness in financial decision-making. Recognizing the influence of personal characteristics and biases can help individuals make more informed investment choices, ultimately improving risk management strategies in the cryptocurrency market. As the cryptomarket continues to evolve, understanding the behavioral underpinnings of investment intentions remains essential for fostering a more stable investment environment.

Keywords: Cryptocurrencies, investor behavior, decision-making, risk propensity, personality traits.

Resumo

As criptomoedas tem atraído atenção significativa de investidores, mídia e acadêmicos devido à sua natureza inovadora. Emergindo de um *white paper* de 2008, esses ativos digitais revolucionaram as finanças. No entanto, o criptomercado ainda está em um estágio inicial, permanecendo altamente volátil e imprevisível. Apesar dos avisos, o influxo de investidores de varejo cresceu exponencialmente, e eles parecem negociar principalmente com base em sentimentos e aparentemente negligenciando riscos, tendo expectativas de resultados extremos. Nesse contexto, os elementos que impulsionam as decisões de investimento individuais ainda não estão claros, deixando o mercado de criptomoedas um domínio amplamente inexplorado.

Esta tese é dedicada a desvendar o intrigante mundo das criptomoedas, investigando particularmente a natureza dos investidores individuais neste mercado e os fatores comportamentais que podem estar levando-os a comprar criptomoedas. O objetivo principal é responder à seguinte questão de pesquisa: Quais são os principais fatores comportamentais, demográficos e psicológicos que moldam a intenção pessoal de investir em criptomoedas e como eles interagem para influenciar o comportamento real? A pesquisa se desdobra por meio de quatro estudos interconectados.

O primeiro estudo (Capítulo 2) revisa sistematicamente a literatura acadêmica sobre criptomoedas para fornecer uma compreensão estruturada e abrangente das atitudes dos investidores. Analisando 507 artigos revisados por pares, nosso trabalho destaca as ineficiências do mercado de criptomoedas, os desafios da previsão de preços e os benefícios incertos da diversificação associados aos criptoativos. Além disso, ele identifica uma lacuna significativa de pesquisa sobre o comportamento individual do

investidor no criptomercado, ressaltando a necessidade de investigações empíricas sobre as características psicológicas e demográficas que moldam a atitude de investimento em relação às criptomoedas.

Os três capítulos subsequentes utilizam pesquisa por meio de questionário online, que reuniu 826 respostas. O primeiro estudo empírico (Capítulo 3) examina o papel do excesso de confiança na distinção entre investidores em criptomoedas e não investidores. Utilizando SPSS e modelagem de regressão logit, as descobertas confirmam que o excesso de confiança prevê significativamente o investimento em criptomoedas. Embora o excesso de confiança e a propensão ao risco estejam intimamente ligados, eles derivam de traços de personalidade distintos. Idade e experiência de mercado se correlacionam positivamente com o excesso de confiança, mas negativamente com a propensão ao risco, enquanto o conhecimento financeiro não afeta significativamente as decisões de investimento. Esses resultados indicam que vieses psicológicos, em vez de educação financeira, podem ser os principais impulsionadores do comportamento de investimento no criptomercado.

Também examinamos como os traços de personalidade influenciam as intenções de investimento (capítulo 4). Empregando a Modelagem de Equações Estruturais de Mínimos Quadrados Parciais (PLS-SEM), descobrimos que a agradabilidade, a conscienciosidade e o neuroticismo afetam negativamente as intenções de investimento, enquanto uma maior propensão ao risco aumenta a probabilidade de investimento e media a ligação entre a conscienciosidade e as atitudes em relação às criptomoedas. Além disso, nossa pesquisa destaca o papel significativo do excesso de confiança na formação das intenções de investimento e do comportamento real (capítulo 5). Os resultados confirmam que a intenção comportamental media a ligação entre as características pessoais e as ações de investimento. Além disso, uma análise comparativa com a adoção de serviços bancários online sugere que a familiaridade com plataformas financeiras digitais pode facilitar o envolvimento com criptomoedas.

Sintetizando resultados da revisão sistemática e estudos empíricos, esta tese avança a literatura sobre finanças comportamentais ao integrar dimensões psicológicas e tecnológicas na análise de investimento em criptomoedas. As descobertas contribuem para o marco teórico sobre excesso de confiança e propensão ao risco, contextualizando-as dentro da natureza volátil e especulativa do criptomercado. Ao examinar traços de personalidade juntamente com vieses comportamentais, esta pesquisa oferece uma perspectiva mais holística sobre a tomada de decisões de investimento.

Do ponto de vista prático, as descobertas têm implicações para formuladores de políticas, instituições financeiras e investidores. Órgãos reguladores podem alavancar esses resultados para projetar programas de educação para investidores que levem em conta vieses psicológicos e variações demográficas. Consultores financeiros também podem incorporar as informações obtidas sobre personalidade para oferecer estratégias de investimento personalizadas que se alinhem ao perfil de risco do cliente. Para investidores de varejo, esta pesquisa destaca a importância da autoconsciência na tomada de decisões financeiras. Reconhecer a influência de características e vieses pessoais pode ajudar os indivíduos a fazer escolhas de investimento mais informadas, melhorando, em última análise, as estratégias de gerenciamento de risco no mercado de criptomoedas. À medida que o criptomercado continua a evoluir, entender os fundamentos

comportamentais das intenções de investimento torna-se essencial para promover um ambiente de investimento mais estável.

Palavras-chave: Criptomoedas, comportamento do investidor, tomada de decisão, propensão ao risco, traços de personalidade.

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List of Abbreviations

AJG	Academic Journal Guide
APA	American Psychological Association
AVE	Average Variance Extracted
BIS	Bank for International Settlements
BK	Baruník-Krehlík
CDBC	Central Bank Digital Currencies
CMB	Common-Method Bias
CR	Composite Reliability
DLT	Distributed Ledger Technology
DOSPERT	Domain-Specific Risk-Attitude Scale
EMH	Efficient Market Hypothesis
ES	Expected Shortfall
ETF	Exchange-traded funds
FFM	Five-Factor Model
FTX	FTX cryptocurrency exchange
G-20	Group of 20 - comprising 19 sovereign countries, the European Union, and the African Union
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
GBDT	Gradient Boosting Decision Tree
GDP	Gross Domestic Product
GoF	Goodness-of-Fit
HTMT	Heterotrait-Monotrait
ICO	Initial Coin Offerings
IMF	International Monetary Fund
IOT	Internet of Things
M1	Money supply that is composed of currency, demand/liquid deposits
MBTI	Myers-Briggs Type Indicator

OECD	Organization for Economic Cooperation and Development
P2P	Peer-to-Peer
PLS-SEM	Partial Least Squares Structural Equation Modeling
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
SEC	Securities and Exchange Commission
SJR	Scimago Journal & Country Rank
SRMR	Standardized Root Mean Square Residual
TW-MDS	Threshold Weighted-Minimum Dominating Set
UN	United Nations
VaR	Value at Risk
VIF	Variance Inflation Factor
VIX	Volatility Index

Chapter 1: Introduction

1.1 Motivation

The journey toward exploring the cryptocurrency phenomenon began with a strikingly personal motivation. While teaching finance at a university in Brazil, I noticed an intriguing pattern among my students. They would approach me after class or during breaks, eager to discuss a topic that was both recent and unfamiliar to the majority of the population: cryptocurrencies. Initially, I responded very briefly, based on a rudimentary understanding of the subject, available at the time. However, the frequency and enthusiasm of these inquiries revealed an emerging trend and raised a concern in my mind.

What stood out most was that many of these young individuals, despite their limited understanding of cryptocurrencies, had already made their first purchases. This behavior prompted important questions to me: What drives people to invest impulsively in a product as complex and unusual as cryptocurrencies? What psychological and environmental factors might influence such decisions? The more I observed, the more it became clear that what my students were presenting was not just a fleeting curiosity but a growing trend, warranting deeper investigation. This realization motivated me to explore this financial phenomenon systematically, aiming to understand the behaviors, motivations, and perceptions driving cryptocurrency investment. The concern for better understanding the phenomenon of cryptocurrencies is more relevant than ever, as we see the newly elected American president launching his own cryptocurrency, which soared in value quite rapidly, taking with it the Bitcoin to an all-time high of $109,071 (Howcroft *et al*., 2025).

The first step in the discovery of this intriguing whole new world was to carry out a systematic literature review, which was followed by three other empirical studies. In this section, we outline the research paradigm, the research scope, the main research question, and the research objectives, as well as the contributions proposed and the dissertation structure. Subsequently, we present four chapters comprising the theoretical and empirical studies, followed by the general conclusions of our work.

1.2 Research paradigm

Research is inherently predicated on a set of assumptions. Throughout the investigative process, researchers must make epistemological assumptions concerning the nature of knowledge, ontological assumptions regarding the reality being investigated, and axiological assumptions about the role and influence of researcher values. These fundamental assumptions shape the researcher's understanding of the research questions, methodological choices, and interpretation of findings, collectively forming the research philosophy that underpins all aspects of the study (Burrell & Morgan, 1979; Crotty, 1998; Saunders *et al*., 2016). This research is grounded upon a post-positivist philosophy**,** which considers reality to be objective, although difficult to fully capture. In this view, procedures are deductive and a degree of uncertainty is accepted, admitting that some phenomena are driven by probabilistic rules instead being governed by causal laws (Della Porta & Keating, 2008). Post-positivism represents a refinement of traditional positivism, recognizing the inherent theory-laden nature of all observation and emphasizing for researchers to critically examine their assertions. Within this framework, knowledge is understood as conjectural, consisting of conjectures supported by the strongest available warrants at any given time, and remaining always open to revision (Phillips & Burbules, 2000).

In line with this philosophy, the study employs a hypothetico-deductive approach**,** where theory-driven hypotheses are formulated and tested using empirical data (Jary, 2006). In this methodology, instead of the accumulation of facts, as in the inductive model, the hypotheses are the basic element of an investigative process, representing generalized proposals on which empirical tests are carried out.

Following this paradigm, a quantitative methodological choice is adopted to examine relationships among numerically measured variables. Quantitative studies aim to capture information from the empirical world, expressing findings in numbers, and requiring the definition of measures previously to the data collection (Neuman, 2014).

A survey strategy was selected as the most suitable method for data collection. Surveys, along with experiments and case studies, are among the most widely used research strategies in social sciences, benefiting from advancements in sampling theory, multivariate analysis, and scaling methods (Aldridge & Levine, 2001). They are particularly effective in assessing thoughts and opinions to infer general principles of behavior (Shaughnessy *et al.*, 2012). The survey was carried out through a self-completion, closed-question questionnaire distributed online to collect data in a single instance, that is, the time horizon adopted was cross-sectional.

1.3 Research scope

The research presented in this study stems from a desire to uncover the elements influencing attitudes toward cryptocurrencies and their adoption as investment vehicles. The increasing global relevance of cryptocurrencies, alongside their potential to disrupt traditional financial systems, underscores the importance of this inquiry. While cryptocurrencies currently account for a small fraction of value in comparison to some important economic indicators, as the GDP or M1 in the Euro area (European Central Bank, 2019), scholars like Fernández-Villaverde and Sanches (2018) predict significant growth in their adoption.

Cryptocurrencies represent a paradigm shift in the concept of money and payment systems. Unlike traditional currencies, they operate without a central authority, relying instead on blockchain technology and decentralized networks. They are developed privately, in an autonomous way, that is, their issuance is not dependent on monetary policies decisions, and their general name has its origin in the cryptographic techniques used to ensure the secure validation of transactions (Robleh *et al*., 2014). The emergence of Bitcoin in 2009 marked the beginning of a revolutionary era in financial transactions, by enabling peer-to-peer (P2P) transactions without intermediaries, thus reducing intermediation costs and enabling a greater number of transactions, especially those of small value (Nakamoto, 2008).

Money is a social institution, and as such, it is transformed by the evolution of this society, therefore being affected by recent technological innovations, especially the widespread use of the internet. The impact of the global computer network is very significant and has caused profound changes in the way people interact, collect information and make payments (European Central Bank, 2012). However, these innovations only represented gains in efficiency, in a model that basically remained the same: a centralized, regulated and supervised financial transfer system.

Looking back to the first stage of development of the banking system, money was deposited in banks solely for the purpose of safekeeping and saving, with minimal use for transfers to third parties. At this phase, therefore, banks acted purely as intermediaries between depositors and borrowers, and this situation lasted until the industrial revolution, when bank deposits began to be used much more widely as a means of payment and led to the need for greater control and supervision of the system, requiring the action of a monetary authority (Chick, 1993).

Cryptocurrencies broke with this existing paradigm, by introducing a revolutionary financial architecture, where the transfer of property occurs in an absolutely decentralized manner, without dependence on or control of a main authority. constituting a new form of money, which has its own settlement and transfer system, and can be used in transactions involving both virtual and real goods and services (Robleh *et al*., 2014). However, their conversion rate to fiat currencies fluctuates widely (Kallinterakis & Wang, 2019; Phillip *et al*., 2019).

Three key aspects are decisive in defining a cryptocurrency system (Bank for International Settlements, 2015). First, cryptocurrencies are assets, with some monetary characteristics, such as a means of payment, for example, but they are not typically issued as sovereign currencies, do not represent liabilities of any entity and are not backed by an authority. Furthermore, their intrinsic value is zero, deriving their price only from the prospect that their owners have of using them in exchange for goods or services or for other currencies. Second, the ownership is transferred through a "distributed ledger" system, that is, transfer records are kept decentralized. And third, there is the presence of a large number and diversity of third parties involved in the development and operations of the system.

There have also been initiatives in the cryptomarket to launch some particular sort of assets intended to reduce the volatility exhibited by cryptocurrencies, creating a type of crypto-asset pegged to some stable reference. They are referred to as stablecoins and their applications vary, ranging from facilitating intragroup and interbank payments to targeting broader consumer use (Bank for International Settlements, 2019). As they in fact simulate a fiat currency, the most frequent use is to enable seamless inter-exchange transfers by minimizing price volatility during transaction processing (Kristoufek, 2021). Considering these particular features, stablecoins fall outside the scope of this study.

Naturally, the profound changes in the way our society operates, resulting from the widespread use of the internet and easy access to electronic devices, such as personal computers and smartphones, provided the basis for the viability of the idea of a means of payment that does not require any other party involved in the process other than the payer and the recipient (European Central Bank, 2012).

Therefore, the internet-based cryptocurrencies trading system appears to be the most disruptive innovation in global finance. In fact, the payments industry is closely monitoring developments in this area, because cryptocurrencies have the potential to completely transform the global financial infrastructure market (Raymaekers, 2015).

Innovations in payment methods have important implications for the security and efficiency of the financial system, and have been the subject of close attention from central banks (e.g., the reports Bank for International Settlements, 2015; European Central Bank, 2012). Naturally, the concern of monetary authorities on this subject arises from their primary role in preserving confidence in payment and fund transfer methods, and in the stability of the financial system as a whole.

One distinctive aspect of the cryptocurrency innovation is the way in which ownership is transferred. The usual mode to transfer money from a payer to a recipient depends on a centralized transaction registration structure, which, because it is supervised by financial authorities, provides security and reliability to the process. A major change brought by cryptocurrencies is the decentralized transaction registration methodology, which allows the transfer of values directly between users, without the need for clearing houses, as occurs in all other financial systems, and without the intervention, control or supervision of a central government entity (Mendoza-Tello *et al*., 2019).

Transactions with cryptocurrencies directly on a P2P network (also called a decentralized exchange) can be made using free, open-source software, found on community portals (see for example Bisq, 2024). This system operates on a pure P2P infrastructure, using desktop software, a Tor browser, local wallets and no central account, with the exception that, obviously, it is necessary to use traditional payment channels to transfer the national currency that is being given in exchange for the cryptocurrency. No user registration is required. To prevent counterparty risk, that is, one of the parties not fulfilling the amount that it should deliver, the system requires a security deposit.

Concurrently, the accessibility and ease of cryptocurrency trading via centralized exchanges have increased significantly. This kind of platform offers an infrastructure similar to that of conventional equity markets, encompassing analogous protocols and equivalent trade execution rules, facilitating liquidity provision (Aspris *et al*. 2021).

However, it is very difficult to obtain reliable data on transactions carried out in this segment (Alexander & Dakos, 2020). There are several internet portals that provide information on the total volume of transactions by centralized exchanges, however, in random comparisons made at the beginning of our work, it was found that data available on three well-known portals (coinmarketcap.com, openmarketcap.com and coingecko.com), although related to the same period of time, were not coincidental.

Illustrating the seriousness of this matter, the Securities and Exchange Commission (SEC) has expressed concerns about the structure of the cryptocurrency market and the lack of concrete evidence of the effective functioning of arbitrage that can prevent price manipulation, with there being no comprehensive, accurate and regulated source of data that informs bitcoin prices or transactions (Securities and Exchange Commission, 2018). The SEC also mentions that it has no concrete evidence that any of the current trading platforms acting on the global environment of cryptocurrencies is operating under the conditions of a regulated market.

This concern is further reinforced by the slow pace in defining the rules for supervising the cryptomarket, as demonstrated by the fact that only in April 2021 did the

Banco de Portugal regulate the registration of financial institutions that operate with crypto assets (Banco de Portugal, 2021) and a similar regulation is just a work in progress in Brazil as of May 2024 (Banco Central do Brasil, 2024). On the other hand, Portuguese tax law considers a cryptoasset as any digital representation of value or rights that can be transferred or stored electronically using distributed ledger technology or similar, while also determining that it is taxed as a financial asset (Lei n.º 24-D/2022, 2022).

In summary, the cryptomarket is marked by unique characteristics that make of it an exceptionally risky environment. Interestingly enough, despite warnings, the influx of retail investors has grown exponentially, and they seem to trade mostly based on sentiments, neglecting risks. Understanding the behavioral drivers of cryptocurrency investment is crucial in unpacking this phenomenon (Burggraf *et al*., 2020; Shrotryia & Kalra, 2022; Smales, 2022)..

A primary factor influencing cryptocurrency investments may be the cognitive bias of overconfidence. Cognitive biases refer to systematic distortions in human cognition that produce representations misaligned with objective reality (Haselton *et al*., 2016). Such biases manifest as systematic errors in judgment, often leading individuals to make decisions based on flawed reasoning. They can cause investors to take risks that they do not acknowledge and misjudge potential outcomes, emerging overconfidence as one of the most likely to influence investment decisions (Kahneman & Riepe, 1998). Existing research highlights a gap in understanding the role of overconfidence in the cryptomarket (Almeida & Gonçalves, 2023; Shrotryia & Kalra, 2022).

Then, to conduct the empirical phase of our exploratory investigation, we turned to the rich and insightful domain of behavioral finance. Behavioral finance provides a valuable framework for exploring individual decision-making processes in financial contexts. It integrates insights from psychology to illuminate individual-level behavior, frequently intertwining these perspectives with elements from sociology and economics, and a particular attention has been given to phenomena such as overconfidence (Lim *et al*., 2013).

Research has also been devoted to examine the pivotal role personality traits play in shaping investment choices and their connection with risk behavior (Aren & Hamamci, 2020). Risk propensity is considered a powerful explanatory variable of how individuals make decisions (Hung & Tangpong, 2017), and the Five-Factor Model provides a robust framework for understanding how personality influences risk behavior (Nicholson *et al*., 2005). By examining personality traits, this study seeks to uncover how individual differences contribute to cryptocurrency investment behaviors.

Also, the interplay between demographic factors and investment decisions warrants attention. A large stream of literature has made efforts to explaining individual financial behavior, with emphasis on the role of demographic or socioeconomic elements (Aydemir & Aren, 2017). Factors such as age, income, education, and cultural context influence how individuals perceive and engage with cryptocurrencies. This study incorporates demographic variables to provide a comprehensive understanding of the factors driving cryptocurrency investment.

This research adopts a multidisciplinary approach, integrating insights from finance, psychology, sociology, and economics. The growing field of behavioral finance, as Statman (2014) notes, expands the domain of finance beyond traditional metrics such as risk and return. Investment decisions are influenced by a multitude of considerations beyond the traditional evaluation. For instance, ordinary investors may value the convenience of managing an investment as a key factor in their decision-making process (Pellinen *et al*., 2015). This broader perspective is aptly captured by Fisher and Statman (1997), who draw a compelling analogy: just as people do not judge meals solely by their nutritional value, investors do not assess investments solely based on risk and expected return.

By exploring the psychological and social dimensions of investment decisions, this study contributes to a broader understanding of cryptocurrency adoption. The scope of this research extends beyond theoretical exploration, encompassing empirical investigations into the behavioral and psychological dimensions of cryptocurrency investment. The study begins with a systematic literature review, providing a foundation for understanding the current state of knowledge on this topic. This is followed by three empirical studies.

The literature review synthesizes existing knowledge on cryptocurrencies, identifying key gaps and research opportunities. The empirical studies use survey data and statistical techniques, such as Logit regression and Partial Least Squares Structural Equation Modeling (PLS-SEM), to explore the relationships between cognitive biases, personality traits, demographics, and investment behaviors.

1.4 Research question and research objectives

This thesis aims to provide a comprehensive understanding of the behavioral, demographic, and psychological dimensions influencing investment decisions in cryptocurrencies. By addressing gaps in the extant literature and exploring the dynamic interplay between individual characteristics, biases, and technology familiarity, the research contributes with a specific focus on the cryptomarket.

1.4.1 Main research question

The main research question of this doctoral thesis is:

What are the key behavioral, demographic, and psychological factors shaping the personal intention to invest in cryptocurrencies, and how do they interact to influence actual behavior?

This overarching question is further divided into specific questions and objectives that were the initial trigger to each chapter of the thesis:

1.4.2 Specific questions and objectives

Chapter 2: Cryptocurrencies - unveiling the seductive realm of private digital currencies

Question: What are the role and characteristics of cryptocurrencies within the broader financial landscape, and what gaps exist in the current understanding of investor behavior in this market?

Objectives:

- Investigate the emergence and contextualize the role of cryptocurrencies in financial markets, highlighting their relationship with other investment assets.

- Analyze cryptocurrency price dynamics, identifying anomalies, biases, and bubbles.
- Examine investment decision-making and individual behavior in the cryptomarket.
- Identify gaps in the literature to provide a foundation for future research and practical insights for investors and policymakers.

Chapter 3: Are Crypto-investors overconfident? The role of risk propensity and demographics. Evidence from Brazil and Portugal

Question: How does overconfidence impact individual decisions to invest in cryptocurrencies, and how does it interact with demographic traits and risk propensity?

Objectives:

- Assess the prevalence of overconfidence among crypto-investors compared to non-crypto-investors.
- Analyze the relationship between overconfidence and risk propensity.
- Examine the correlation of demographic factors such as gender, education, income, age, investment experience, and nationality with overconfidence and risk propensity.
- Identify critical factors influencing cryptocurrency investment decisions, including financial knowledge.

Chapter 4: Personality, risk propensity and cryptocurrencies - understanding investor behavior in the digital asset market

Question: How do personality traits and risk propensity influence individuals' intentions to invest in cryptocurrencies?

Objectives:

- Empirically verify the relationship between personality traits and cryptocurrency investment intentions.
- Explore the role of risk propensity in shaping this relationship.

Chapter 5: Overconfidence and Online Banking as Drivers of Behavioral Intentions in the Cryptomarket

Question: How do overconfidence and familiarity with internet-based financial technologies, such as online banking, influence individuals' intentions to invest in cryptocurrencies and their actual participation in the cryptomarket?

Objectives:

- Examine the impact of overconfidence on both the intention to invest and actual participation in the cryptomarket.
- Investigate the influence of overconfidence on the adoption of online banking and the subsequent impact of online banking usage on cryptocurrency investment. The study adopts the assumption that individuals with a higher tolerance for uncertainty are more inclined to embrace technological innovations. Building on this premise, it posits that

overconfident individuals are more likely to invest in cryptocurrencies in a relationship hypothesized to be moderated by a predisposition to adopt new technologies, represented in this study by online banking as a proxy.

1.5 Contributions proposed

This thesis provides significant theoretical and practical contributions, advancing knowledge in behavioral finance and offering actionable insights for stakeholders in the cryptocurrency market. By exploring individual characteristics, biases, and technological readiness, the research sheds light on the factors shaping investment behaviors in the rapidly evolving cryptomarket.

Theoretical contributions

The systematic literature review that we develop in one of the following chapters contributes to the field by offering a comprehensive mapping of existing research on cryptocurrencies. It identifies gaps and proposes new avenues for exploration, particularly in understanding investor behavior, price anomalies, and biases. This foundational work deepens scholarly comprehension and sets the stage for subsequent empirical studies.

The study highlights the impact of overconfidence and risk propensity on cryptocurrency investment decisions. It expands the existing literature by empirically examining these factors and their interplay with demographics, such as age, gender, income, and investment experience. By including data from Brazil and Portugal, the research broadens the geographical and cultural understanding of cryptocurrency behaviors, contributing to global studies.

This research also addresses the gap in literature on how personality traits influence cryptocurrency investment intentions. It demonstrates that traits like agreeableness, conscientiousness, and neuroticism are inversely related to investment intentions, while risk propensity mediates this relationship. These findings enrich existing models by revealing interconnected dynamics between personality, risk attitudes, and financial decisions, particularly in the cryptomarket context.

Moreover, the study integrates insights from behavioral intention models and technology adoption theories, showing how overconfidence and online banking usage influence cryptocurrency investment. By linking technological engagement to investment behavior, the research underscores cryptocurrencies as a natural extension of digital financial platforms, and challenges assumptions about the role of education in investment decisions. It also emphasizes the demographic segmentation of crypto users, with younger males exhibiting greater participation.

Practical contributions

The findings provide actionable insights for designing public policies and regulatory frameworks to enhance market stability and investor protection. Policymakers are encouraged to:

- Develop financial literacy programs that address cognitive biases like overconfidence and emphasize informed decision-making.
- Implement educational campaigns targeting specific demographic groups, particularly younger, risk-prone investors.
- Encourage cryptocurrency platforms to incorporate risk-awareness

initiatives and investor protection measures in their operations.

For retail investors, the research highlights the importance of understanding personal biases and characteristics that influence financial decisions. Recognizing overconfidence and risk propensity can lead to better financial strategies and reduced susceptibility to irrational behaviors. Educational interventions, such as lessons on investor psychology and bias mitigation, are proposed to empower individuals in managing their investments effectively.

The findings offer valuable profiles of cryptocurrency investors, enabling private entities to design targeted campaigns and services. Trading platforms can benefit by prioritizing investor protection and fostering prudent investment practices. Additionally, understanding the role of personality traits, risk propensity, and demographics helps tailor financial products and marketing strategies to the needs of diverse investor groups.

Cryptocurrencies, as intangible and sentiment-driven assets, require distinct approaches to risk management. The research emphasizes the necessity for systemic interventions to address the unique risks of the cryptomarket, including educational initiatives, augmented regulations, and policies that prioritize transparency and investor safety. As cryptocurrencies become increasingly integrated into mainstream finance, these measures are essential for fostering a secure and sustainable market environment.

In summary, this thesis makes substantial contributions by advancing theoretical frameworks, enriching empirical insights, and providing practical recommendations for stakeholders. It bridges critical gaps in the literature, offering a nuanced understanding of how behavioral, demographic, and technological factors shape cryptocurrency investment. By combining theoretical rigor with actionable insights, the research supports the development of more robust financial systems and informed investment practices, ensuring a safer and more equitable market for all participants.

1.6 Research design and dissertation structure

Consistent with the adopted research philosophy and methodological approach, this research employs a confirmatory-explanatory design to address the research questions. While the confirmatory component focuses on testing pre-defined hypotheses through statistical techniques such as regression analysis and structural equation modeling (SEM), aiming to refine the analysis by narrowing things down to identify the best possible options (McQuarrie, 2015), the explanatory component complements this by evaluating data and synthesizing ideas to generate answers to the established research questions (Saunders, 2016). This combination allows for both rigorous hypotheses testing and the development of deeper insights into the underlying phenomena. The study proceeded through the following phases:

- Systematic literature review on cryptocurrencies to identify and analyze scientific documents published since the emergence of this asset class. The goal is to gain a broad, deep, updated, and systematized understanding of the subject, particularly regarding the attitudes of individual investors.
- Bibliographic research on investment behavior to ascertain the current state of knowledge in this field.
- Development of the research instrument, ensuring alignment with the theoretical framework and methodological requirements.

- Data collection and analysis, guided by established quantitative methods.
- Results discussion and conclusions, based on empirical evidence and theoretical insights.

A survey strategy was chosen for data collection, as it effectively captures thoughts and opinions to derive general behavioral principles (Shaughnessy *et al*., 2012). The research employs a self-completion, closed-question questionnaire distributed online to collect data in a single instance (cross-sectional time horizon). Since online questionnaires do not require direct interaction between the researcher and the respondents, we took great care when designing ours: clear instructions for self-completion as well as concise and straightforward language were used to avoid the risk of ambiguity or misinterpretation (Lavrakas, 2004; Rowley, 2014). Quantitative methods were used to analyze the data collected.

Ethical issues were carefully observed in the elaboration and development of the research, preserving respect and consideration for all the respondents. Emphasis was put on the following key aspects (Aldridge, 2001; Bell, Bryman & Harley, 2018):

1. Informed consent: Respondents were transparently informed about the research objectives, potential beneficiaries, and institutional approvals. The study has been approved by the University of Lisbon, and the contact details of the responsible researcher was provided;
2. Confidentiality and anonymity: participants' identities remained anonymous, facilitated by the online survey format, which requires no registration or login;

3. Sensitivity: particular attention was given to ensuring that survey items are free from potentially offensive or discriminatory language related to race, gender, age, or disability.

4. Permissions and approvals: ethical standards set by the University of Lisbon were strictly followed. This research was previously authorized by the ISEG Ethics Committee.

This dissertation is organized into five chapters besides this introductory one, each addressing a specific aspect of cryptocurrency investment behavior, with a focus on understanding the interplay between individual characteristics, behavioral biases, and technological familiarity. Together, these chapters provide a comprehensive exploration of the cryptomarket from theoretical and empirical perspectives, which is finalized in a general conclusion section. An illustration of the research design and dissertation structure is depicted in Figure 1.1.

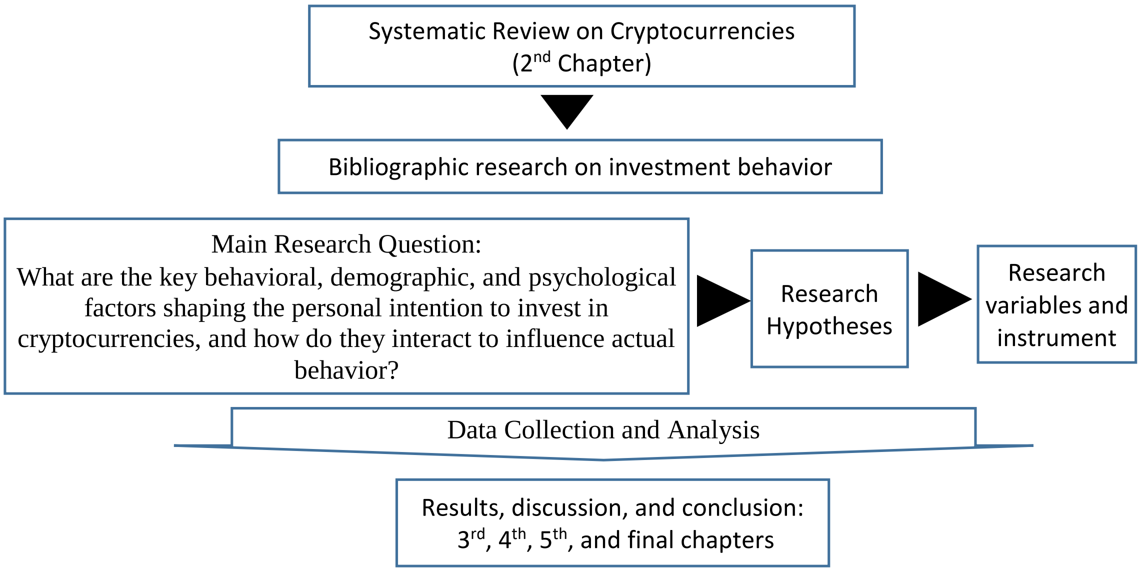

Figure 1.1 Research design and dissertation structure

The second chapter provides a thorough examination of the existing academic literature on cryptocurrencies. By systematically reviewing 507 scientific articles, this chapter maps the foundational knowledge surrounding the cryptomarket, with a particular focus on individual investor behavior and decision-making processes. It discusses key challenges in this nascent market, such as inefficiencies, unclear diversification benefits, and the influence of behavioral biases among retail investors. Additionally, this chapter identifies significant gaps in the literature, emphasizing particularly the need for further empirical studies on investor behavior in the cryptomarket.

The third chapter explores overconfidence as a key driver of investment behavior in the cryptomarket. Using survey data collected from Brazil and Portugal, this study examines the relationships between overconfidence, risk propensity, and demographic characteristics in shaping cryptocurrency investment decisions. The methodological approach involves statistical analysis and logit regression modeling, providing insights into the cognitive and demographic factors that influence engagement in this volatile market.

In the fourth chapter, the focus shifts to the role of personality traits in shaping attitudes toward cryptocurrency investments. By employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique, this study investigates the relationships between personal characteristics, risk propensity, and investment intentions. The chapter addresses the gap in understanding how personality dimensions interact with risk attitudes to influence financial decision-making in the context of cryptocurrencies.

The fifth chapter examines the intersection of cognitive biases and technological proficiency in cryptocurrency adoption. Specifically, it explores how overconfidence and familiarity with online banking platforms influence individuals' behavioral intentions and actual participation in the cryptomarket. Using an exploratory research design and PLS-SEM for data analysis, this chapter highlights the role of digital financial ability and cognitive bias in shaping intention toward and engagement with this emerging asset class.

The final chapter presents the conclusions that we can identify after developing the different parts of this thesis, namely identifying the main factors influencing cryptocurrency investment. This research explored behavioral, psychological, and demographic influences on investor decisions in this volatile market. Through a multidisciplinary approach and empirical analysis, it investigated why individuals invest in cryptocurrencies, examining cognitive biases, risk propensity, and personality traits. The conclusion integrates the literature review and the three empirical studies, providing a comprehensive understanding of these influences, offering valuable perspectives for academics, practitioners, and policymakers.

A note on referencing: the references within Chapters 2 through 5 adhere to the target journal's submission guidelines. Chapters 1 (Introduction) and 6 (Research Conclusions) follow APA style conventions, and the references cited therein are listed at the end of the thesis.

Chapter 2: Cryptocurrencies: unveiling the seductive realm of private digital currencies [1]

Abstract

This study undertakes an in-depth examination of the singular realm of cryptocurrencies, a market that has captivated attention from investors all over the world, with the objective of shedding light on its complexities and potential trajectories for development. Through a systematic review of 507 scientific articles, we scrutinize cryptocurrency trading, revealing insights into its underlying mechanisms. Our focus lies particularly on the examination of the individual investor behavior within the market and how they make their decisions.

Our findings unveil the challenges that surround this market still in its infancy, highlighting its inherently contentious nature. It is considered predominantly inefficient, and there is not a definitive conclusion regarding the optimal explanatory variables that describe its price dynamics. Also, the diversification benefits of cryptocurrencies are yet unclear. In this complex setting, we encounter a multitude of retail investors characterized by minimal experience and susceptibility to behavioral biases. Their tendency to emulate each other's actions rather than adopting consistent portfolio management techniques adds another layer of complexity to the cryptomarket.

Furthermore, we detected a significant gap in the literature, pertaining to the

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[1] This study was accepted to be presented as a full paper in the 51st EBES Conference, Rome, on April 11th - 12th, 2025.

exploration of investors' behavior in the cryptomarket, requiring further empirical studies to elucidate their attitude toward this unique asset class.

Keywords: Cryptocurrencies, investor behavior, decision-making, risk attitude, bias.

JEL Classification: G11, G14, G15, G18.

2.1 Introduction

Cryptocurrencies have emerged as a focal point of interest for investors, media outlets, and scholars due to their unique attributes (Huang *et al*. 2022) and because their seamless convertibility into fiat currency renders them versatile assets with far-reaching implications within the global financial landscape (Hu *et al*. 2019a). Originating from a white paper by Nakamoto (2008), cryptocurrencies represent a revolutionary peer-to-peer electronic cash system that transcends geographical and governmental boundaries, heralding a new era in digital finance. Operated within a virtual realm, these digital currencies are created, stored, and exchanged through cryptographic mechanisms, leveraging intensive computational resources for the validation of ownership and transactions. Moreover, the dynamic nature of cryptocurrency protocols ensures ongoing advancements in security measures, safeguarding this evolving form of currency against emerging threats (Harwick, 2016). This confluence of technological innovation and financial ingenuity underscores the profound impact of cryptocurrencies on contemporary economic discourse and investment strategies.

Bitcoin was the pioneering cryptocurrency. A lot of others followed, such as Ethereum, Tether, Cardano, and Dogecoin, to name a few. With an exponential surge in its adoption on a global scale, cryptocurrencies have been seen much more as an opportunity for investment than a means of exchange.

Against this backdrop, our endeavor aims to unravel the intriguing realm of cryptocurrencies through an exhaustive and systematic literature review. Adhering to rigorous best practices and recommended procedures, we have scoured numerous databases to assemble a robust collection of 507 meticulously analyzed documents, forming the cornerstone of our exploration. The revelations unveiled herein help for a deeper discernment of this field besides serving as a springboard for future investigations.

It is worth noting that since its inception, this novel type of digital market has undergone large and profound technological transformations (Grobys & Sapkota 2020). The very essence of cryptocoins lies in the spirit of open source, inviting enthusiasts worldwide to contribute and improve their technological architecture.

As we delve further, an intriguing landscape unfolds, where the arrival of a myriad of new coins, innovative fintech platforms, and connected financial products and services emerge in parallel with the ascent of initial coin offerings (ICOs), causing ripples of concern among regulators (Financial Action Task Force 2019).

Cryptocoins flood the market, numbering in thousands, and every single day new ones come into existence, creating a wide range of opportunities but placing sizable challenges at the same time. (Arias-Oliva *et al*. 2019). However, despite the rapid growth witnessed in the crypto industry, it remains in its nascent phase. The products and services it offers are still in their fledgling stages of development, evolving within a relatively unregulated environment. This precarious situation lays the groundwork for potential fraud and mismanagement, capable of causing damage not only on customers but may extend to other players, in a contagion effect, as witnessed in the crash of stablecoin TerraUSD and the bankruptcy of FTX, the world's second-largest cryptocurrency exchange (Chow 2022; Fletcher 2023; Huang 2022; Lang *et al.* 2022; Shen 2022; Yaffer-Bellany 2023).

Moreover, high levels of volatility, a hallmark of the cryptomarket (Phillip *et al*. 2019), present relevant risks for both investors and the financial system itself. While banks maintain a cautious stance and limit their exposures to cryptoassets (Bank for International Settlements 2019), small users remain susceptible to significant risks (Pop & Colonescu 2021).

This dynamic landscape underscores the contentious nature of the cryptomarket, characterized by its burgeoning potential and the accompanying need for robust regulatory frameworks to ensure its sustainable growth and stability. In such complex circumstances, motivations for investing in cryptocurrencies, apart from the allure of easy gains (Chu *et al*. 2020; Fruehwirt *et al*. 2021; Katsiampa 2019; Nguyen *et al*. 2020a), are still unclear.

Accordingly, this research is performed with the following objectives:

- Investigate and contextualize the emergence of cryptocurrencies, understanding its role, and relations with other investment assets;
- Analyze its price dynamics and the existence of anomalies, biases, and bubbles;
- Examine the investment decision-making and individual investor behavior

in this market.

In addition, we seek to identify gaps in the extant literature, paving the way for future research. Hence, as a result of our investigation, we expect to provide useful insights for investors and policymakers.

This work unfolds in the following way: Section 2 details the material and methods employed to explore and analyze publications on the topic. Section 3 presents a multifaceted discussion, synthesizing the key issues unearthed during our investigation. Finally, Sections 4 and 5 provide an integrative synthesis of our work and indicate the possibilities for future research in the field.

2.2 Material and methods

2.2.1 Research protocol

The systematic review is a reproducible, transparent, and methodical process to provide a synthesis of the existing literature on a determined topic, identifying, selecting, appraising, and analyzing existing empirical studies (Perestelo-Pérez 2013; Tranfield *et al*. 2003). Unlike traditional reviews, it employs a systematic and accountable method for identifying and analyzing relevant studies, avoiding any oversights or biases (Gough *et al*. 2012).

A critical step in conducting a systematic review is developing a clear and objective review protocol. We follow the PRISMA methodology (Page *et al*. 2021) to ensure transparency and accuracy in documenting the purpose, methods, and findings of our review. The protocol covers several parameters, including search strings (based on the research objectives), database selection, document inclusion criteria, and quality standards (Kraus *et al.* 2020; Pittaway *et al*. 2014), making the review unique but reproducible.

To maximize coverage, we searched multiple academic databases (Bramer *et al*. 2017), including Web of Science, Scopus, and others. Our search focused on peer-reviewed English articles with full texts. The research timeframe extended from the earliest available date to March 31, 2022.

We employed the following criteria, aligned with our research objectives: at the outset, we looked for documents with general terms like "cryptocurrency," "cryptocoin," and similar words in the title, finding 4,312 articles. However, we recognized the need for balance between width and depth (Kraus *et al.* 2020) and refined our search with subject terms like investor behavior, decision-making, psychological factors; bias, beliefs, and risk attitude, resulting in a final selection of 769 documents.

2.2.2. Organizing and refining data

We organized the data using an electronic worksheet (Petticrew & Roberts, 2006). This facilitated the process of analysis, inference, and synthesis. Accordingly, we constructed a bibliometric database containing essential information such as article title, authors' names and affiliations, publication year, keywords, journal details, and publisher. While building the spreadsheet, we identified and eliminated 192 duplicate articles, resulting in a set of 577 documents.

Next, we assessed the journals' importance and academic influence by referring to the SJR (Scimago Journal & Country Rank) and the Academic Journal Guide by the Chartered Association of Business Schools. Scimago focuses primarily on the quality of citations that a journal receives from its peers, rather than the absolute number (Falagas *et al*. 2008), classifying them into quartiles, with Q1 representing the most influential group. The AJG is a reliable resource that covers an extensive number of publishers (Morris *et al*. 2009), based upon peer review, editorial, and expert judgments.

After excluding articles not classified by Scimago or the Academic Journal Guide, our refined database contained 513 documents, which we downloaded for further analysis. We conducted a first reading of all documents to evaluate their relevance, refine the database, and extract additional qualitative information for the bibliometric worksheet, adding new fields to provide a comprehensive overview of each study, including objectives, main findings, methodology, limitations, and future research suggestions.

During this phase, we excluded six non-eligible documents that did not align with our research objectives or were not academic, peer-reviewed articles. Consequently, the final pool of articles for analysis comprised 507 documents. A complete list of included studies and their data can be obtained from the corresponding author. We then proceeded to read the articles in detail.

A summary of the process of collecting and selecting documents to form the database of studies to be reviewed is displayed in Figure 2.1.

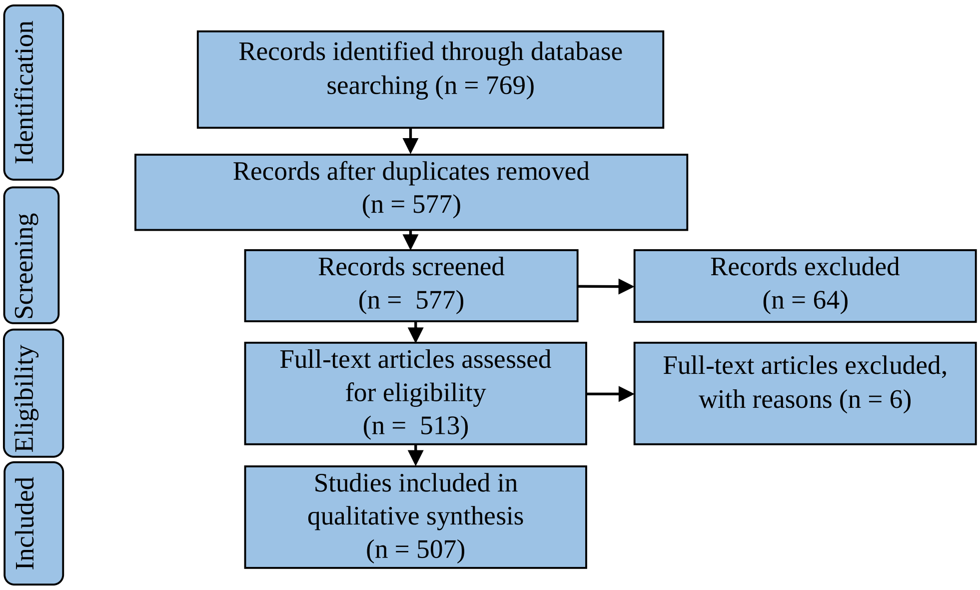

Figure 2.1 PRISMA flow diagram

Source: Prepared by the authors according to the PRISMA Statement (Moher, Liberati, Tetzlaff, Altman, The PRISMA Group, 2009).

As the work evolved, occasionally some additional documents, focused on connected subjects, were examined due to their relevance for a better understanding of the topic under analysis. Also, with the sole purpose of getting complementary and updated information about issues like government policies, regulation, and market data, we resorted to amplified literature (Gabbott 2004), making use of working papers from state or multilateral agencies (such as central banks and the BIS) as well as to information delivered by major global news providers (such as Reuters).

2.2.3 Analysis

Our approach adopts the strategy indicated by Tranfield *et al.* (2003), based on earlier works of Clarke and Oxman (2001), and the NHS Centre for Reviews and Dissemination (2001). Therefore, this literature review is executed in three progressive stages: planning, conducting, and reporting. Accordingly, we performed a careful preparation (the moment when the research objectives and the review protocol were defined), followed by data extraction, elimination of duplicates, quality assessment and analysis (conducting), culminating the whole process with a report. Figure 2.2 summarizes the entire process and methodology used to carry out this review.

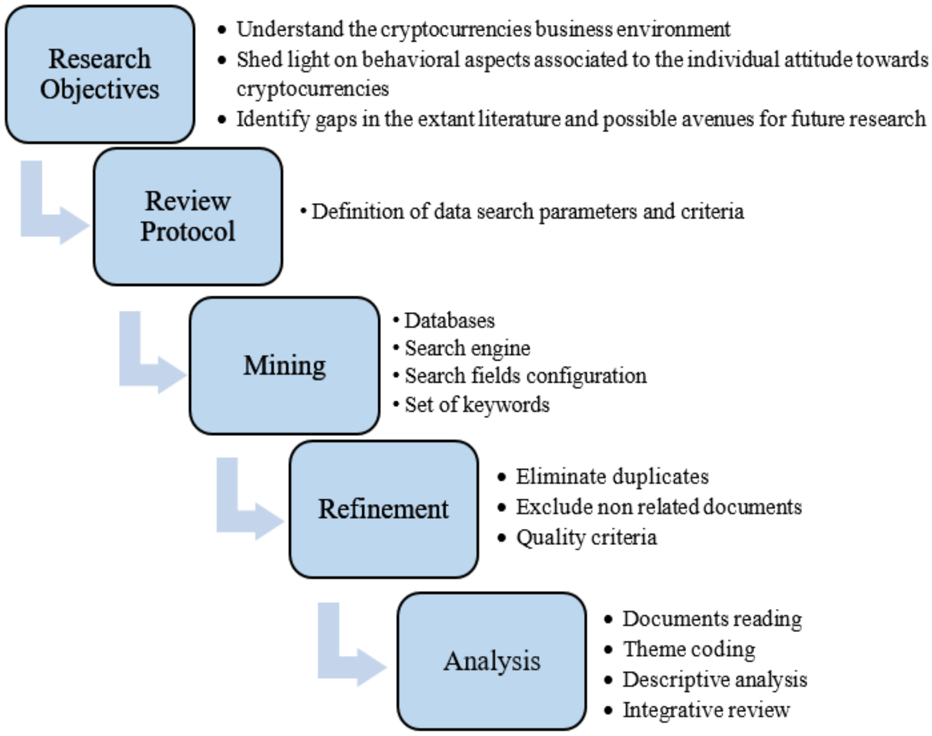

Figure 2.2 Methodological steps followed to perform the systematic review

Source: Prepared by the authors

In examining the articles, our attention focused on the central themes explored in the studies. According to Ryan and Bernard (2003), themes represent the fundamental concepts that describe the subject explored by an author. Fisch and Block (2018) suggest that this style of writing centered on the main concepts exposed in each scientific work should constitute the microstructure of a systematic review. Thorpe *et al*. (2005) add that organizing a systematic review based on themes and sub-themes facilitates the capture by the reader of the central ideas, arguments, and conceptual connections related to the reviewed papers.

This systematic approach allows for the inductive categorization of subjects, providing a comprehensive and integrative view of the research (Liñán & Fayolle, 2015). It serves as an alternative to deductive methodologies that rely on pre-determined analytical frameworks, which can be reductionist and decontextualize information (Jones *et al*., 2011).

There are several distinctive and relevant features of this systematic literature review:

i) It encompasses an extensive range of databases (13 different sources), ensuring comprehensive access to academic works.

ii) The number of examined articles exceeds the minimum target of 100 documents recommended by specialized literature review journals (Frank & Hatak, 2014).

iii) It addresses an emerging and pivotal topic with the potential for transformative impacts on transactional and investment practices (Ababio, 2020; Gil-Alana *et al*., 2020; Zhang *et al*., 2018).

iv) It sheds light on individuals' attitudes toward cryptocurrencies.

2.3 Results and discussion

2.3.1 Descriptive results

The first proposal of a cryptocurrency was launched a little more than a decade ago (Nakamoto 2008) and scientific investigation on the matter is still at a nascent stage. Indeed, the first academic studies under the scope of this review were detected only in 2016. However, research in this area is growing consistently (Klarin 2020). This increasing interest certainly fosters the production of a solid body of knowledge to help develop the field.

A large number of articles focus only on Bitcoin, as it is the first and still the most prominent cryptocurrency, presenting the highest trading volume and market capitalization, besides possessing the largest mining network (Pavković *et al*. 2019; Saiedi *et al*. 2020). Although more investigation should be done on other coins daily arriving on the market, we believe this trend will remain strong for some time as new financial products, such as future contracts, are bitcoin-denominated.

We identified documents in 151 different journals, revealing a broad dissemination of academic output on cryptocurrencies. Noteworthy is the important concentration of articles in journals ranked in the Scimago first quartile, attesting to the quality of the research made. Figure 2.3 depicts the distribution of papers according to the Scimago journal categorization.

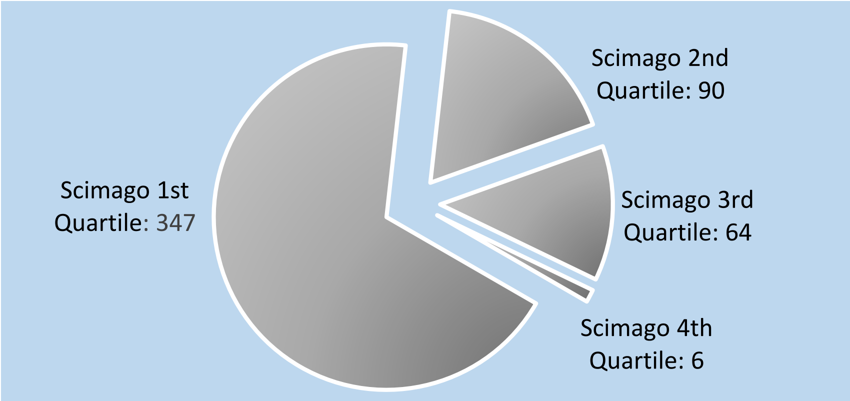

Figure 2.3 Number of academic articles according to the journal where they were published

Source: Prepared by the authors based on data provided by the Ebsco search engine.

The works are mostly done in teams of 2 to 5. The average number of authors per paper is 2.8 with individual papers making up approximately 16% of the total. Teamwork is predominantly characterized as multidisciplinary, involving professionals from a wide spectrum, such as finance, accounting, law, and technology. A study executed by a multiplicity of authors adds more value to the final result as the team members may act as pre-reviewers, notably if there is a combination of more experienced scholars with younger researchers (Kraus *et al.* 2020).

We also observe that some articles result from a joint work of academics from different institutions, from traditional universities to governmental and non-governmental agents committed to research and science dissemination, as well as institutions dedicated to the supervision and control of the financial system, as is the case of central banks.

In addition, we mapped the affiliation institution and the respective country of each first author, which gives us an insight into how and where cryptocurrency research is taking place in the world, as represented in Figure 2.4. The higher the academic output, the darker the country is portrayed. The top ten countries are labeled on the map and their production is presented as a percentage of the total. Together, they account for 57.2% of total research, with China being the most active.

Figure 2.4 Research according to country of origin

Source: Prepared by the authors.

Going further in the review, we proceeded to the content analysis of the documents. For this purpose, we followed the recommendations of Fisch and Block (2018), Ryan and Bernard (2003), and Thorpe *et al*. (2005) and first stratified the entire set of articles into smaller categories in view of what was presented in the abstract and keywords of each study. This method facilitates the capture of ideas, arguments, and conceptual connections among the reviewed papers. The coding process yielded 13 different categories, which were then grouped into three broader themes: Finance, Market Overview, and Law & Regulation. The visual perspective of the keywords density distribution for each group confirms that our codification adequately captured and grouped the themes and subthemes addressed in the literature pool.

Figure 2.5, powered by VOSviewer software, presents the density maps for the keywords. The term cryptocurrency(ies) was disregarded for obvious reasons. The category of Finance displays asset pricing, liquidity, connectedness, market efficiency, and volatility among the strongest clusters. Bitcoin is the most cited keyword, denoting its central role in the econometric analyses scholars do. Ethereum also draws attention but at a lower level. In turn, the map for the Market Overview portrays a flat distribution of words. Bitcoin and blockchain are the most relevant, but also other less intense expressions such as market manipulation, trust, e-commerce, ICO, casinos, and ethics are equally important to perceive this category as more general, dealing with a large number of different topics that give us a broad description about the cryptomarket structure and how it works. The density map for Law & Regulation shows internet, business, economics, drugs, cryptomarkets, and crime as the most substantial clusters, implying a major concern among academics about negative dimensions of the crypto business, related mostly to drug dealing on the dark web and cybercrimes.

In Table 2.1 we provide a structured overview of the article distribution across themes and subthemes, setting the stage for detailed discussions in the following subsections.

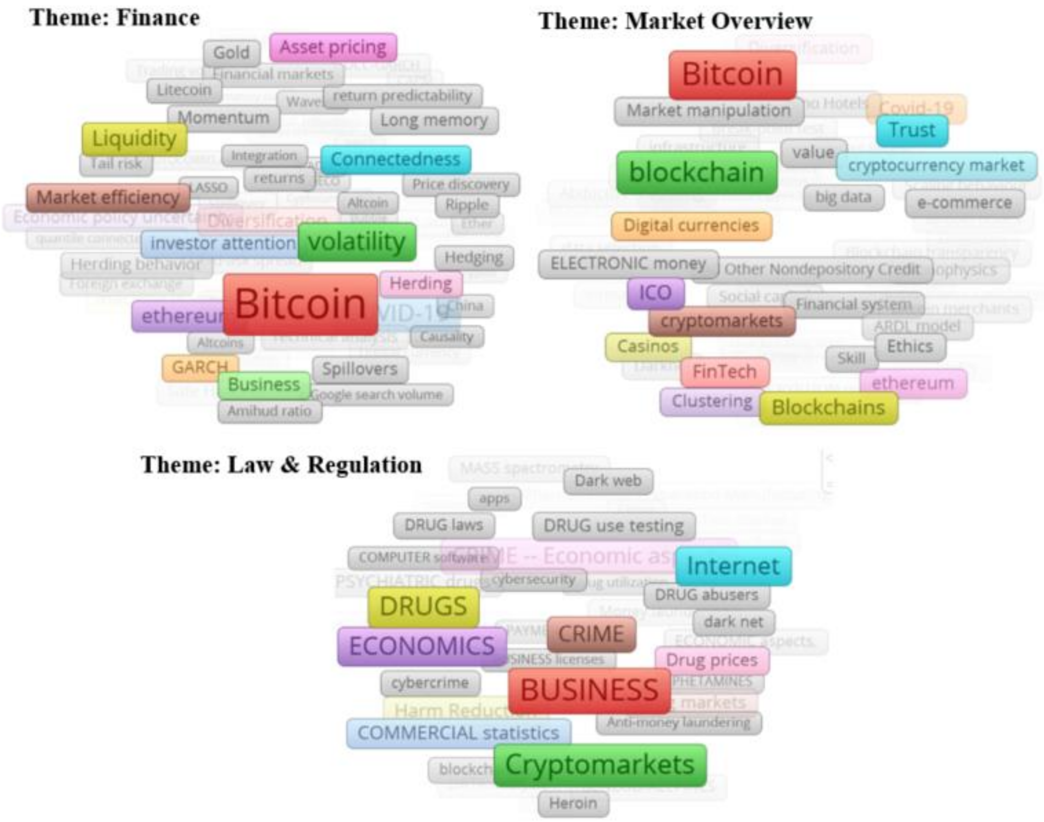

Figure 2.5 Density visualization of keywords

Source: Prepared by the authors.

Table 2.1 Articles overview by theme and subtheme

Theme	Number of articles	%	Subtheme	Number of articles	%
Finance	374	74%	Price Dynamics and Market Efficiency	221	44%
			Investment Strategies	86	17%
			Behavioral Studies	39	8%
			Monetary Essays	24	5%
			Derivatives	4	1%
Market Overview	82	16%	Market Features & Descriptive Data	64	13%
			Consumer behavior	8	2%
			Perspectives	5	1%
			Business Ethics	5	1%
Law & Regulation	42	8%	Drug dealing, Terrorism & M. Laundering	22	4%
			Regulatory Framework and Supervision	12	2%
			Cybercriminality	5	1%
			Frauds	3	1%
Literature Review	9	2%	-	9	2%
TOTAL	507	100%		507	100%

Source: Prepared by the authors.

2.3.2 Finance

The absolute majority of works found in the literature review are related to the area of finance or economics, with 374 studies covering a wide range of topics. The flourishing of academic research on cryptocurrencies is probably due to their increasing market value and the dramatic fluctuation in prices (Fry & Cheah 2016).

A careful look at the keywords helps us to build a big picture of the most addressed issues. Within the 922 different keywords found, we computed how frequently they are cited and ranked in Table 2.2 those keywords detected ten or more times, not considering the term cryptocurrency(ies) which appears 289 times. A first look at the table allows us to see that researchers are heavily focused on analyzing the price movements of cryptocurrencies, with a strong emphasis on bitcoin and secondly on Ethereum, performing econometric analyses mainly focused on volatility, liquidity, and connectedness. The dominance of bitcoin is not a surprise as it was the first coin to be launched and, followed by Ethereum, holds the largest market cap. We also see Covid-19 near the top, signaling a great concern in academia about the financial effects brought about by this unprecedented public health crisis. We found 39 studies particularly addressing this topic.

Scrolling down the records on the table, we come upon expressions like cryptocurrency market and market efficiency, denoting a concern in understanding the operational mechanisms of cryptomarkets and how the process of price discovery happens in them. At the bottom of the list, we find the keywords asset pricing and diversification, indicating a persistent effort to offer insights, tools, and techniques to plan and optimize portfolio strategies.

Table 2.2 Most cited keywords in the studies grouped in Finance

Keywords	Frequency
Bitcoin	122
Volatility	30
COVID-19	26
Liquidity	17
Ethereum	15
Connectedness	11
Cryptocurrency market	11
Market efficiency	11
Asset pricing	10
Diversification	10

Source: Prepared by the authors based on data provided by the Ebsco search engine.

Upon meticulous scrutiny of the documents, it emerges that scholars have investigated relevant cryptocurrency singularities, discussed in the following.

2.3.2.1 Price dynamics and market efficiency

The cryptocurrency environment peculiarities have led some authors to view it as a complex system based on speculation (Mnif *et al*. 2020). Cryptocurrencies have exhibited extreme price fluctuations, with rapid surges and significant drops, making them highly volatile and risky assets (Anastasiou *et al*., 2021; Ben & Xiaoqiong, 2019). They exhibit long memory, leverage, stochastic volatility, and heavy tails (Assaf *et al*. 2021; Phillip *et al*. 2018; Zhang *et al*. 2018). Returns are not normally distributed and best-fitting distributions are highly-peaked and thick-tailed (Acereda *et al*., 2020; Szczygielski *et al*. 2020). Liquidity shows a positive correlation with returns (Leirvik

2022) and there is a mild connectedness among major cryptocurrencies (Hasan, *et al*. 2022). They demonstrate interdependencies with other markets, showing weak connections to the energy sector but better integration with commodity markets (Ji *et al* 2019a), raising some questions about diversification benefits, a topic discussed in the next subsection.

An often debated issue is the occurrence of bubbles in the cryptomarket, a phenomenon that turns out to be inherently arduous to identify because, technically, a bubble is a deviation from the fundamental price, a concept insufficiently understood in the realm of cryptocoins (Enoksen *et al*. 2020; Gronwald 2021) due to the absence of a value anchor to provide a point of reference (Kaiser & Stöckl 2020). In an attempt to map bubbles, rapid price accelerations followed by sharp declines, known as explosivity, have been traced, revealing multiple exponential price peaks and the existence of interdependent price movement, also termed co-explosivity. (Agosto & Cafferata 2020; Bouri *et al*. 2019c; Enoksen *et al*. 2020; Geuder *et al*. 2019). Also, the existence of overreaction behavior – a large positive or negative asset price change and subsequent reversals in comparable magnitude – has been observed, which is supposed to happen because of the inexistence of cryptocurrencies' intrinsic value (Borgards and Czudaj, 2020). A singular point of view on the matter is introduced by Fernández-Villaverde (2018) who interprets cryptocurrencies as fiat money and ponders they are by definition a bubble due to their intrinsically worthless condition. Indeed, a bitcoin is nothing more than what users make of it and its perceived attributes (Treiblmaier 2021).

On the other hand, the cryptomarket's wilder volatility, when compared to conventional currencies (Phillip *et al*. 2019), has prompted researchers to explore variables that could explain or predict price variations in cryptocurrencies. Catania *et al*. (2019) find significant improvements in forecasting by considering gold, silver, stock indexes, interest rates, and VIX[2] as predictors. Meanwhile, Walther *et al*. (2019) highlight the superiority of Global Real Economic Activity in volatility predictions. Interestingly, variables directly linked to economic activity, such as consumer price and industrial production, do not seem to affect cryptocurrency prices, but the exchange rate between the dollar and the euro does. Regarding behavioral variables, investor attention, measured by the use of internet search tools, seems to improve accuracy when incorporated to prediction models, being its increase associated with higher returns, and should be considered a non-negligible pricing factor (Smales 2022; Zhu *et al*. 2021). Furthermore, sentiment derived from social media platforms like Twitter can impact cryptocurrency returns (Aharon *et al*., 2022; Kraaijeveld & De Smedt, 2020). Contradictorily, Bleher and Dimpfl (2019) and Katsiampa *et al*. (2019b) find some evidence that information demand on the internet presents insignificant predictive ability for returns but they can help to forecast cryptocurrency volatility and trading volume.

Various analytical tools have been employed to analyze price-related risks in the cryptomarket. GARCH models were applied to intra-day data, leading to the discovery of a strong positive correlation in pairwise price returns, indicating a notable level of interdependence among cryptocurrencies (Katsiampa *et al*., 2019a). Analogous results are reported utilizing the novel Threshold Weighted-Minimum Dominating Set (TW-MDS) approach (Papadimitriou *et al*. (2020). The Diebold-Yilmaz framework has been

[2] Real-time index reflecting market's expectation for price volatility in the stock market in the next 30 days.

utilized to reveal a rise in return and volatility spillovers over time, highlighting the growing interconnectedness among cryptocurrencies and the subsequent increase in contagion risk within the market (Koutmos 2018). Similarly, the BK method (Baruník-Krehlík) has been used to argue that risk spillovers are higher in the short term compared to medium and long-run horizons (Mensi *et al*. (2021). The use of a flexible semi-nonparametric approach is also put forward. By utilizing the median shortfall measure, it provides a conservative yet accurate result in assessing risk, acknowledging the diverse nature of cryptocurrencies and the need for caution when dealing with crypto assets (Jiménez *et al*. 2022).

To perform financial modeling, it is proposed an algorithm combining vine copulas and GARCH procedure to calculate VaR and ES and better assess risk in a cryptocurrency context (Trucíos *et al*. 2020), and the adoption of a Gradient Boosting Decision Tree (GBDT) algorithm to forecast price trends (Sun *et al*. 2020). Regarding risk components, size and reversal effects are deemed as appropriate factors to consider for cryptoassets, along with market returns, in constructing a three-factor pricing model (Shen *et al*. 2020). Alternatively, momentum was proposed as a relevant risk component (Jia *et al*. 2022; Liu *et al*. 2020), offering another perspective on explaining returns in the cryptocurrency market.

A different appraisal is presented by Kraaijeveld and De Smedt (2020), who adopt a descriptive method, taking into account various factors that may influence cryptocurrency pricing. Their analysis goes beyond simple supply and demand dynamics, and together with Geuder *et al*. (2019) and Rehman *et al*. (2020), they argue that cryptocurrency price movements are influenced by a complex web of interacting forces.

Based on these studies, Figure 2.6 summarizes the main factors to influence price behavior.

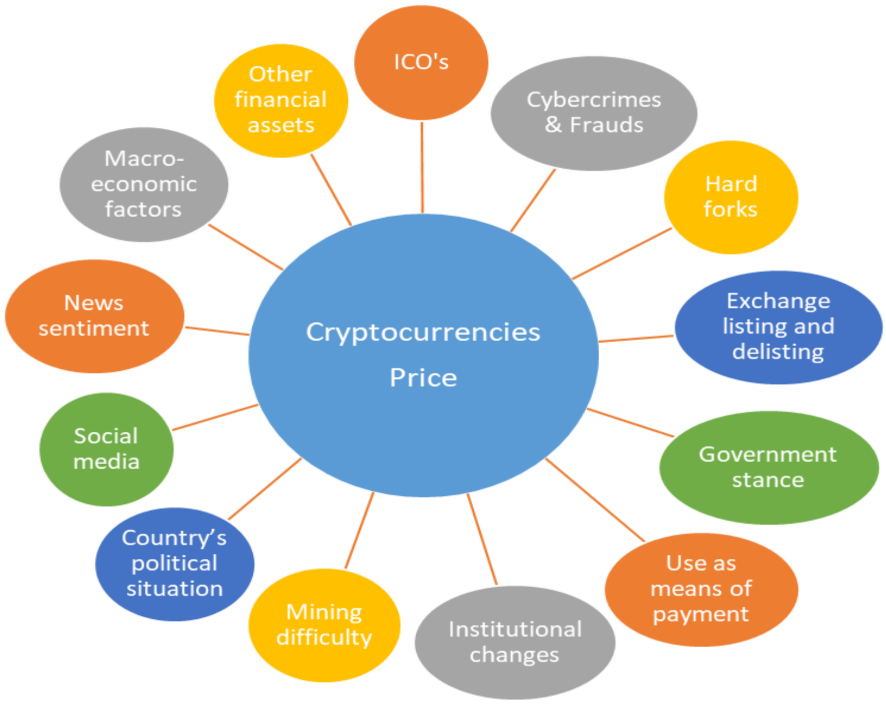

Figure 2.6 Most influential factors on cryptocurrencies price

Sources: Created by the authors, based on the works of Geuder *et al*. (2019), Kraaijeveld and De Smedt (2020), and Rehman *et al*. (2020).

Indisputably, there is a strong call for the development of robust risk management and forecasting models that can enhance financial decision-making in cryptocurrency markets and ongoing studies are delving deeper (Li *et al*. 2022; Nascimento *et al*. 2022). A revolutionary movement in the pursuit of enhanced risk assessment tools is already in course, with the incorporation of deep learning techniques into pricing architectures (Livieris *et al*. 2020). Machine learning, which encompasses the subfield of deep learning and neural networks, has already been used by some researchers to analyze future cryptocurrency prices (Chiang *et al*. 2021; King & Koutmos 2021) and the outcome of trading strategies, with satisfactory results in terms of risk control and accuracy, indicating they are valuable resources to develop price predictability and capture risk premiums but incapable of consistently earning abnormal returns (Anghel, 2021; Rahmani Cherati *et al*. 2021; Sebastião & Godinho 2021). Admittedly, machine learning still presents some limitations since it cannot completely mimic human cognitive functions, requiring adaptability in situations of new markets or order structure. (Fang *et al*. 2021).

It is also important to scrutinize the cryptocurrency realm through the lens of the Efficient Market Hypothesis (EMH). In an environment where investing opportunities are accessible around the clock (Alexander & Dakos, 2020; Torres *et al*., 2020; Vidal-Tomás 2021), informational efficiency becomes critical. We find that reaction to unexpected information is influenced by liquidity, with average delays decreasing over time (Köchling *et al*., 2019). Active traders and arbitrageurs collaborate to form a stronger market and reduce volatility for the most liquid coins, however when turnover is low and transaction costs are high, their interest diminishes considerably, affecting efficiency levels (Wei 2018). Similar results showing that cryptocurrencies become more efficient as liquidity increases are provided by Al-Yahyaee *et al*. (2020), Brauneis and Mestel (2018), and Köchling *et al*. (2019). This turns on a yellow light concerning the fledging coins. The best options for novice investors in the cryptomarket should be well-established coins.

Rather significant, the market does not fully reflect in price the major news events immediately after their announcement (Hashemi Joo *et al*. 2020). Comparing the influence of unanticipated facts in the cryptomarket with the informational flow in traditional currency markets, not only dissimilar reactions are verified but it is also perceived that just positive news seems to affect Bitcoin returns while negative ones are ignored by investors (Rognone *et al*. 2020). This unusual attitude suggests unreasonable investors' enthusiasm. Academic work on such attitudes is still scarce and opens up a whole avenue of research to investigate behavioral aspects and personality traits exhibited by agents in the cryptomarket.

The inefficiency of cryptomarkets has been reported by several scholars (Fidrmuc *et al*. 2020; Fil & Kristoufek 2020; Hu *et al*. 2019b; Palamalai *et al*. 2021; Shen *et al*. 2020). Additionally, cryptomarkets show signs of size effect, i.e. small value cryptocoins tend to perform better (Li *et al*. 2020).

Contrastingly, some authors pose that the cryptocurrency market is more efficient than expected (Burggraf and Rudolf 2021; Grobys and Sapkota 2019), while others postulate that it is inefficient in the short-term and efficient over the long run (Tzouvanas *et al*. 2020). Furthermore, Yaya *et al*. (2021) and Wang and Chong (2021) found price unpredictability and market efficiency in the weak form. Ante, Fiedler, and Strehle (2021) add that stablecoins help in the cryptocurrency price discovery process, promoting market efficiency. However, stablecoins are closer to being money than cryptocurrency (European Central Bank 2019). Lastly, Chu *et al*. (2019) demonstrate that market efficiency varies over time according to the adaptive market hypothesis, questioning the significance of sentiment and news events as factors to determine efficiency.

All the research above mentioned certainly offers important contributions to understanding the complex interactions that take place in a round-the-clock worldwide market. However, it is important to note that they offer diverse and sometimes conflicting explanations, underscoring the controversial nature of this market (Shahzad *et al*. 2022) and highlighting that it is early to reach a definitive conclusion on the best explanatory variables to describe its price dynamics and the level of market efficiency.

In addition, a word of caution should be given in the face of important fragilities detected in the process of collecting and analyzing cryptocurrency data. In a sample of 152 empirical studies published in academic journals from January 2017 to March 2019, over half of them contain one or more of the following flaws (Alexander & Dakos, 2020: 1) dubious sources; 2) asynchronous time-series; 3) non-traded prices. Such errors may compromise the accuracy of results of price volatility and market efficiency studies. The potential conflicts of interest arising from the fact that certain companies providing information used in academic literature also accept advertisements from exchanges are also highlighted. This raises concern about the impartiality of rankings and introduces a degree of skepticism regarding their reliability. Moreover, the use of different methodologies by private websites to aggregate cryptocurrency data (Charfeddine *et al*., 2020) further emphasizes the need for a cautious approach when employing econometric techniques in this field.

2.3.2.2 Investment strategies

The extreme price movements noticed in cryptocurrencies and their singular nature make them a highly speculative asset (Enoksen *et al*. 2020; Liu & Serletis 2019), hence investors should use portfolio management methodologies to handle risks and optimize results. Unquestionably, the acute volatility levels require the adoption of adapted risk measure techniques to help improve financial decision-making in such a challenging context (Platanakis & Urquhart 2019; Trucíos *et al*. 2020). Some important research in this domain includes the use and results of trading rules (Ahmed *et al*. 2020; Caporale *et al*. 2018; Corbet *et al*. 2019a; Grobys *et al*. 2020); the employment of algorithmic trading techniques (Aslan & Sensoy 2020; Petukhina *et al*. 2021) and Q-learning portfolio management tools (Lucarelli, & Borrotti 2020); and the prediction of cryptocurrencies discontinuation (Grobys & Sapkota 2020).

Several academics have turned their attention to the possibility of diversification benefits from using cryptocurrencies, since they apparently do not respond to major world events like other asset classes (Schaub & Phares 2020). Whereas investors are permanently in search of alternative assets as part of their portfolio strategies (Guesmi *et al*. 2019), academic work on this matter is welcome. A good deal of studies focuses on interdependence, an issue of preeminent interest for those seeking portfolio risk reduction as well as achieving excess returns (Fruehwirt *et al*. 2021). Notwithstanding the common tendency to view all cryptocurrencies as a single asset, they are intrinsically diverse, at least due to their underlying mechanisms and algorithms, and may not react identically (Baumöhl 2019; Corbet *et al*. 2020b; Huang *et al*. 2022). On this account, some researchers started by examining the possible benefits of diversification3 in a cryptoasset-only scenario. Apparently, diversification benefits can be obtained by including some particular groups of cryptocoins, such as the proof-of-stake type (Schinckus *et al*. 2022) or by simply employing straightforward techniques like an equal-weighted scheme (Dempsey *et al*. 2022; Nguyen *et al*. 2020a). Interestingly enough, cryptocurrencies that

[3] We assumed in this review the concepts of diversification, hedging and safe haven presented by Baur and Lucey (2010).

use different algorithm to generate the blocks in the blockchain have the potential to provide diversification benefits (Huang *et al*. 2022).

However, the effectiveness of portfolio selection criteria remains a subject of debate. While some find no statistically significant difference between naive and optimal diversification methods (Platanakis *et al*., 2018; Brauneis & Mestel, 2019), other researchers have expanded the scope of analysis by testing a variety of methodologies. These include multi-criteria approaches that consider factors such as value at risk, liquidity, market capitalization, and attractiveness (Aljinović *et al*., 2021; Liu, 2019; Mensi *et al*., 2019). Overall, diversification has shown the potential to enhance risk-return performances in various methodologies, suggesting its value in cryptocurrency portfolios, although it is alerted that cryptoassets complexities are not completely understood yet and estimation errors in mean and covariance could compromise the results.

Despite the apparent benefits of diversifying into a cryptocurrency-only portfolio, it is important to consider the systematic risk inherent in this market. Solely relying on digital assets for portfolio diversification may have limitations (Canh *et al*., 2019; Tiwari *et al*., 2020). According to some studies, when cryptocurrencies are combined with other asset classes such as gold, crude oil, stocks, or bond indices, their correlation becomes negligible, making them suitable for diversification and hedging purposes (Aslanidis *et al*., 2019; Gil-Alana *et al*., 2020; Okorie & Lin, 2020). They may well be an instrument for hedging in times of turmoil, due to their negative correlation with economic uncertainty (Balli *et al*. 2020) and to the fact that they are left- and cross-tail independent to equity markets (Feng *et al*. 2018). However, several other authors (Pavković *et al*. 2019; Charfeddine *et al*. 2020; Milunovich 2018) find positive but limited effects in combining cryptocurrencies with other assets for diversification purposes. Indeed, the benefits of diversification have diminished since 2017 (Demiralay & Bayraci 2020) and diversification advantages seem to be short-term in nature (Corbet *et al*. 2018).

In terms of hedging, cryptocurrencies present superior potential for metal and agricultural commodities compared to the energy group (Naeem *et al*. 2021a) and particularly Bitcoin and gold are likewise regarded as vital assets for hedging albeit the former is influenced by its past volatility and the latter has a much higher probability of large appreciation in situations of extreme shortfall (Feng *et al*. 2018; Huynh *et al*. 2020). Additionally, most cryptocurrencies consistently demonstrate zero or negative betas over time. This characteristic positions them as natural hedging instruments for investors aiming to decrease the correlation of their portfolios with the overall market (Koutmos *et al*. 2021).

Alongside Bitcoin, some other cryptocurrencies like Ethereum, Litecoin, and Ripple may play a strong role as diversifiers, hedgers, and safe havens (Bouri *et al*. 2020; Cheikh *et al*. 2020; Tzouvanas *et al*. 2020). There are contrasting results in the literature. Wang *et al*. (2019) show that while cryptocurrencies act as safe havens for most indices, they do not serve as effective hedges. Safe haven characteristics are more pronounced in developed markets and subgroups with larger market capitalization and higher liquidity. Similarly, Trucíos *et al*. (2020) compile mixed results regarding the hedging and safe haven abilities of cryptoassets in turbulent times.

Specific tests conducted during the Covid-19 period provide additional insights. Corbet *et al*. (2020c) find that Bitcoin does not effectively hedge or serve as safe haven during periods of financial disturbance. On the other hand, a significant growth in cryptocurrency returns and volume is observed following early sentiments related to Covid-19 in social media (Corbet *et al*. 2020a). Later on, it was demonstrated that cryptocurrency market liquidity sharply increased during the pandemic, suggesting their role as a store of value and a safe haven during the financial market distress that took place at that time (Corbet *et al*. 2022).

In the concrete, the interaction between cryptocurrencies and other financial products is a topic of ongoing research, with contradictory evidence emerging in the literature (Akyildirim *et al*., 2020b). Even the role of stablecoins, which are intended to provide stability and mimic traditional fiat currencies (Ante, Fiedler & Strehle 2021; Kristoufek 2021), remains contentious. While some studies suggest that certain stablecoins, such as gold-backed coins, can act as safe haven investments (Wasiuzzaman & Rahman, 2021), others find that they fail to fulfill their intended role during periods of market volatility (Jalan *et al*., 2021). These controversial results call for more comprehensive studies to determine the true benefits cryptoassets may offer as diversifiers, hedgers, or safe havens. We also note that the studies carried out so far are very diverse concerning the assets and indices investigated, not to mention the many sorts of techniques used to make the analyses, making it difficult to compare results. By analyzing sample characteristics, technical approaches, and results of each empirical investigation focusing on diversification benefits, it can be observed that some works explore only Bitcoin, or a very small number of cryptocurrencies while others make use of a restricted list of alternative assets.

Furthermore, it is crucial to acknowledge that legal uncertainties surrounding cryptoassets can significantly impact their price dynamics and their relationship with other types of investments, potentially affecting their diversification and hedging potential (Charfeddine *et al*., 2020). Given the complex nature of cryptocurrencies and the evolving landscape, understanding their role in diversified portfolios undeniably requires continuous research and analysis.

Finally, there are some other perils of which investors should be strongly aware (Bank for International Settlements 2019), like liquidity, credit, and operational risks. European authorities emphasize the absence of protection and misleading information as serious flaws, warning of potential losses due to fraud or failure (Charfeddine *et al*. 2020; Pavković *et al*. 2019).

2.3.2.3 Behavioral studies

In ass*et al*location decisions, maximizing returns while considering risk is imperative. Markowitz's normative theory and subsequent contributions provide guiding principles for optimal portfolio selection. Even if not able to make more detailed and complex computations, a common investor only needs to pay attention to the plain, easy-to-get information on an asset price fluctuation (technically, its mean and variance) to understand the relation between risk and return and build a portfolio with the best options (Ababio 2020).

However, empirical evidence has led some authors to hypothesize that market participants lack an understanding of fundamental factors related to asset pricing (Nguyen *et al*. 2020a). In fact, the massive presence of lay investors in the cryptocurrency markets with no or minimal investment history has drawn attention from researchers (Fruehwirt *et al*. 2021). Markedly, the general public is not taking notice of the frequent warnings to be careful, increasingly investing with speculative purposes in search of quick profits (Chu *et al*. 2020; Katsiampa 2019; Mirtaheri *et al*. 2021). These retail investors commonly possess little trading skills, are often susceptible to behavioral biases (Kallinterakis & Wang 2019), and quite influenced by any information that grabs their attention – habitually sentiments conveyed through social media – venturing into cryptocurrencies without understanding the risks (Bouri *et al*. 2019a; Naeem *et al*. 2021b; Subramaniam & Chakraborty 2020). Noticeably, investors often overlook the unique characteristics of cryptocurrencies, relying solely on market performance and neglecting risks (Bouri *et al*. 2019a). This mindset leads to investments without careful evaluation, akin to gambling behavior (Delfabbro *et al*. 2021; Oksanen *et al*. 2022).

A salient topic studied under the lens of behavioral finance, notably in equity markets, is herding behavior. In the domain of cryptocurrencies some academics have mapped unfounded, senseless patterns, arguing that investors sometimes opt to mimic others' decisions, giving up their own beliefs (Ballis & Drakos 2020), and associating emotions to trading volume and price fluctuation (Ahn & Kim 2021). Herding behavior in the cryptomarket is mostly due to irrational non-professional investors pushed by social influence and informational cascades and exacerbated by the lack of a fundamental value reference point (Kaiser & Stöckl 2020). There is some evidence that the smallest cryptocoins move in tandem with the largest ones (Vidal-Tomás *et al*. 2019), and herding behavior varies over time and tends to occur as uncertainty increases, that is, when traders are less comfortable they disregard their own assumptions and follow the market (Amirat & Alwafi 2020).

Equally significant, we have seen that positive shocks have a stronger impact on increasing volatility compared to negative shocks, driven by noise traders and the fear of missing out (Baur & Dimpfl 2018), Furthermore, high returns are associated with larger trading volume, suggesting optimistic individuals engage more intensively in buying cryptocoins when their price increases ((Naeem *et al*. 2020a). In addition, Rehman *et al*. (2020) state that collective optimism has a strong impact on cryptocurrency trading. With respect to individual specifics, it has been observed that all age groups, from 18 to +65 years old, engage in cryptocurrency trading, and, men are more active and speculative but achieve lower returns than women (Hasso *et al*. (2019).

Other contributions unveil the presence of small price bias, finding it much more pronounced in cryptocurrencies when compared to stocks (Aloosh & Ouzan 2020). It also has been detected that cryptocurrency investors are driven by excitement-seeking (Pelster *et al*. 2019) and show confirmatory bias with respect to government statements (Zhang *et al*. 2019). Despite being restricted to a specific topic and market, this latter work opens an interesting avenue for research, once confirmatory bias may induce overconfidence.

Finally, it's crucial to note the scarcity of studies extracted by our systematic review addressing aspects related to crypto investors' behavioral biases and psychological factors, highlighting a significant gap in the literature.

2.3.2.4 Monetary essays

The role of central banks is an important issue in economic essays related to cryptocurrencies. They focus on a theoretical discussion about the effectiveness of monetary policies in a hypothetical new economic order permeated by the widespread use of cryptocurrencies, as well as the issuance of virtual government currencies based on blockchain. The old debate about the existence of a global currency is back, sparked by the now-available mechanism of decentralized, supranational digital currencies (Balvers & McDonald 2021).

Empirical analyses attempt to unveil relations between the direction (contractionary or expansionary) of monetary policies and the return of cryptocurrencies. Research has been conducted in the two major world economies. A statistically significant positive response in cryptocurrency prices is observed when China increases its basic interest rate. However, there is no sufficient evidence supporting a relation in the opposite direction, and when it comes to the United States no association between monetary policies and cryptocurrency return is perceived at all (Nguyen *et al*. 2019). Although authors argue about possible capital flights from stock to cryptocurrency markets in times of monetary policy tightening, results are very limited and do not allow for generalization.

Beyond the influence exerted on cryptocurrency markets either by means of monetary policy or regulation, central banks are on their way to launching their own virtual currency. Some of the world's leading financial authorities are working together to develop sovereign classes of cryptocurrency (Bank for International Settlements *et al*. 2021).

This initiative comes allegedly in response to the downward tendency in the use of cash amidst the general public and the emergence of blockchain-based digital money. It is considered that non-bank private cryptocoins will not reach widespread use either because of network effects or because it does not have legal tender status and governments do not accept them in tax payments (Kirkby 2018; Luther 2016). The implementation of a large base of crypto-users requires a robust and costly coordination effort, something that could be achieved in situations of significant monetary instability or in cases where the government supports the idea (Scott 2016; Rosales 2019; Renteria *et al*. 2021).

Apart from preserving monetary policy effectiveness, the issuance of a comprehensive version of CDBC (Central Bank Digital Currencies) – in which all kinds of entities, as well as common individuals, are permitted to hold virtual money and make transactions based on a centralized ledger technology – may offer the benefits of narrowing monetary policy transmission channels and providing a more secure deposit system in comparison to the fractional reserve model. On the other hand, such a design may reduce significantly the importance of private banks, concentrating too much information in the hands of central banks and raising concerns about the balance of power among institutions (Cukierman 2020; Jun & Yeo 2021; Kirkby 2018), certainly posing some challenging questions on the way ahead.

2.3.2.5 Derivatives

The world of cryptocurrency derivatives is still largely unexplored, with only a handful of papers dedicated to this emerging field. The inception of the futures market for cryptocurrencies began in late 2017 when prominent exchanges like the Chicago Board Options Exchange and the Chicago Mercantile Exchange introduced bitcoin future contracts (Sebastião & Godinho 2020).

Despite its incipient state, this segment has demonstrated the capacity to dominate price discovery over the spot market, highlighting its importance in shaping a more stable and reliable market for cryptocurrencies. The information flow transmitted from future to spot markets is mostly due to the action of sophisticated institutional investors. Although some differences between the products currently offered by the two exchanges, evidence is robust to indicate their relevance for the price discovery process, being an effective hedging instrument (Akyildirim *et al*. 2020a; Sebastião & Godinho 2020).

Establishing a thriving futures market is a critical milestone for cryptocurrencies on their path in the direction of broader financial acceptance and integration with the real economy (Brody *et al*. 2020). To achieve this, a resilient institutional framework is needed, encompassing a wide range of structured financial products akin to those available for traditional fiat currencies. Interest rate derivatives play a pivotal role in this regard and Brody *et al*. (2020) present a theoretical model for virtual currencies based on distributed ledger technologies, adjustable to the initial yield curve and market data. Expanding this line of research will undoubtedly contribute to the development of a more efficient cryptocurrency market.

2.3.3 Market overview

In this category, the studies focus on providing a comprehensive understanding of the general features of the cryptocurrency market. While occasionally touching on other subjects, the primary emphasis is on systemic and operational aspects, like scalability and privacy.

A notable observation in this body of research is the relatively balanced distribution of keyword frequencies. Alongside "cryptocurrency(ies)," "bitcoin" and "blockchain" emerge as the most frequently cited terms.

Through descriptive data analysis, researchers offer a panoramic view of the origins and development of cryptocurrencies. Historical data and future market development perspectives are presented, shedding light on the evolution of this dynamic landscape. Eventually, the discussions move into critical areas of business ethics. Consumer behavior, mainly in relation to e-commerce and the acceptance and trust in the use of cryptocurrencies, is also addressed.

Additionally, these studies highlight the singularities of cryptoassets, heavily reliant on distributed ledger mechanisms and the blockchain platform. They discuss the groundbreaking concept of initial coin offerings (ICO), which have emerged as a significant source of venture capital.

2.3.3.1 Market features and descriptive data

An authoritative explanation about cryptocurrencies is provided by the European Central Bank (2019), highlighting their distinctive nature. While users consider them valuable, they lack a corresponding liability or claim on any party, making them fundamentally different from traditional financial assets. This uniqueness should be carefully pondered by individuals contemplating investments in this market. Furthermore, economic fundamentals or variables that typically explain returns for traditional assets have not been enough to elucidate the price movements of cryptocurrencies (King & Koutmos, 2021).

On the flip side, the term cryptoassets includes a wide range of private assets primarily dependent upon cryptography and DLT (distributed ledger technology), among them the virtual currencies (regarded as payment/exchange-type tokens), investment tokens, and utility tokens, which are used to access a good or service (European Banking Authority, 2019).

Accordingly, cryptocurrencies can be considered a type of asset, resembling money while lacking intrinsic value. They could allow people to obtain goods and services (Fernández-Villaverde 2018) but their role as a medium of exchange is pretty limited. They are inadequate as a unit of account due to the impossibility of managing a supply-demand relationship to keep them at a stable value (Ammous 2018; Catania *et al*. 2019; King & Koutmos 2021), being viewed much more like an investment possibility.

These digital assets are suitable to be included in any portfolio even in individual retirement accounts, although they remain awaiting a clear legal definition (Bouri *et al*. 2019b; Hu *et al*. 2019a), and do not neatly fit into traditional asset categories such as equities, bonds, commodities, or even currencies (Liu *et al*. 2021; Trucíos *et al*. 2020). They serve as the cornerstone of a new financial ecosystem, continually giving rise to innovative products like derivatives (Akyildirim *et al*., 2020a; Sebastião & Godinho, 2020; Zhang *et al*., 2019). In fact, they can be considered a synthetic asset, a novel financial instrument, notably for investment purposes (Bariviera *et al*. 2018; Corbet *et al*. 2020c; Gil-Alana *et al*. 2020).

Cryptocurrencies do not have the same constraints as conventional currencies (Jariyapan 2022) and may be traded in exchange platforms all over the world, 24 hours a day, seven days a week (Bariviera *et al*. 2018). Their closing prices are usually measured at 23:59:59 UTC4 (Alexander & Dakos 2020). Their comprehensive and sophisticated technological features drawn on an encryption-based blockchain (Marella *et al*. 2020) provide the possibility of completely virtual transactions with the use of electronic addresses only, potentially offering anonymity (Masciandaro 2018). While allowing for public auditing, this unique feature preserves users' privacy, avoiding the identification of payers and recipients on the network. Regrettably, this characteristic has been the basis for the use of this asset for illicit activities (Sun Yin *et al*. 2019). Another distinctive feature is that, unlike traditional developed markets, where institutional investors dominate, most cryptocurrency traders are individuals (Zhang *et al*. 2019), many of them lay investors (Fruehwirt *et al*. 2021).

The creation of cryptocurrencies can be viewed as a response to the 2008 global financial crisis, indicating a loss of confidence in the international monetary system (Rosales 2019; Trucíos *et al*. 2020). They can also be seen as a reflection of libertarian beliefs, a desire for a self-governing system, not controlled by a nation state or central authority (Dallyn 2017; Spithoven 2019).

Since the first commercial transaction in 2010, the number of cryptocurrencies has flourished, exceeding the thousands (Arias-Oliva *et al*. 2019), with all other cryptos launched after the pioneer Bitcoin referred to as altcoins. (Li *et al*. 2020; Papadimitriou *et al*. 2020; Song *et al*. 2019). Forks have contributed to the proliferation of new coins,

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[4] Coordinated Universal Time (UTC) shares the same current time with Greenwich Mean Time (GMT), and they do not change for Daylight Saving Time (DST).

often as a result of divergences within developers and protocol changes protocol changes (Berentsen & Schar 2018; Harwick 2016; Marthinsen & Gordon 2021). Although not all new cryptocoins gain popularity, with less than 10% being traded at least once a day, it is important to note that the increase in numbers is accompanied by an increase in diversity (Phillip *et al*. 2018; Rehman *et al*. 2020), with new cryptocurrencies widely varying in some key characteristics like maximum supply, consensus mechanism, transaction speed, and block building time.

Among the flood of new cryptocoins, one type holds particular significance, representing a direct connection to start-up fundraising (Spithoven 2019). They are launched into the market under the flag of Initial Coin Offerings (ICO), defined by the Swiss Financial Market Supervisory Authority (2018) as a transfer of funds by investors in exchange for a certain amount of tokens, generated and stored on specifically created or existing blockchains.

There is no generally accepted taxonomy for tokens. An attempt to classify them is depicted in Figure 2.7.

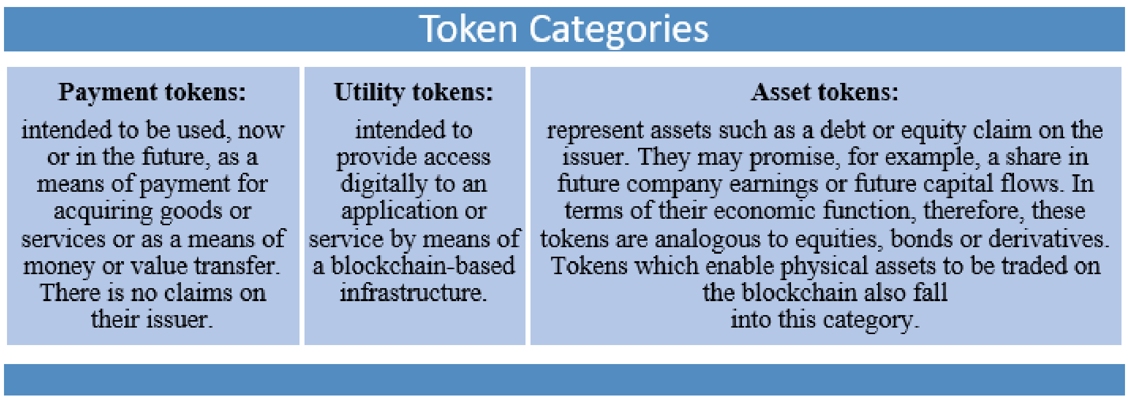

Figure 2.7 Token stratification

Source: Guidelines for enquiries regarding the regulatory framework for initial coin offerings (ICOs). Swiss Financial Market Supervisory Authority (2018).

It may be observed that the first segment, payment tokens, are effectively virtual coins. The other two resulted from the emergence of ICOs and refer to i) a form of security associated with an investment (asset tokens) or ii) consumptive rights, in the case of utility tokens (Bogusz *et al*. 2020; Howell *et al*. 2020; Thies *et al*. 2021). In a different view, Hu *et al*. (2019) consider cryptocurrencies to be divided into two distinctive forms, based on their usage and underlying technology: a) coins, which typically have their own blockchains and their main purpose is to serve as means of exchange or investment b) tokens, which can benefit from existing blockchains, via smart contracts, and work as a funding mechanism for new ventures.

To conclude a comprehensive overview of the cryptomarket, it is essential to identify its key participants:

- Issuers – entities driven by diverse motives, whether it's launching a new cryptocurrency for business ventures, introducing national currencies, or strategic moves by tech giants like Facebook (Momtaz 2021; Saiedi *et al.* 2020);
- Clients – the seekers of cryptocoins, including those who embrace them for transactions and individual investors, as well as the institutional participants (European Central Bank 2019; Hu *et al.* 2019a; Papadimitriou *et al.* 2020);
- Merchants - sellers who accept cryptocurrencies as payment, particularly in the realm of e-commerce (Manahov 2021);
- Miners - players armed with vast computational resources to validate transactions on the network and to keep a safe record of them, receiving

remuneration for their work (Bação *et al*. 2018; Cukierman 2020; Klarin 2020).

- Exchanges – online intermediaries, to facilitate the purchase and sale of cryptocurrencies. They can act either as market makers or a simple matching platform, in centralized or decentralized (non-custodial) arrangements (Aspris *et al*. 2021; Dallyn 2017; Marella *et al.* 2020; Wei 2018).

There are also some organizations dedicated to spreading the word and even lobbying to foster the cryptocurrency market (Spithoven 2019).

2.3.3.2 Consumer behavior

Most of the studies related to consumer behavior in the cryptocurrency field involve e-commerce activities. In this context, cryptocurrencies are viewed as digital tender, prompting scholars to embark on a quest to discern the pivotal determinants underpinning their utilization within the realm of online trading.

Technological skills are the main driver for the widespread embrace of cryptocurrencies. Exploratory factor analysis indicates that the allure of these digital assets stems from a compelling quintet of reasons. Inherent benefits bestowed by blockchain technology, users' dominion over exchanges, unrivaled celerity in transaction processing, low-cost international transactions, and development training stand among the most relevant motivations for their usage. (Sobhanifard and Sadatfarizani 2019).

Also, performance expectancy – defined as how convenient a technology would be to enhance individual performance – looms as an explanatory variable for the intention to use cryptocurrencies (Arias Oliva *et al*. 2019). When analyzing the influence of social media in the adoption of cryptocurrencies in electronic payments, perceived usefulness is considered the most important factor in motivating the usage of virtual coins (Mendoza-Tello *et al*. 2018).

2.3.3.3 Perspectives

The cryptocurrency market is growing at lightning speed, with the prospect of becoming more diversified and sophisticated every day, as the launch of related investment funds, financial derivatives and spot ETFs (Bouri *et al*. 2020; Lang *et al*. 2024) indicates. Additionally, the entry of institutional participants, asset managers, and traditional exchanges is going to make the market more robust, bringing in more rational players and analytical information (Bouri *et al*. 2019a; Hu *et al*. 2019a).

Bitcoin is the top cryptocurrency. Its prominence is largely supported by its extensive, well-established mining network, high trading volume, strong liquidity, and historical acceptance (Pavković *et al*. 2019; Saiedi *et al*. 2020). A technique of correlation-based agglomerative hierarchical clustering and minimum spanning tree, applied by Song *et al*. (2019), confirmed the dominance of Bitcoin and Ethereum, followed by six clusters comprised of less-traded cryptos.

Nonetheless, a significant number of strong competitors have arisen, with improved technological efficiency (Corbet *et al*. 2020b), and may affect bitcoin dominance, particularly when it comes to the speed of processing transactions and consolidating the blocks (Rehman *et al*. 2020). A concern for the current leader should be the extremely slow transaction validation process it features, at a time when other platforms such as Ethereum, are already addressing the limitations of Bitcoin scripts and previous-generation DLT, offering a more user-friendly environment, smart contracts, and making operations easier and quicker for their clients (Lipton 2021; Phillip *et al*. 2019). Scalability will certainly constitute a major challenge for Bitcoin.

The use of cryptocurrencies has moved far from the original idea of being a medium of exchange free from government interference. Indeed, they have been used much more frequently as a speculative asset (Gagarina *et al*. 2019), becoming an investment choice for many individuals (Berentsen & Schar 2018; Bouri *et al*. 2019a; Hashemi Joo *et al*. 2020).

Conversely, their adoption in commercial transactions, even among e-retailers, remains at a low level mainly because of fears related to its constant fluctuation in value and possible market manipulations by big players (Wu *et al*. 2022). Cryptocurrencies' role as means of payment is more observed in some specific contexts. Their unique features are an incentive for usage in highly unstable countries, mainly with the purpose of protection against persistent purchasing power loss of local currencies (Rosales 2019; Scott 2016). Take for example the republic of El Salvador, where the government made Bitcoin legal tender (Renteria *et al*. 2021). Also, cryptocurrencies may be meaningful in countries where economic and political freedom is limited (Ahmed *et al*. 2020), allowing people to escape from authoritarian government control. The utilization of cryptocurrencies is also detected in some illegal activities where transactions are of small value, repetitive, and with the same counterparty (Foley *et al*. 2019).

From another perspective, cryptocurrencies are viewed as a milestone in the development of entrepreneurial finance as they increase their presence in crowdfunding via initial coin offerings. ICOs constitute a whole new market that allows raising capital without the need to go public, shortening the distance between fund providers and entrepreneurs on a truly global scale, making it a very convenient method for start-up companies (Bogusz *et al*. 2020; Howell *et al*. 2020; Liu *et al*. 2022). However, despite being such a good instrument to raise capital for projects at an embryonic stage, there have been some abuses, which are drawing the attention of regulators (Corbet *et al*. 2020b; Lee 2019).

The cryptomarket is considered to be still immature (Feng *et al*. 2018; Huang *et al*. 2020) and in an attempt to distinguish the factors that may influence its development, the Bank for International Settlements (2015) signals the capacity to reach a significantly higher number of transactions without losing efficiency and the financial incentives to private agents to maintain the distributed ledger scheme running as important points to affect future cryptocurrencies supply. On the demand side, security breaches, ease of use (mainly for commercial payments), processing speed, and volatility are also open issues that may deeply shape the adoption of cryptocoins.

2.3.3.4 Business ethics

A note is due on ethical issues. Although the topic of cryptocurrencies has drawn a lot of attention lately and research into many of its aspects has evolved considerably, so far very little has been dedicated to addressing its ethical significance (Dierksmeier & Seele 2018).

There is a strong concern that people involved in the launch of new coins as well as employees working at exchange platforms can easily take advantage of sensitive data either by knowing in advance market upcoming events or by tracking history and patterns of customer transactions (Rehman *et al*. 2020).

The still absent accountability in the crypto industry, confirmed by several cases of over-representation of profits, may mislead investors, presenting some cryptocurrencies as a reliable investment option when they are not (Fry 2018; Nolasco Braaten & Vaughn 2019), and contributes to amplify the risks. Money laundering, legal issues, and reputational risks further complicate matters and should be a main concern, especially for exchanges and other entities involved in the business. An additional point of contention is the lack of an ethical consensus regarding research on the anonymous web, a singular territory where the practice of illicit activities is common, and sometimes scholars resource to in their search for information (Martin & Christin 2016). As we noted in the descriptive results section, a broad spectrum of areas is involved in cryptocurrency investigation, with researchers coming from disciplines with different normative backgrounds, making it more difficult to reach an agreement.

Ethics certainly deserves more attention. The complex, sometimes obscure, characteristics observed in the cryptocurrency universe point to moral ambiguities and demand awareness and debate to lead to the construction of an ethical framework and provide more transparency to this business.

In addition, due to the high consumption of energy required by mining activities, policymakers should take steps to foster initiatives related to the UN's sustainable development goals of clean energy and climate change (Mustafa *et al*. 2022).

2.3.4 Law and regulation

Within the realm of law and regulation, a comprehensive analysis reveals a tapestry interwoven with various topics. Starting by scrutinizing the abstracts and keywords, prominent expressions emerge: internet, business, cryptomarkets, and the economic dimensions of crime and drugs. Indeed, the contentious issue of the cryptocurrency unregulated situation has engendered fervent debate among scholars, policymakers, and the media at large.

A profound implication arising from this regulatory void is the potential for illicit transactions spanning a wide spectrum of criminal activities, including drug trafficking, money laundering, and even acts of terrorism. The documents reviewed shed light on the alarming vulnerability of exchange platforms to cyberattacks. Furthermore, the cryptomarket world is rife with fraudulent activities, further underscoring the urgent need for a comprehensive regulatory framework.

2.3.4.1 Drug dealing, terrorism, and money laundering

Some estimations point to staggering figures: around a quarter of Bitcoin users are involved in illegal activities (Foley *et al*. 2019). In April 2017, it was calculated that about 46% of total Bitcoin transactions were linked to criminal operations, amounting to billions of dollars, quite similar in value to the European and American illegal drugs market. Much of this activity is developed on the dark web5. Effectively, unnoticed virtual places for illicit products, especially drugs, are growing fast, strongly supported by hard-to-track cryptocoin payments (Aldridge *et al*. 2018). The international drug traffic is nothing new, but the emergence of cryptocurrencies expanded market possibilities and many vendors are shipping illegal substances across borders to directly access retail customers, a move that tends to prosper as cryptocurrencies gain more users all over the world (Décary-Hétu *et al*. 2016). Despite their illegality, a distinctive fact about such online markets connected to the cryptocurrency world is that they are associated with fewer threats and violence than alternative drug dealing places (Barratt *et al*. 2016). Also, the use of cryptocurrencies for money laundering or terrorism funding is also a major concern (Barone & Masciandaro 2019; Nolasco Braaten & Vaughn 2019; Schaub & Phares 2020).

2.3.4.2 Regulatory framework and supervision

The possibility of unnamed transactions in the cryptocurrencies world disquiet governments, because the damage caused by associated illegal activities extends far beyond the individual level, reaching all sorts of companies and even nation states, as they undermine governance and decrease tax revenues, leading some countries to adopt the easiest solution, banning cryptocurrency business instead of regulating it (Sun Yin *et al*. 2019). Bolivia, China, Egypt, Ecuador, Indonesia, and India, to name a few, are among those that have imposed an absolute or implicit ban on cryptocurrency trading. China is

[5] The dark web is part of the World Wide Web but works with specific software, settings or authorization to access. The so-called darknets may consist of small peer-to-peer networks, as well as large and popular networks such as Tor, Freenet and I2P (Corbet *et al*. 2019b).

an emblematic example. In 2017, when the country accounted for 90% of global bitcoin trading, the government decided to shut down local crypto exchanges. In 2019 access to all domestic and foreign exchanges and ICO websites was blocked, and more recently, in May 2021, financial institutions and payment companies were banned from providing services related to cryptocurrencies initiatives (Borri & Shakhnov 2020; Shen & Siu 2021). However, other nations are heading in the opposite direction, creating a friendly but regulated environment that will help foster doing business with cryptocurrencies. That is the case of El Salvador, which in 2021 became the first nation to make bitcoin legal tender, ruling its mandatory acceptance as a means of payment all over the country (Renteria *et al*. 2021).

Although the cryptocurrency's original proposal aimed at creating a self-governing system, their anonymity architecture is an open avenue for a wide range of criminal action, posing significant risks for investors in particular, and market integrity in general (Huang *et al*. 2020). So, at the very core of the debate among scholars and policymakers stands a tricky point: does the cryptomarket have the self-ruling capability to avoid dishonest practices and preserve its integrity thus assuring the necessary conditions to be a payment and investment system free of government interference?

Spithoven (2019) argues that the cryptocurrency ecosystem does not have the necessary provisions to function in a completely independent way. Nevertheless, no official agency in Europe is responsible for regulating or supervising the issuance and negotiation of virtual currencies. As it may be seen on their web pages, some even advise that there is no legal protection to guarantee reimbursement rights for consumers using virtual currencies, and users may lose their money on trading platforms. Unequivocally, there is weak control. The current regulation for cryptoassets markets is yet incipient, next to nothing in comparison to the sound, well-established official oversight found in the equity markets (Bouri *et al*. 2019a; Hu *et al*. 2019a). On account of this, an urgent effort has to be made to implement adequate supervision and the related legislation, to bring more safety and stability to the cryptoassets business and prevent possible risk of contagion to other financial markets in the future (Li & Huang 2020).

In conclusion, it seems to be clear that regulation and supervision by trusted third parties are needed, to provide a more secure environment. In this direction, methods and techniques are proposed to incorporate effective surveillance into the system so that illegal activity can be monitored (Foley *et al*. 2019), as well as integration between blockchain and IOT (internet of things) to increase security in storing cryptocoins and to monitor transactions (Ghalwesh *et al*. 2020), and the use of supervised machine learning to predict the type of yet-unidentified entities, therefore eliminating the anonymity cover for illegal operations (Sun Yin *et al*. 2019). The current scenario shows a long road to go if we want to see a new cross-border payment system take place in a safe and sound form. The ground rule to move forward to a consistent regulatory framework is certainly full cooperation at the international level (Li & Huang 2020).

2.3.4.3 Cybercriminality

Aside from the illegal activities committed by commercial platforms on the dark web, involving the sale of numberless forbidden products in exchange for cryptocurrencies, there is another, even worse, problem: the cybercrimes, comprising wrongdoings like ransomware attacks, exchange hacks and frauds (Ghalwesh *et al*. 2020).

A cybercrime is a dishonest act launched from a computer into a network or against a specific site or data processor machine either to disable them or to gain access and manage confidential information (Caporale *et al*. 2020) and these illicit activities have been abundantly observed in the cryptomarket (Bischoping 2018; Nguyen *et al*. 2020a; van Hardeveld *et al*. 2017) with reports of massive sums of money stolen from exchanges, triggering sudden and sharp declines in cryptocurrencies price and sometimes prompting the financial intermediary to interrupt trading momentarily or even definitely (bankruptcy).

Such hacker attacks constitute exogenous shocks to the cryptoassets environment and apart from raising security concerns (Demiralay & Bayraci 2020), another detrimental effect is the additional volatility they add to an already unstable market (Caporale *et al*. 2020; Marella *et al*. 2020).

2.3.4.4 Frauds

In addition to criminal actions perpetrated by external agents as it happens in cybercrimes, sometimes the enemy is inside. A lot of fraudulent schemes against cryptocurrency consumers are carried out by those who should care most about market integrity: trading platforms and cryptocurrency issuers. Certainly, there are just a few deceitful agents in the market, but their devious commercial practices can be very harmful to investors. Among the most common methods are pump-and-dump practices, price manipulation, and the use of exaggerated, distorted, or even false information (Baur & Dimpfl 2018; Fry & Cheah 2016; Kamps & Kleinberg 2018; Katsiampa *et al*. 2019a). Furthermore, social platforms like Twitter and Telegram have been flooded with false hype about cryptocurrencies, making them the preferred vehicle for scammers to entice victims into investing, driving up the prices. Later on, the fraudsters sell their holdings at the artificially inflated prices (Mirtaheri *et al*. 2021).

The development and proliferation of illegitimate activities connected to cryptocurrency trading certainly undermine confidence and damage the business as a whole, affecting law-abiding people who are just interested in making legal profits. Such a situation calls for immediate action and poses a serious challenge to regulators.

2.4 Concluding remarks

Our contribution to the literature on cryptocurrencies stems from a systematic review covering 507 works centered on the cryptomarket. Through rigorous appraisal and analysis of existing empirical studies, we offer a comprehensive perspective on the research landscape, with a specific emphasis on scrutinizing the rationality – or lack thereof – within this market, while also pinpointing crucial gaps necessitating further investigation.

Our primary findings elucidate the inner workings of the cryptomarket, its challenges, and prospects for a sustainable development. The innovative concept of cryptocurrency, paired with its underlying technology, has the potential to revolutionize global financial operations since they do not have the common constraints featured by conventional currencies and may be traded without the intervention of financial institutions and government agencies. Their decentralized nature eliminates the need for third-party intermediaries and effectively signals an important paradigm shift.

Cryptocurrencies differ from traditional assets; they lack intrinsic value and do not represent claims on any party or government. Their acceptance and value hinge solely on public consensus, which plays a part in making cryptocurrencies a market of a diffuse and controversial nature. On top of that, results indicate an immature and predominantly inefficient market, where uncertainty persists regarding the variables driving price dynamics.

The influx of investors seeking lucrative opportunities has expanded the user base exponentially. However, unlike established stock markets, cryptocurrency exchanges are more vulnerable to cyber-attacks and insider fraud, which along with the excessive volatility and inadequate regulatory supervision exposes investors to substantial risks. Interestingly enough, despite warnings, retail investors continue to enter the market, and trade mostly based on sentiments, neglecting risks. This irrational attitude underscores the need for a deeper understanding of personal characteristics that may be influencing the decision-making regarding cryptocurrency investments.

Scholars in the field stand to gain from our study, as it offers not only a thorough mapping of existing knowledge but also provides suggestions for new avenues of research. Moreover, it holds practical implications for the finance industry stakeholders, enabling them to navigate the complexities of the cryptomarket and make informed decisions.

2.5 Future research

Cryptocurrencies are a quite recent subject and research is still in its early stages. Hence, huge possibilities for investigation lie ahead, inviting us to look for answers to the many questions that are emerging. Global instability and the occurrence of strong price movements in the cryptomarket, require further investigation of the volatility dynamics of cryptocurrencies, and their diversification role (Ji *et al*. 2019b; Lucarelli, & Borrotti 2020; Stosic *et al*. 2018). A good starting point might be the stratification of cryptocurrencies and exploring the influence their different features may have on risk levels (Antonakakis *et al*. 2019). Also, the emergence of future markets for cryptocoin trading opens up remarkable opportunities to investigate how the newly derivatives affect the efficiency of the spot market as well as implications for risk management and portfolio guidance (Aslan & Sensoy 2020; Bouri *et al*. 2019b; Geuder *et al*. 2019)

Moreover, the investors' demographics and their motives for buying have not yet been sufficiently researched (Steinmetz *et al*. 2021). Exploring whether crypto-addiction is associated with some psychological characteristics (Mills & Nower 2019) and the inclusion of control variables like age and gender when measuring the intention to use cryptocoins (Sohaib 2019) is suggested. The broad adoption of cryptocurrency by individual investors across various countries, despite widespread reports of financial losses in this market, underscores the need for further empirical investigations into investors' attitudes and the behavioral factors influencing them. Such research would benefit both retail investors and policymakers (Smales, 2022).

2.6 Limitations

One of the first limitations that can be attributed to the present study is a natural consequence of the research scope, that is, we reviewed only the literature related to cryptocurrencies in the business domain, applying specific search terms. Thus, issues such as underlying technology details (e.g. proof of work, time-stamping, hash), or sovereign currency functions, to name a few, were not addressed. Undeniably, the cryptocurrency ecosystem presents much broader possibilities for analysis, which were not the specific object of this research.

Another limitation is given by the decision to adopt a quality criterion to select the journals where academic papers are published. Although following the widely adopted practice of ranking the quality of journals based on institutional lists (Morris *et al*. 2009), we acknowledge the possibility of missing valuable information from articles published in journals whose merit and quality have not yet been ranked.

Finally, the existence of documents that are not accessible in electronic databases can also be a limitation. We tried to minimize this possibility by including all databases available at the educational institution where the research was carried out.

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Chapter 3: Are Crypto-investors overconfident? The role of risk propensity and demographics. Evidence from Brazil and Portugal [6]

Highlights

- Pioneering work examining the presence of overconfidence bias among crypto-investors, using a robust data set collected from a binational survey.
- Verifies the relations among overconfidence, risk propensity, and demographics
- Examines the influence of age and experience on investment decisions, revealing a positive relationship with overconfidence and a negative correlation with risk propensity.
- Logistic regression is used to determine the combined effect of overconfidence, risk propensity, and demographics on the decision to invest in cryptocurrencies.

Structured abstract

Purpose

The crypto market is growing quickly, marked by a lack of fundamentals, and the risks are not yet fully comprehended by participants. Our goal is to investigate overconfidence in this market and analyze the role that risk propensity and certain demographics play.

[6] This study was published by the Journal of Risk Finance on 11/22/2024. DOI: https://doi.org/10.1108/JRF-04-2024-0109.

Design/methodology/approach

We conducted a survey in Brazil and Portugal, leveraging an online questionnaire disseminated via social media channels to engage a diverse adult population. We collected a total of 826 responses, addressing ethical considerations throughout the process. The data analysis was conducted using SPSS statistical software and logit regression modeling.

Findings

Our study reveals that overconfidence is a notable bias that distinguishes individuals who invest in cryptocurrencies from those who do not. Although overconfidence and risk propensity are closely linked, they originate from distinct personal characteristics. Furthermore, our findings indicate that age and market experience positively correlate with overconfidence and negatively correlate with risk propensity. Financial knowledge, interestingly, did not prove to be a significant factor for cryptocurrency investment.

Originality/Practical Implications

Our research augments the existing literature on overconfidence, delving into this phenomenon in a new subdomain, and in doing so, enriches our comprehension of the unique and still relatively under-researched cryptomarket. Moreover, we illuminate individual factors that sway the decision to invest in cryptocurrencies and should be considered by market participants.

Keywords: Cryptocurrencies, investor behavior, bias, overconfidence, risk propensity,

demographics

JEL Classification: G11, G12, G14, G15

3.1 Introduction

Scholars have long suspected that the common assumptions of traditional finance were insufficient to explain human decisions. They proposed that financial markets consist of irrational and biased agents whose actual behavior cannot be restricted to the confines of traditional financial theory (De Bondt and Thaler, 1995; Starmer, 2020).

Subsequent research has begun to examine the micro-behavioral influences on decision-making and investigate how individuals shape their expectations and choices (Lim *et al*., 2013). Behavioral finance, which draws from various social sciences, challenges conventional models that presume investment decisions are always rational (Shiller, 2003). Unlike the classical theories that assume strict rationality, behavioral finance integrates insights from diverse disciplines to explain the biases observed in decision-making (Aguirre and Aguirre, 2023). Cognitive biases occur when human cognition consistently distorts representations of objective reality (Haselton *et al*., 2016).

One of the most common explanations for departures from rational behavior is attributed to overconfidence. This is a key issue not only in the equity markets (Costa *et al*., 2017), but also in other areas of finance and among various professional groups (Broihanne *et al*., 2014; Hilary and Hsu, 2011).

The crypto market is undergoing meteoric growth (Liu *et al*., 2022). However, it is characterized by a lack of fundamental stability and significant volatility, making it an exceptionally risky environment (Anastasiou *et al*., 2021; Ben and Xiaoqiong, 2019; Kallinterakis and Wang, 2019). Participants often do not understand the risks and tend to distort their expectations of extreme outcomes as more likely than moderate outcomes (Bouri *et al*., 2019). In this sphere, the elements that drive individual investment decisions remain unclear, leaving the crypto market a largely unexplored domain. Consequently, the existing literature presents a gap regarding behavioral factors, with overconfidence being a significant bias that needs to be explored (Almeida and Gonçalves, 2023; Shrotryia and Kalra, 2022). Investigations are required not only into the prevalence of overconfidence among retail investors but also its relationship with risk propensity, demographics, and financial knowledge. Our research aims to shed light on these aspects.

Brazil has the world's ninth-largest GDP and ranks ninth in the Global Crypto Adoption Index. Portugal, possessing the 48th largest GDP, ranks 59th among 155 countries in cryptocurrency usage. Being an economy integrated into the Eurozone, Portugal has a higher per capita income than Brazil (Chainalysis, 2023; International Monetary Fund, 2024; World Bank, 2024). Both countries share the same language, but despite certain commonalities, they exhibit cultural differences due to the influence of miscegenation, governmental policies, and immigration (Feldman-Bianco, 2001; Lesser, 2013). Scholars have already highlighted the significance of comparative studies between these two countries in various research fields (see, for instance, the works of Carvalho and Galina, 2015; Klein *et al*., 2022; Lopes *et al*., 2024). To the best of our knowledge, no studies have yet drawn a comparison between these countries regarding overconfidence. Therefore, exploring overconfidence in Brazil and Portugal, considering their specific economic and social traits, provides a unique opportunity to gain insights into its impact on financial decisions in different contexts. This exploration aids in constructing a more comprehensive understanding of investor behavior.

Overconfidence is the unjustified faith in one's intuitive reasoning, judgments, and cognitive abilities, often originating from a tendency to overestimate personal abilities (Pompian, 2006). This cognitive bias steers individuals towards making erroneous judgments, resulting in harmful behavior (Baker and Nofsinger, 2002; Schaefer *et al*., 2004).

Since behavioral finance explores the psychological influences and biases that affect investor behavior, the study of overconfidence becomes particularly pertinent. This overconfidence leads investors to overestimate their ability to outperform the market (DeBondt *et al*., 2008). Often, this results in excessive trading, which subsequently diminishes returns (Odean, 1998). It typically occurs because investors are overly confident in their own opinions, failing to appropriately consider the perspectives of others (Barber and Odean, 1999).

Equally significant is the interplay between overconfidence and risk tolerance. Often referred to as risk propensity (Gantz and Philpott, 2013), risk tolerance reflects the overall disposition towards financial risk (Hoffmann *et al*., 2015), and is positively influenced by overconfidence. The more overconfident investors are, the more willing they are to assume increased risk (Broihanne *et al*., 2014). As per the aforementioned, we have established the following:

Research question:

How does overconfidence impact individual decisions to invest in cryptocurrencies, and how does it interact with demographic traits and risk propensity?

The primary objective of this investigation is to examine overconfidence in the cryptomarket by investigating its prevalence among crypto-investors compared to non-crypto-investors. Additionally, the study aims to assess the relationship between overconfidence and risk propensity, while also exploring how demographic factors such as gender, education, income, age, number of children, investment experience, nationality, and country of residence correlate with overconfidence and risk propensity. Finally, the research seeks to identify the relevant factors for cryptocurrency investment by estimating the influence of overconfidence, risk propensity, demographic characteristics, and financial knowledge on investment decisions in cryptocurrencies.

Our study reveals that overconfidence is a crucial bias distinguishing cryptocurrency investors from non-investors, and it is significantly related to risk propensity. Additionally, we discovered that age and market experience are positively associated with overconfidence and inversely associated with risk propensity. These findings underscore the significance of psychological aspects in financial decision-making, particularly as individuals age. Moreover, we uncovered an unexpected absence of correlation between financial knowledge and cryptocurrency investment.

3.2 Literature review and hypotheses

Nakamoto (2008) unveiled in a white paper the concept of a peer-to-peer electronic cash system in an online discussion group, presenting the blueprint for a new method of making payments that is fully electronic and independent of any government.

Cryptocurrencies are coins created, stored, and traded virtually. They can be effortlessly converted into fiat money and may be incorporated into any portfolio (A. S. Hu *et al.*, 2019). Importantly, this unique digital market has undergone significant and transformative technological shifts since its inception (Grobys and Sapkota, 2020). Bitcoin was the pioneer cryptocurrency, with a host of others such as Ethereum, Tether, Cardano, and Dogecoin to name a few, subsequently emerging. These virtual coins have seen a rapid increase in their acceptance and usage (Liu *et al*., 2022).

The main determinants of cryptomarket use and investment can be categorized into several key areas. Technological factors, such as high transaction speed, low-cost international transactions, and the convenience of blockchain technology, play a crucial role (Arias-Oliva *et al*., 2019; Sobhanifard and Sadatfarizani, 2019). Social influences, including the spread of information through social media channels and internet searches, also contribute to the adoption of cryptocurrencies (Bleher and Dimpfl, 2019; Naeem *et al*., 2021; Subramaniam and Chakraborty, 2020). Regulatory environments are another major determinant; in some countries, lax regulation and the anonymity of crypto transactions attract those involved in illicit activities (Aldridge *et al*., 2018; Aldridge and Décary-Hétu, 2016). On the other hand, certain governments have imposed stricter measures, with some banning cryptocurrency businesses entirely rather than regulating them (Yin *et al*., 2019). Yet, other nations are moving in the opposite direction, creating a regulated, but friendly, environment to encourage conducting business with cryptocurrencies Notably, El Salvador became the first country to recognize Bitcoin as legal tender in 2021(Renteria *et al*., 2021). Market-specific factors, such as speculation, are also significant drivers, with traders often believing that cryptocurrency prices will continue to rise (Bouri *et al*., 2019). Additionally, the use of cryptocurrencies is influenced by factors like trade, money supply (Kristoufek, 2015) (Kristoufek, 2015), inflation rates, and economic growth, especially in unstable countries (Rosales, 2019; Scott, 2016).

However, the market is still in its infancy, evolving within a lightly-regulated environment, and it exhibits greater volatility compared to traditional currencies (Phillip *et al*., 2019). Consequently, the risks for investors remain high (Anastasiou *et al*., 2021; Ben and Xiaoqiong, 2019; Kallinterakis and Wang, 2019), particularly for smaller investors (Pop and Colonescu, 2021). In addition, many scholars have reported on the inefficiency of crypto markets (Fil and Kristoufek, 2020; Grobys *et al*., 2020; Y. Hu *et al*., 2019; Shen *et al*., 2020).

Empirical evidence has prompted some authors to hypothesize that market participants lack an understanding of the fundamental factors related to asset pricing (Nguyen *et al*., 2020). Cryptomarkets have been characterized by a significant presence of novice investors with minimal or no investment history (Fruehwirt *et al*., 2021). Notably, the general public has not heeded frequent warnings to exhibit caution (Mirtaheri *et al*., 2021), progressively investing with speculation in hopes of quick profits (Chu *et al*., 2020; Katsiampa, 2019). These small individual investors typically have limited trading skills, are often susceptible to behavioral biases (Kallinterakis and Wang, 2019), and are readily influenced by any information that attracts their attention, venturing into cryptocurrencies without understanding the associated risks (Bouri *et al*., 2019; Naeem *et al*., 2021; Subramaniam and Chakraborty, 2020).

Hence, scholars began studying cryptomarkets from a behavioral finance perspective, searching for cognitive biases. While the literature on deviations from rational investment decisions in the field of cryptocurrencies remains sparse, some academics have already identified baseless, irrational patterns. They argue that investors occasionally choose to mimic others' decisions, abandoning their own convictions (Ballis and Drakos, 2020). Furthermore, they have linked emotions to trading volume and price fluctuations (Ahn and Kim, 2021). Studies have shown that individuals flock to market performance with an unrealistic belief that prices will never fall (Bouri *et al*., 2019), indicating gambling behavior (Oksanen *et al*., 2022). Additionally, the existence of herding complicates the pricing of crypto-assets even further due to the lack of a fundamental value anchor in this market. Less informed individuals tend to act on the influences of society and fashion (Kaiser and Stöckl, 2020).

In this context, it is essential to examine the prevalence of overconfidence bias in cryptocurrency markets. Often, overconfident individuals overestimate the true value of an asset (Biais *et al*., 2005). This situation is exacerbated by the still inadequately understood concept of fundamental value in the cryptomarket due to its distinct nature (Enoksen *et al*., 2020; Gronwald, 2021).

Overconfidence often refers to an individual's excessive belief in their ability to predict market movements and select the best investment options. This cognitive bias tends to inflate one's self-evaluation of knowledge and accuracy, which often leads to flawed judgments and adverse actions (Baker and Nofsinger, 2002; Schaefer *et al*., 2004). Some scholars propose that overconfidence can partially derive from two biases. Self-attribution bias occurs when individuals attribute their successes to their abilities but blame their failures on external adversities, rather than their own insufficient skills. This perspective creates a fulfilling but deceitful sense of high competence. The other is hindsight bias, where individuals are prone to view past events as more predictable than they actually were, causing them to overinflate their ability to foresee future events (Barberis and Thaler, 2003). Other researchers contend that overconfidence may emerge from self-attribution, illusion of control, and optimism (ul Abdin *et al*., 2022).

Deviations from rational behavior in financial markets are often attributed to overconfidence, a phenomenon observed across various branches of finance and professional categories (Broihanne *et al*., 2014; Hilary and Hsu, 2011). The impact of overconfidence on financial decision-making has been extensively studied. This highlights the gap between rational economic theories and actual investor behavior, characterizing overconfidence as a fundamental cognitive bias that illustrates human limitations in information-processing abilities and the resulting irrationality (Hoffrage, 2017). A large body of literature reveals that individuals often overestimate the accuracy of their knowledge, making it one of the most influential biases for irrational decision-making in investing and trading (Debondt and Thaler, 1995; Hirshleifer, 2001).

In the realm of behavioral finance, where financial phenomena are explained using models that account for agents who are not fully rational (Barberis and Thaler, 2003), the exploration of overconfidence proves to be especially pertinent. Overconfident individuals tend to overvalue their knowledge or abilities, leading to various consequences. For instance, they may underestimate risk or overestimate their competence and ability to outperform the market (DeBondt *et al*., 2008), which leads them to trade more frequently (Deaves *et al*., 2009; Glaser and Weber, 2007; Graham *et* *al*., 2009). This excessive trading often reduces returns due to suboptimal choices (Odean, 1998). Investors with overconfidence exhibit excessive certainty about their opinions and fail to sufficiently consider others' perspectives, further compounding their errors (Barber and Odean, 1999). In addition to escalating commission costs caused by excessive trading, overconfidence also tends to lead investors to make suboptimal stock purchases (Baker and Nofsinger, 2002).

In the currency market, Oberlechner and Osler (2012) present persuasive evidence of overconfidence, with traders typically underestimating uncertainty. This is an especially striking finding because one might typically expect the opposite: FX traders, given their significant incentives for accuracy and access to a wealth of information, should theoretically demonstrate more precision. Such findings affirm that overconfidence often leads investors to make impulsive decisions, overlooking available information (García, 2013). The common belief is that repetition aids in overcoming biases, that skilled individuals commit fewer errors, and that strong incentives negate biases. However, these factors only partially mitigate biases. The practical application of learning is often hampered by errors. Expertise, rather than functioning as an advantage, can become an obstacle, with experts exhibiting more overconfidence than laypeople (Barberis and Thaler, 2003).

Overconfidence exhibits many facets and requires diverse measurement techniques. Generally, this phenomenon can be condensed into three major concepts: a) the overestimation of one's actual abilities, performance, level of control, or probability of success; b) the overplacement, which is the belief of being superior to others; and c) overprecision, embodying excessive confidence in the accuracy of one's beliefs (Benoit and Dubra, 2011; Moore and Healy, 2008; Moore and Schatz, 2017). Furthermore, some authors posit that overconfidence can also be demonstrated through the miscalibration of probabilities, better-than-average effect, illusion of control, and unrealistic (or excessive) optimism (Ackert and Deaves, 2010; Broihanne *et al.*, 2014).

In this paper, we consider and measure overconfidence based on the ‘better-than-average’ concept, widely investigated in the socio-psychological domain (Guenther and Alicke, 2010), also termed overplacement (Larrick *et al.*, 2007). Overplacement is the overvaluing of one’s abilities compared to the group and can be assessed either by directly asking participants or by contrasting a person’s perception of their performance with their actual performance in relation to others (Hirshleifer, 2015; Johnson *et al.*, 2006; Olsson, 2014).

Overplacement is especially suitable for the cryptocurrency market due to its peer-influenced nature. The crypto market is highly visible and accessible, with robust activity on social media and online forums (Poongodi *et al.*, 2021; Vilas *et al.*, 2021), where traders and potential investors frequently observe each other’s performance and strategies. This market attracts a diverse group of participants, many of whom are inspired by tales of extraordinary gains (Chiang *et al.*, 2021; Fruehwirt *et al.*, 2021). In such an environment, the belief that one can outperform others can become a significant motivator.

Based on the above, our first hypothesis to be tested is:

H_1: Overconfidence positively impacts investment in the crypto market.

Numerous studies uphold the idea that investors frequently deviate from rational behavior, underestimating stock volatility or overestimating their knowledge accuracy, thus influencing the way overconfidence is represented in financial literature (Glaser *et al*., 2004). Overconfident traders maintain under-diversified portfolios (Odean, 1998), and generally underestimate risk, resulting in riskier behavior than their unbiased peers (Michailova *et al*., 2017; Merkle 2017) delivers a thorough analysis of overconfidence through three aspects: overplacement, overestimation, and overprecision. He discovers that investors often believe their portfolios will outperform the market, anticipate higher-than-likely returns, and underestimate portfolio volatility. Moreover, the author posits that belief in less skilled or informed counterparts (overplacement) boosts an investor's perceived chance of profiting from trades. Notably, the research unveils that risk-taking within portfolios is swayed by overplacement, with investors who consider themselves above average taking more risks. In a separate context, Kraft *et al*. (2017) underline that entrepreneurial risk behavior is significantly affected by overconfidence and fully mediated by risk propensity. They additionally note that overconfident entrepreneurs engage in risky behavior owing to their lack of overconfidence awareness. Similarly, ul Abdin *et al*. (2022) prove that overconfidence, fueled by biases such as self-attribution, the illusion of control, and optimism, exerts a positive and notable effect on risk propensity.

The preceding review suggests the following hypothesis:

H_2: Overconfidence leads to a greater risk propensity

Also, research consistently shows that males tend to exhibit higher levels of overconfidence than females (Dahlbom *et al*., 2011; Niederle and Vesterlund, 2007), leading to a well-founded belief in theoretical finance that overconfidence varies by gender (Fellner and Maciejovsky, 2007). Some studies expose that these gender differences in confidence are context-dependent, with men often displaying greater overconfidence in specific areas (Lundeberg *et al*., 1994). Gender is viewed as a significant determinant in self-evaluation, with men typically scoring higher, especially in tasks perceived as masculine or gender-neutral (Beyer and Bowden, 1997). This trend is conspicuous in the financial domain, where male investors are more apt than females to rate themselves above average (Graham *et al*., 2009). Moreover, overconfidence tends to be more emphatic among men in uncertain situations, accentuating gender as a critical predictor of both overconfidence and risk propensity (Croson and Gneezy, 2009).

The relationship between other socio-demographic characteristics and overconfidence has also been investigated. Bhandari and Deaves (2006) observed that the higher the income, the greater the overconfidence. Mishra and Metilda (2015) provided evidence that overconfidence increases with education and it tends to be higher among men. Other studies have shown that as individuals age, their confidence in financial skills and capabilities remains firm, even in the face of diminishing financial proficiency. Instead of witnessing a narrowing of the overconfidence gap, research indicates that this disparity tends to widen with advancing age (Pak and Chatterjee, 2016). Regarding the influence of experience on individual behavior, one might expect experienced people to act more rationally, but studies have not conclusively shown that experience leads to more rational decision-making (Chen *et al*., 2007). Mishra and Metilda (2015) found that overconfidence increases with financial experience among mutual fund investors, a result echoed by Kirchler and Maciejovsky (2002) in an experimental asset market. Deaves *et al*. (2010) also observed that market experience heightens overconfidence among financial practitioners; however, they acknowledged that the evidence is not robust and further research is needed.

Regarding the relationship between demographics and risk propensity, it is evident that women generally have a lower tolerance for risk compared to men (Fellner and Maciejovsky, 2007). Moreover, men are more likely to perceive risky situations as challenges worth pursuing, while women are more inclined to perceive them as threats to avoid (Arch, 1993). While some suggest that women simply make smaller investments in risky assets, thus appearing more risk-averse than men (Charness and Gneezy, 2012), others hypothesize that differences in investment strategies could be due to varying levels of financial knowledge (Halko *et al*., 2012). Nonetheless, extensive work in psychology and economics documents that males are generally more inclined to make risky decisions than females (Sila *et al*., 2016). As for age, risk propensity tends to decrease over the life span according to Mata *et al*. (2016), and Barber and Odean (2001) report that older people are less likely to hold volatile stocks, while those with higher income tend to invest in riskier assets. Furthermore, Chaulk *et al*. (2003) highlight the presence of children in the family structure as a significant factor affecting financial risk tolerance. Conversely, Sung and Hanna (1996) find no difference in risk propensity among households of varying sizes. Indeed, the relationship between socio-demographic factors and risk propensity is complex, and existing research on the influence of investment experience on risk propensity shows mixed results (Buckley *et al*., 2017; Sulphey, 2020). Some scholars argue that risk propensity can change due to learning acquired from experience, while others suggest it remains stable over time. Also, the role of age is a contentious issue, as Larkin *et al*. (2013) note. Some studies suggest an association between younger individuals and higher risk tolerance, while others argue the opposite, with some even questioning the significance of age as a determinant of financial risk tolerance. However, education is widely acknowledged as a positively associated factor (Grable and Joo, 2004; Sung and Hanna, 1996).

In addition, considering the cross-national comparative aim of this study, we incorporated two more variables for analysis: nationality and country of residence. Thus, we formulated the following hypotheses:

H_{3A}: There is a gender difference concerning overconfidence

There is a significant correlation between overconfidence and

H_{3B}: Education

H_{3C}: Income

H_{3D}: Age

H_{3E}: Number of children

H_{3F}: Investment experience

H_{3G}: Nationality

H_{3H}: Country of residence

H_{4A}: There is a gender difference concerning risk propensity

There is a significant correlation between risk propensity and

H_{4B}: Education

H_{4C}: Income

H_{4D}: Age

H_{4E}: Number of children

H_{4F}: Investment experience

H_{4G}: Nationality

H_{4H}: Country of residence

Finally, considering the relationship between socio-demographic characteristics, overconfidence, and risk propensity, we established our final hypothesis. This is supported by the following key points: a) behavioral finance models commonly predict that overconfident investors take greater risks (Kim and Nofsinger, 2007); b) risk propensity is crucial in understanding the choice to engage in risky situations (Nicholson *et al*., 2005), making it a valuable indicator of individual decisions (Hung and Tangpong, 2017); c) investment in the crypto market is often perceived as a risky endeavor

(Anastasiou *et al*., 2021; Ben and Xiaoqiong, 2019; Kallinterakis and Wang, 2019); and d) financial literacy plays a vital role in establishing conditions for effective money management decisions, making it a significant influencer of investors' behavior (Abreu and Mendes, 2010).

H_5: Risk propensity, demographics, and financial knowledge are relevant factors, along with overconfidence, to invest in cryptocurrencies.

To provide a clear and comprehensive overview of all the hypotheses, we present the conceptual map below.

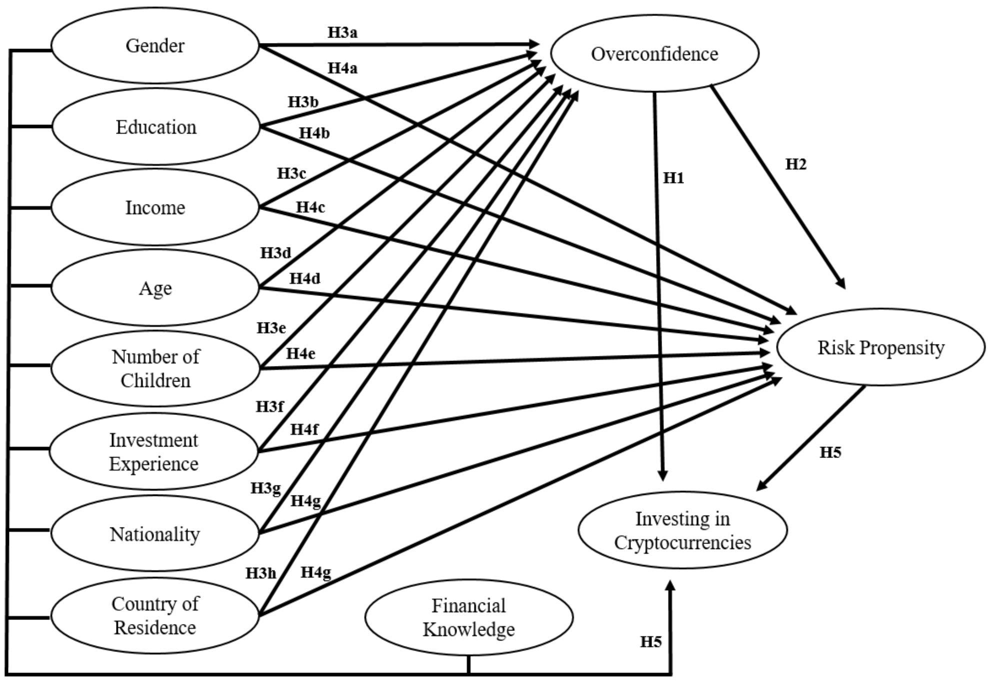

Figure 3.1 Conceptual map (Authors own work)

3.3 Methodology

We deployed an online questionnaire on the LimeSurvey platform, a tool designed for creating and publishing online surveys, gathering responses, reviewing statistics, and exporting the resultant data to other tools. The questionnaire was disseminated via social media channels and online forums related to cryptocurrencies, intending to tap into the broader adult population. Further assistance was provided by one university in Brazil and another in Portugal to publicize the survey. Internet-based surveys have become a prominent trend in research since the onset of this century (Evans and Mathur, 2005). Some of the notable advantages of this method include rapid, cost-effective data collection, enhanced data validation, elimination of transcription errors, capability to manage question skipping, and other types of input checks, all of which considerably reduce measurement errors (Fricker and Schonlau, 2002). Additionally, convenience sampling is widely used in the business sector due to its easy accessibility (Bryman and Bell, 2011). Given that investing is a topic receiving substantial media attention and is frequently discussed among the general population, with individuals likely to have established attitudes toward it (Keller and Siegrist, 2006), we targeted the general adult population, specifically those over 18 years old, in Brazil and Portugal.

As questionnaires are designed to eliminate the need for direct interaction between the researcher and respondents, we took great care in designing ours. They included clear instructions for self-completion (Lavrakas, 2004) and precise statements to stimulate responses, aiming to garner accurate information for the achievement of our research objectives (Rowley, 2014). We worked to avoid misunderstandings and ambiguity that could potentially lead to measurement errors (Alwin, 2007). Furthermore, to capture the attention of participants and promote a higher response rate, we placed the most compelling items at the beginning and left demographic questions to the end (Shaughnessy *et al.*, 2012).

We utilized closed-ended questions to gather information related to nominal demographic variables (e.g., gender, educational level). When addressing numerical data, we either employed free-format response fields (such as age) or predefined ranges as answer options (like income). The question of income level needed special attention while converting Euros (Portugal) to Reais (Brazil). To preserve a balanced equivalence of purchasing power in each country, the corresponding table for Brazil was converted, considering the equivalent value in terms of the minimum wage (1,320 Reais in Brazil and 760 Euros in Portugal, as of 2023).

To assess overconfidence, we utilized questions sourced from a toolkit developed by the Organization for Economic Cooperation and Development. This instrument is widely recognized, even by G-20 nations, and has been successfully used to gather information in more than 40 countries (OECD, 2018). It provides a comprehensive tool that goes beyond financial knowledge to capture attitudes and behaviors. For instance, one of the questions we used was, “How would you rate your overall knowledge about financial matters compared with other adults?”. We used this as a self-assessment measure for overconfidence, based on (Johnson *et al.*, 2006), who assessed overconfidence by asking participants how they ranked their own individual capabilities compared to the group. Respondents gauge their knowledge of financial markets compared to the average, using a Likert scale ranging from 1 (very low) to 7 (very high).

Each question in the instrument targets a specific aspect of financial literacy, and responses can be combined to create various analytical scores according to the OECD methodology. We utilized this information to construct a second measure of overconfidence by comparing how subjects perceive their own financial knowledge in relation to others (the self-assessment question) with their actual positioning within the group (individual score minus the average score of all financial question respondents), following Hirshleifer (2015) and Olsson (2014).

To assess risk propensity, we requested participants to self-evaluate their willingness to take risks in making investments, in line with the framework of Dohmen *et al*. (2011). Respondents were asked to specify their primary nationality, choosing between Portuguese and Brazilian. Investment experience and involvement in crypto-assets were assessed using numerical response queries, specifically, “How many years have you been investing in the financial market?” and “How many years ago did you make your first cryptocurrency transaction?”.

The questionnaire was translated and then back-translated to maintain its fidelity to the original language. It also underwent a two-stage pretesting process to fine-tune the initial outline, looking for intricacies typically only noticeable to the target population, such as specific word meanings (Reynolds *et al*., 1993). This enabled us to accumulate essential information concerning unclear or ambiguous aspects and ascertain the best sequential order for the topics.

Ethical issues were meticulously addressed from the beginning of the survey planning. Following approval by the Ethics Committee, the questionnaire was made available for 3 months on the LimeSurvey platform, from May 9th to August 7th, 2023. During this period, we obtained 826 responses. We found only five inconsistent values concerning the variable ‘age’. We then applied the MCAR test (Little, 1988), which led to the conclusion about their randomness. Consequently, we replaced these values with the sample average (Hair *et al*., 2019).

3.4 Results and Discussion

Table 3.1 provides the descriptive statistics. We received a total of 826 responses, with around one-fourth of the respondents being cryptocurrency investors. This was consistent across both countries. Official statistics on cryptocurrencies are hard to come by, particularly in Brazil where regulation is still in its initial stages (Banco Central do Brasil, 2024), which makes our findings quite insightful. For comparison, a national survey comprising over 2000 respondents in the USA conducted by Morning Consult in February 2023 indicated that 20% of Americans own cryptocurrencies (Coinbase, 2023).

Furthermore, the ages of the respondents in our survey range from 18 to 85, with a mean age of 35.85 and a median age of 32, adhering to a typical age pyramid distribution. The sample is well-balanced in terms of gender, with approximately 57% of respondents identified as men. Over half of the survey participants have attained at least a bachelor’s degree. Regarding income, the median for Portuguese residents falls into level 4 (28,001 to 35,000 Euros), whereas for those in Brazil, it corresponds to level 2 (25,001 to 37,000 Reais). These results align well with the per capita GDP figures of both countries, according to the IMF (International Monetary Fund, 2024).

Table 3.1 Descriptive statistics (Authors own work)

		N	%
AGE	18 - 30	382	46.2%
	31 - 40	166	20.1%
	41 - 50	116	14.0%
	51 - 60	84	10.2%
	> 60	78	9.4%
Gender	Male	475	57.5%
	Female	351	42.5%
Nationality	Portuguese	213	25.8%
	Brazilian	613	74.2%
Residence	Portugal	228	27.6%
	Brazil	598	72.4%
Investors in cryptocurrencies	Yes	224	27.1%
	No	602	72.9%
Investment Experience	< 2 years	330	40.0%
	2 - 4 years	154	18.6%
	> 5 years	342	41.4%

		N	%
Annual Gross Income - Brazil Residents	0 to 25.000 Reais a year	229	38.3
	25.001 to 37.000 Reais	72	12.0
	37.001 to 50.000 Reais	41	6.9
	50.001 to 62.000 Reais	35	5.9
	62.001 to 75.000 Reais	30	5.0
	above 75.000 Reais	191	31.9
	Total	598	100.0

		N	%
Annual Gross Income - Portugal Residents	0 to 14.000 Euros	32	14.0
	14.001 to 21.000 Euros	41	18.0
	21.001 to 28.000 Euros	33	14.5
	28.001 to 35.000 Euros	30	13.2
	35.001 to 42.000 Euros	26	11.4
	above 42.000 euros	66	28,9
	Total	228	100.0

		N	%
Educational Level	Primary	2	0.2%
	Lower Secondary	5	0.6%
	Upper Secondary	155	18.8%
	Professional	34	4.1%
	Bachelor's	233	28.2%
	Postgraduation or specialization	223	27.0%
	Master's	125	15.1%
	Doctorate	49	5.9%
Number of Children	0	584	70.7%
	1	107	13.0%
	2	113	13.7%
	3	15	1.8%
	4	3	0.4%
	5	4	0.5%

Overconfidence 1st measure (self-assessment 7-point Likert-type question) - Code FKSA	Mean	4.3
	Median	5.0
	Std. Deviation	1.711
	Minimum	1
	Maximum	7

		N	%
Overconfidence 2nd measure (categorical variable) - Code OVC	Underconfident	209	25.3
	Neutral	434	52.5
	Overconfident	183	22.2
	Total	826	100.0

Risk Propensity	Mean	2.7
	Median	2.0
	Std. Deviation	1.617
	Minimum	1
	Maximum	7

Total number of respondents:	826

To ascertain the presence of overconfidence in the crypto market, our initial steps followed the method of Johnson *et al*. (2006), focusing exclusively on respondents' perceptions of their financial knowledge (coded as variable FKSA). Figure 3.2 illustrates our chart analyses for crypto-investors and non-crypto-investors. The Wilcoxon signed-rank results, shown in Table 3.2, suggest that crypto-investors rate their financial knowledge (represented by a blue line) significantly above the average (depicted by a green line). In contrast, non-crypto-investors do not show this pattern. These observations are backed by p-values of <0.001 and 0.814, respectively.

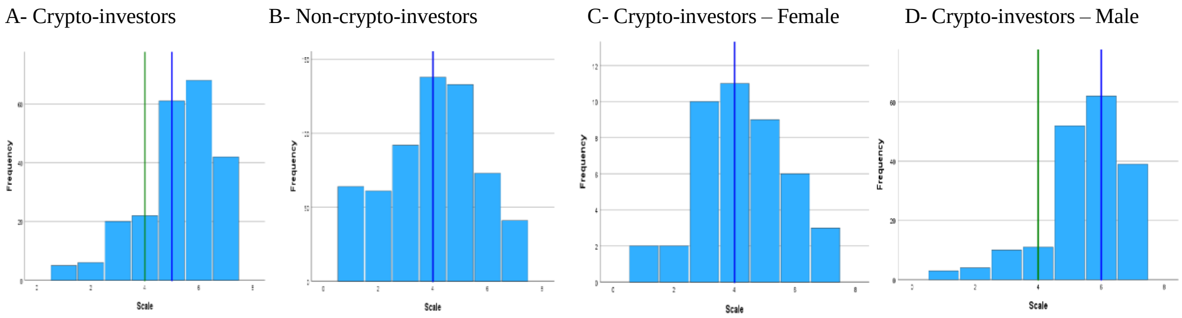

Figure 3.2 Overconfidence in Cryptomarket – FKSA measurement (Authors own work)

Table 3.2 Wilcoxon signed-ranked test results for Overconfidence - FKSA (Authors own work)

Subsamples	N	p-value	Standardized Test Statistic	Result	
Crypto-investors	224	<0.001	9.558	Reject Null Hypothesis	Predominantly overconfident
Crypto-investors - Female respondents	43	0.273	.273	Accept Null Hypothesis	No predominance
Crypto-investors - Male respondents	181	<0.001	9.673	Reject Null Hypothesis	Predominantly overconfident
Non-crypto-investors	602	0.814	-.235	Accept Null Hypothesis	No predominance

Additionally, we tested for the mean difference using Mann-Whitney's method (see Table 3.3) and confirmed H_1. Research on overconfidence has a long history, with most studies focusing on how overconfidence influences behavior within specific markets. These studies typically explore the effects of overconfidence on trading volume, market volatility, and returns (see, for example, the works of Barber and Odean, 1999; Daniel *et al*., 1998; Glaser and Weber, 2007; Odean, 1998). Our investigation sets itself apart by testing whether overconfidence is a significant factor influencing the decision to invest or not in the crypto market. The finding that cryptocurrency investors exhibit significantly higher levels of overconfidence than non-crypto-investors is a major contribution of this study. This information is valuable for government and private sector stakeholders in designing educational initiatives aimed at raising awareness among crypto-investors about the risks associated with these assets. This is in line with the growing recognition that the financial system requires updates and that cryptocurrencies play a crucial role in the evolving landscape. Some trading platforms have already committed to collaborating with policymakers to launch public campaigns addressing the challenges faced by investors in the cryptocurrency market (Coinbase, 2023).

In the entire sample, men exhibit a higher average level of overconfidence than women, which verifies the literature (Dahlbom *et al*., 2011; Niederle and Vesterlund, 2007) and our hypothesis H_{3A}. Furthermore, we also observe that, among crypto-investors, overconfidence is significantly higher in men than in women, a point illustrated in Figure 3.2 and corroborated in Table 3.3. This observation aligns with Graham *et al*. (2009), who show that male investors generally tend to perceive themselves as being above average more than their female counterparts do. A probable reason for this conduct is the perception of investing, especially in cryptocurrencies, as a masculine or gender-neutral activity where men typically register higher in self-assessments (Beyer and Bowden, 1997).

Table 3.3 Mann-Whitney test results (Authors own work)

Mann-Whitney test results for Overconfidence

<table>
<tr><th>Subsamples</th><th>N</th><th>Mean Rank</th><th>Sum of Ranks</th><th>U</th><th>Z</th><th>Asymp. Sig. (2-tailed)</th></tr>
<tr><td>Crypto-investors</td><td>224</td><td>542.14</td><td>121439.50</td><td rowspan="2">220111.500</td><td rowspan="2">-9.597</td><td rowspan="2"><0.001</td></tr>
<tr><td>Non-crypto-investors</td><td>602</td><td>365.63</td><td>220111.50</td></tr>
<tr><td>Female</td><td>351</td><td>296.33</td><td>104010.50</td><td rowspan="2">104010.500</td><td rowspan="2">-12.318</td><td rowspan="2"><0.001</td></tr>
<tr><td>Male</td><td>475</td><td>500.09</td><td>237540.50</td></tr>
<tr><td>Crypto-investors – Female</td><td>43</td><td>68.91</td><td>2963.00</td><td rowspan="2">2017.000</td><td rowspan="2">-5.052</td><td rowspan="2"><0.001</td></tr>
<tr><td>Crypto-investors – Male</td><td>181</td><td>122.86</td><td>22237.00</td></tr>
</table>

Mann-Whitney test results for Risk Propensity

<table>
<tr><th>Subsample</th><th>N</th><th>Mean Rank</th><th>Sum of Ranks</th><th>U</th><th>Z</th><th>Asymp. Sig. (2-tailed)</th></tr>
<tr><td>Crypto-investors</td><td>224</td><td>526.99</td><td>118045.00</td><td rowspan="2">42003.000</td><td rowspan="2">-8.558</td><td rowspan="2"><0.001</td></tr>
<tr><td>Non-crypto-investors</td><td>602</td><td>371.27</td><td>223506.00</td></tr>
</table>

In terms of the overall relationship between overconfidence and demographics in the complete sample, we identify a statistically significant correlation with all individual specifics (refer to the correlations table in the Appendix), barring the number of children. This confirms hypotheses H_{3B}, H_{3C}, H_{3D}, H_{3F}, H_{3G}, and H_{3H}, and refutes H_{3E}. Our observations denote a positive influence of education, income, and age on overconfidence; all three demographic factors exhibit a subsequent increase in overconfidence, which aligns with existing literature (Bhandari and Deaves, 2006; Mishra and Metilda, 2015; Pak and Chatterjee, 2016). Moreover, our study contributes significantly to the enduring debate over the impact of experience on overconfidence (Chen *et al*., 2007). It reveals that a greater investment experience – gauged by years of activity in the financial market – correlates with heightened levels of overconfidence. This concurs with the findings of Deaves *et al*. (2010), Kirchler and Maciejovsky (2002), and Mishra and Metilda (2015) in other contexts. Regarding nationality and country of residence, the results suggest a higher incidence of overconfidence on the Portuguese side in both scenarios. This could be ascribed to the distinct historical and cultural evolutions in Brazil, despite the profound influence of Portuguese colonization. The extensive miscegenation and immigration that transpired in Brazil (Feldman-Bianco, 2001; Lesser, 2013) probably instigated significant shifts in behavioral attitudes. In addition, factors specific to each region, such as local economic conditions, may also influence overconfidence. Notably, income was discovered to have a positive correlation with overconfidence, and there exists a considerable disparity in purchasing power parity between Brazil and Portugal (World Bank, 2023).

Additionally, we tested H_1 by using a second measure of overconfidence – based on the comparison of the subjects' self-assessed evaluation with their actual rank in the group (Hirshleifer, 2015; Olsson, 2014). To this end, we first calculated the difference between individual financial knowledge (the combined score of seven financial questions) and the sample average. Then, we compared it with the individual's self-assessment of his/her financial knowledge (FKSA) response, which formed the categorical variable OVC. This variable can adopt three possible categorical values: neutral, under, and overconfident.

Upon rerunning the Wilcoxon test (Table 3.4), we reaffirm that, despite a less skewed distribution, the results mirror the original measure – the group of crypto-investors is predominantly overconfident (p = 0.007). By contrast, the group of non-crypto-investors exhibits underconfidence (p = 0.004), suggesting they estimate their financial knowledge to be lower than it actually is. As previously noted, among crypto-investors, men are predominantly overconfident, while women are not. All of these observations align with and bolster our preliminary findings.

Table 3.4 Wilcoxon signed-ranked test results for Overconfidence – OVC (Authors own work)

Subsamples	N	p-value	Standardized Test Statistic	Result	
Crypto-investors	224	0.007	2.712	Reject Null Hypothesis	Predominantly overconfident
Crypto-investors - Female respondents	43	0.039	-2.065	Accept Null Hypothesis	No predominance
Crypto-investors - Male respondents	181	<0.001	4.185	Reject Null Hypothesis	Predominantly overconfident
Non-crypto-investors	602	0.004	-2.911	Reject Null Hypothesis	Predominantly underconfident

In analyzing risk propensity, we can interpret from the results demonstrated in Figure 3.3 that non-crypto-investors possess a median much lower than the midpoint.

This indicates that this group has a considerably lower appetite for risk compared to those who invest in cryptocurrencies, whose median is 4. Indeed, when the Mann-Whitney test is applied, crypto-investors reveal a significantly higher average risk propensity (Mean Rank of 526.99 versus 371.27 with a p-value < 0.001), as depicted in Table 3.3.

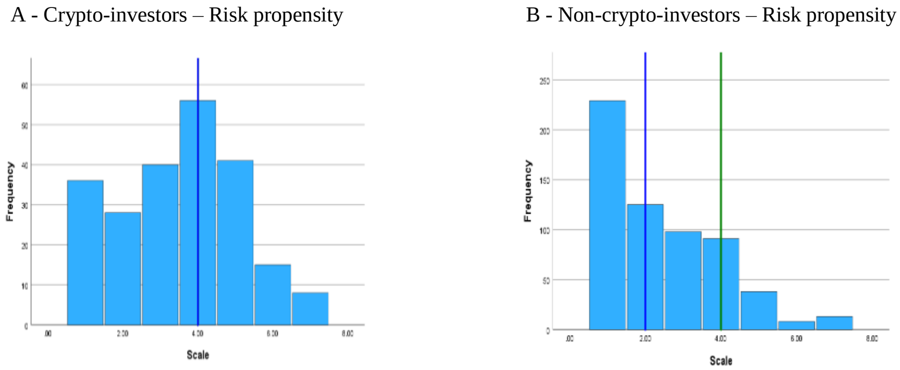

Figure 3.3 Risk propensity difference between groups (Authors own work)

Regarding the entire sample, an analysis of the correlations table provided in the Appendix reveals that risk propensity is positively linked to overconfidence (on both measures) at a 0.01 significance level. This result confirms H_2 and supports the general perception that overconfident individuals often underestimate risks (Kraft *et al.*, 2017; Merkle, 2017; Michailova *et al.*, 2017; ul Abdin *et al.*, 2022). There is also a robust relationship between risk propensity and gender, with women exhibiting a lower inclination towards risky decisions, as predicted by (Fellner and Maciejovsky, 2007), thereby confirming H_{4A}. This behavior might stem from the perception of the crypto market as a high-risk environment (Anastasiou *et al.*, 2021; Ben and Xiaoqiong, 2019; Kallinterakis and Wang, 2019; Pop and Colonescu, 2021), and from the masculine view of risky situations as challenges to overcome, while women are more likely to regard them as threats to evade (Arch, 1993).

At the 0.05 threshold, we find that risk propensity is tied to the country of residence, affirming H_{4H} and indicating that Brazilian residents tend to take fewer risks than their Portuguese counterparts. We speculate this could stem from the differing economic conditions between the two countries, such as employment rates and inflation, which are typically higher in Brazil in comparison to Portugal and may impact the propensity to take risks. In countries with stable economies, people may feel more secure and willing to take risks, whereas, in less stable environments, risk aversion might be more dominant.

No significant relationship was discovered between risk propensity and variables such as education, income, children, or nationality. Therefore, we reject hypotheses H_{4B}, H_{4C}, H_{4E}, and H_{4G}. These findings diverge from previous studies reporting positive associations between higher education and income levels and more significant financial risk tolerance (Barber and Odean, 2001; Grable and Joo, 2004; Sung and Hanna, 1996), and the influence of children in the family structure on financial risk tolerance (Chaulk *et al*., 2003). However, they align with Sung and Hanna (1996), who detected no difference in risk propensity amongst households of varying sizes when controlling for other variables. These results combined with contrasting evidence from the literature, suggest that the relationship between demographic factors and risk propensity might be influenced by additional variables. For instance, studies by Griskevicius *et al*. (2011) and Zhuang and Sun (2024) imply that environmental factors can affect risk-taking behavior. Ethnicity and conservatism have also been highlighted as differentiating risk propensity factors (Choma *et al*., 2014; Sung and Hanna, 1996).

Additionally, our findings reveal a significant relationship between risk propensity, age, and experience, supporting hypotheses H_{4D} and H_{4F}. Notably, the negative correlation coefficients suggest that as individuals mature and gain more experience, they become less inclined to take risks. These insights provide valuable nuance to the literature concerning how these factors influence risk propensity and address the mixed results reported in previous studies (Larkin *et al*., 2013; Sulphey, 2020). It seems that both specific experience (in financial markets) and general life experience (related to age) can effectively shape a propensity which, though an expression of personality traits (Keinan *et al*., 1984), appears not to be constant over time.

To finalize our analysis and gain a comprehensive understanding of the influence overconfidence has on investing in cryptocurrencies, combined with the intertwined impacts of risk propensity and demographics, we construct a logistic regression model. This model is a method used to determine the relationships of potential predictors with a dichotomous dependent variable (Kleinbaum and Klein, 2002). The logit model with multiple regressors is further explained using (Stock and Watson, 2015):

$$\Pr(Y = 1 \mid X1, X2, \ldots, X_k) = F(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k)$$

where F is the cumulative standard logistic distribution function, Y is the binary dependent variable, which in our case is to invest (value 1) or not (value 0) in cryptocurrencies, β_k are the coefficients to be estimated by the maximum likelihood method and X_k are the regressors, which we included in two blocks. The logit regression results are presented in Table 3.5.

Table 3.5 Logit regression results (Authors own work)

Block 1

Variables in the Equation

	B	Sig.	Exp(B)
Overconfidence (FKSA)	0.415	0.000	1.514
Risk Propensity	0.310	0.000	1.363
Constant	-3.830	0.000	0.022

Block 2

Variables in the Equation

	B	Sig.	Exp(B)
Overconfidence (FKSA)	0.228	0.002	1.256
Risk Propensity	0.200	0.001	1.221
Age	-0.026	0.005	0.974
Gender	-0.901	0.000	0.406
Residence	-0.435	0.078	0.647
Educational Level		p > 0.05	
Annual Gross Income		0.016	
Annual Gross Income(1)	0.389	0.219	1.476
Annual Gross Income(2)	1.329	0.001	3.777
Annual Gross Income(3)	0.183	0.649	1.200
Annual Gross Income(4)	0.483	0.243	1.622
Annual Gross Income(5)	0.200	0.528	1.221
Number of Children		p > 0.05	
Experience		0.000	
Experience(1)	1.829	0.000	6.227
Experience(2)	0.929	0.000	2.532
Financial Knowledge	0.122	0.191	1.129
Constant	-21.833	0.999	0.000

Block 1

Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Step	127.977	2	<.001
Block	127.977	2	<.001
Model	127.977	2	<.001

Block 2

Omnibus Tests of Model Coefficients

	Chi-square	df	Sig.
Step	109.302	23	0.000
Block	109.302	23	0.000
Model	237.279	25	0.000

Block 1

Hosmer and Lemeshow Test

Chi-square	df	Sig.
15.521	8	0.050

Block 2

Hosmer and Lemeshow Test

Chi-square	df	Sig.
8.321	8	0.403

Block 1

Classification Table

		Predicted		
		Crypto-investor		Percentage Correct
		NO	YES	
Cryptocurrency investors	NO	555	47	92.2
	YES	166	58	25.9
Overall Percentage				74.2

Block 2

Classification Table

		Predicted		
		Crypto-investor		Percentage Correct
		NO	YES	
Cryptocurrency investors	NO	546	56	90.7
	YES	117	107	47.8
Overall Percentage				79.1

In the first stage, we considered only the variables of risk propensity and overconfidence, determining the model's goodness-of-fit to be inadequate (Hosmer and Lemeshow, p-value = 0.050). In the second stage, we introduced demographic variables. Additionally, realizing the critical role of financial literacy in making informed financial decisions, which greatly impacts investor behavior (Abreu and Mendes, 2010), we integrated a financial knowledge variable into the regression analysis. This was calculated based on the number of correct answers to seven financial knowledge questions, covering themes such as spending power, simple interest (with two items), compounding, risk and reward, inflation, and risk diversification.

To avoid multicollinearity, we excluded the variable "nationality" and retained "country of residence". All other correlations among variables are well below the 0.8 threshold (Senaviratna and Cooray, 2019). The results in the second stage improved considerably, with the chi-square in the Omnibus test rising from 127.977 to 237.279 and the new Hosmer and Lemeshow p-value being 0.403 (Hosmer *et al.*, 2013).

Positive or negative coefficients in Column B determine the direction of the probability of the dependent event occurring (increasing or decreasing). Conversely, Column Exp (B) clarifies the predictor's influence on the odds ratio, which is the probability of the dependent event happening divided by the probability of it not happening.

The model's overall accuracy is 79.1%, with key predictors being overconfidence, market experience, risk propensity, gender, and age (p-value < 0.01). These findings align with our expectations. Investors with more experience in financial markets are generally more confident investing in the crypto market. The positive coefficient for risk propensity supports the perception of cryptocurrencies as high-risk investments (Anastasiou *et al.*, 2021; Ben and Xiaoqiong, 2019; Kallinterakis and Wang, 2019; Pop and Colonescu, 2021), indicating that the willingness to take risks strongly predicts cryptocurrency investment. This lends weight to the gender result, which reveals that men are more likely to invest in cryptocurrencies, tying back to the generally lower risk tolerance observed in women (Fellner and Maciejovsky, 2007). Moreover, the negative coefficient for age corresponds with the idea that younger individuals are more inclined to take risks. This negative coefficient might also suggest a greater familiarity with technology and the internet among younger people compared to the older generation. As for income, the first and third income levels surfaced as significant predictors, suggesting that individuals in the lower income brackets are more likely to invest in cryptocurrency.

Factors such as education, country of residence, number of children, and financial knowledge did not significantly influence individual investments in cryptocurrencies. Therefore, H_5 was only partially confirmed. The finding that these factors do not play a distinctive role in determining cryptocurrency investment suggests that the appeal of the crypto market spans various segments, attracting individuals from a wide array of backgrounds. More importantly, the absence of a connection between financial knowledge and investment in cryptocurrencies is an unexpected and significant finding. This serves as a critical warning for policymakers, emphasizing the need for educational campaigns to raise awareness about the risks associated with the crypto market, especially for those lacking in-depth financial knowledge.

3.5 Conclusions

This study reveals that overconfidence is a predominant trait among crypto-investors, setting them apart from those who do not invest in such assets. Additionally, it strongly correlates with risk propensity, corroborating past studies. Despite the moderate risk appetite exhibited by subjects across the sample, crypto-investors show a significantly higher inclination towards risky choices compared to the non-investing group. Moreover, overconfidence is significantly associated with all demographic variables tested, excluding the number of children. On the other hand, risk propensity does not display notable links with nationality, education, income, or number of children. This indicates that while these two traits are closely related, their origins lie in different individual specifics. We also contribute to the ongoing discussion regarding the influence of age and experience on investment decisions by demonstrating a positive correlation with overconfidence and a negative correlation with risk propensity. This raises important questions about the psychological factors influencing financial decision-making in the context of aging. It proposes a complex interplay between an individual's self-assessment of financial competence and the increasing need for financial security with age. This leads to the plausible explanation that throughout their lives, individuals gain experience, and foster overconfidence in their financial skills, but also develop a heightened awareness to create a more conservative portfolio that will not jeopardize their lifetime savings when necessary.

Secondly, our model delineates the pertinent factors that influence the decision to invest in cryptocurrencies. These factors encompass the positive impact of overconfidence and risk propensity, and the role of select demographics - specifically gender, age, income, and experience in the financial market. Some scholars have postulated that variances in investment strategies between genders could stem from differing financial knowledge. However, this variable was also incorporated into the regression model and proved statistically insignificant. This suggests that the gender disparity likely stems predominantly from the inherent ways in which men and women approach risky situations.

In conclusion, this study successfully addressed its research question and objectives, highlighting the significant impact of overconfidence on investment decisions within the cryptocurrency market, and its association with risk propensity and demographics. The analysis revealed a positive correlation between overconfidence and risk propensity. From a demographic perspective, overconfidence was significantly associated with all tested variables, except for the number of children; whereas risk propensity displayed no significant connection with nationality, education, income, or number of children. Of note, age and market experience were positively linked with overconfidence, but negatively associated with risk propensity, underscoring the intricate interplay among these factors in investment behavior. Gender, age, income, and experience emerged as pivotal determinants of investing in cryptocurrencies, together with overconfidence and risk propensity. Intriguingly, financial knowledge did not prove to be a significant factor in cryptocurrency investment, indicating that some individuals engage in this market without sufficient preparation or complete understanding of the associated risks.

3.6 Theoretical contributions and implications for practice

This paper offers insightful perspectives on risk management within the crypto market. Through the examination of overconfidence, risk propensity, and individual factors, we contribute to a more profound comprehension of this unique and under-researched market. Our findings augment the behavioral finance literature, assisting in refining models and expanding their applicability across various market contexts. Furthermore, by providing empirical data from Brazil and Portugal, we present a comparative perspective that facilitates understanding this global phenomenon. These insights can aid researchers in constructing a more comprehensive image of financial behaviors globally.

Given that cryptocurrencies are intangible, lack intrinsic value, and are not backed by any entity, their worth is entirely dependent on public perception. This emphasizes the role of overconfidence in the crypto market and underscores the importance of targeted interventions. Information provided by this study is crucial for both governments and private sector stakeholders when designing education initiatives to increase awareness about the risks encrypted with cryptocurrencies. As cryptocurrencies are playing an increasingly important role in the evolving financial landscape, immediate action is necessary to ensure systemic safety and stability. Our observations support the creation of public policies, which include informational programs that target the general public and augmented regulation to motivate trading platforms to favor investor protection over profit. An unanticipated lack of correlation between financial knowledge and investment in cryptocurrencies reinforces the necessity for policymakers to concentrate on educational campaigns about crypto market risks, especially for those with limited financial literacy.

For retail investors, it is crucial to be aware of factors such as overconfidence and risk propensity to make improved financial decisions. These elements should be managed by meticulous planning of investment strategies and through the establishment of sound trading rules. Furthermore, this paper encourages investors to recognize the impact of overconfidence and to base financial decisions on actual abilities and experience, rather than on emotions. While self-confidence is necessary for everyday functioning, excessive confidence tends to backfire, leading to risky decisions that a more rational appraisal would otherwise reject (Russo and Shoemaker, 1992). To tackle this issue, methods such as informing people about their tendency to perceive themselves as better-than-average, paired with lessons on investor psychology, have been tested in field experiments. These micro-level actions have been proven effective in reducing decisions driven by overconfidence (Kaustia and Perttula, 2012).

3.7 Limitations and future research

A limitation arising from this study pertains to the number of countries where the survey was conducted. A valuable recommendation for future research would be to broaden the geographical scope.

Overconfidence encompasses various facets, and in our exploration, we focused on one of them, known as overplacement, using two distinct measures to assess its prevalence among crypto-investors. Notably, only a small number of studies have investigated two or more aspects simultaneously (Olsson, 2014), indicating this as an area for consideration in future research endeavors.

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Appendix 3.1

Overconfidence - Correlations Table

		Crypto investors	Gender	Nationality	Residence	Educational Level	Annual Gross Income	Age	Number of Children	Investment Experience
Overconfidence - FKSA	Pearson Correlation	-.322**	-.418**	-.139**	-.185**	.187**	.251**	.117**	.035	.393**
	Sig. (2 tailed)	0.000	0.000	0.000	0.000	0.000	0.000	<0.001	0.320	<0.001
	N	826	826	826	826	826	826	826	826	826

**. Correlation is significant at the 0.01 level (2-tailed).

Risk Propensity - Correlations Table

		Crypto investors	FKSA	OVC	Gender	Nationality	Residence	Educational Level	Annual Gross Income	Age	Number of Children	Investment Experience
Risk Propensity	Pearson Correlation	-.297**	.324**	.163**	-.302**	-0.029	-.069*	-0.045	0.049	-.108**	0.007	-.200**
	Sig. (2 tailed)	0.000	0.000	0.000	0.000	0.403	0.048	0.192	0.163	0.002	0.832	<0.001
	N	826	826	826	826	826	826	826	826	826	826	826

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Chapter 4: Personality, risk propensity and cryptocurrencies: understanding investor behavior in the digital asset market [7]

Abstract

This study examines how personality traits influence individuals' intentions to invest in cryptocurrencies, addressing a gap in the financial decision-making literature regarding the factors that drive cryptocurrency investments. Using survey data analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM), the findings reveal that agreeableness, conscientiousness, and neuroticism negatively impact investment intentions, while higher risk propensity increases the likelihood of investment and mediates the link between conscientiousness and attitudes toward cryptocurrencies. By exploring the interplay between personal characteristics and risk propensity, the research offers novel insights into behavioral factors shaping investment decisions in the context of emerging financial instruments like cryptocurrencies.

Keywords: Cryptocurrencies, investor behavior, risk propensity, personality traits, five-factor model

4.1 Introduction

Technological advances have made electronic financial transactions widely accessible, enabling payments, transfers, and investments via smartphones and digital

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[7] This study was submitted to the journal Review of Behavioral Finance, on March 2nd, 2025.

wallets (Luther, 2016). In this context, cryptocurrencies emerged, led by Bitcoin (Nakamoto, 2008), as a peer-to-peer version of electronic cash. Since then, thousands of cryptocurrencies have been developed, attracting increasing attention from investors, media, and academia (Arias-Oliva *et al.*, 2019; Cross *et al.*, 2021). Their 24/7 trading across borders (Bariviera *et al.*, 2018) and perceived potential for easy gains (Chu *et al.*, 2020) have drawn significant interest of potential investors.

However, the cryptocurrency market has been marked by high volatility (Kallinterakis & Wang, 2019). Despite rapid growth (Liu *et al.*, 2022), this market remains immature (Bouri *et al.*, 2019), with limited regulation compared to traditional financial systems (Hu *et al.*, 2019), posing risks to investors and financial stability, with banks maintaining cautious exposure to crypto-assets (Basel Committee, 2019).

Moreover, both the fact that the anonymity of cryptocurrency trading facilitates illicit activities (Huang *et al.*, 2020), and the recent examples of the collapse of high-profile exchanges, like TerraUSD and FTX (Chow, 2022; Shen, 2022), underscore the risks posed by fraud and mismanagement in this loosely regulated environment. Additionally, fraudulent schemes, often involving social media hype, may artificially inflate prices (Mirtaheri *et al.*, 2021). In this complex environment retail investors are frequently influenced by sentiment and attention-grabbing factors (Kallinterakis & Wang, 2019; Subramaniam & Chakraborty, 2020) and show similarity with gamblers (Delfabbro *et al.*, 2021).

The motivations for investing in cryptocurrencies, beyond the appeal of quick profits, remain underexplored, with important gaps to be investigated in the domain of investor behavior (Burggraf *et al.*, 2020; Shrotryia & Kalra, 2022; Smales, 2022). Personality is known to influence financial decisions (Furnham & Boo, 2011), with certain traits linked to risk-taking behavior (Meertens & Lion, 2008). However, limited research has explored the impact of personality on investment intentions (Lai, 2019). Gupta *et al.* (2021) highlights the gap in the extant literature on the factors driving investments in cryptocurrencies arguing that this exploration is crucial for understanding their adoption in society. Similarly, Oehler *et al.* (2018) emphasize the importance of integrating personality traits of market participants to enrich our knowledge on financial markets.

This study addresses the abovementioned gap in the literature by examining the relationship between personal characteristics and attitudes toward cryptocurrencies. The objectives are to i) empirically verify the link between personality traits and cryptocurrency investment intentions, and ii) analyze the role of risk propensity within this link. Our findings reveal that agreeableness and neuroticism are negatively associated with cryptocurrency investment intentions. While the other traits show no direct effect, conscientiousness emerges as significant when considering indirect effects. We also observe that conscientiousness, agreeableness, and neuroticism negatively impact risk propensity, while openness and extraversion show no such association. Older individuals, women, and those with higher education are less likely to invest in cryptocurrencies. A strong link between risk propensity and cryptocurrency attitudes was also found.

The paper is organized as follows: Section 2 reviews the literature on investment attitudes, decision theory, risk propensity, and personality; Section 3 outlines the conceptual framework and hypotheses; Section 4 details material and methods, including data collection, questionnaire design, and measures; Section 5 presents the results of the measurement and structural models; Section 6 and 7 discuss the findings, contributions, limitations, and suggestions for future research.

4.2 Literature review

Research on investment intentions is often grounded in a theoretical framework that presumes investors are rational and seek to maximize returns given a defined level of risk aversion within a particular domain (Pennings & Smidts, 2000). Investing involves choice-making – or in other words, decision-making – and classical decision theory was developed to evaluate options and identify optimal choices, serving as a normative model (Edwards, 1996). Central to this approach is the concept of utility, which functions as a single measure of decision optimality (Savage, 1954; Von Neumann & Morgenstern, 1953).

The assumption that investors are rational and seek to optimize returns relative to risk is in the base of classical finance theory, guided the initial investigations into individual investment intentions, and have been frequently applied by asset managers to structure investment portfolios (Jain *et al.*, 2023; Lim *et al.*, 2013). Seminal works in this field are the portfolio selection model (Markowitz, 1952) and the efficient market hypothesis - EMH (Fama, 1970). The former explores a fundamental principle guiding investing: the preference for expected return over variance of return. Central to the analysis is the assumption that investors can, and should, assess the likelihood of different outcomes and act consistently with their estimations. The latter builds upon a market where prices serve as reliable indicators for resource allocation. In an ideal scenario, investors operate rationally, assuming that security prices accurately reflect all available information, a state referred to as market efficiency.

However, while widely accepted, the EMH has struggled to account for certain market anomalies, with individual investors causing stock returns to deviate from fundamental values, challenging its rational assumptions (Sharma & Kumar, 2019). It is worth noting the seminal work of Kahneman and Tversky (1979), who identified cognitive biases such as risk-seeking behavior in the face of certain losses (the certainty effect) and the tendency to ignore shared information across options (the isolation effect), leading to inconsistent preferences. Their alternative framework, prospect theory, suggests that individuals value gains and losses rather than final assets, using decision weights in place of probabilities—often overestimating low probabilities, which heightens the appeal of gambling. More descriptive approaches then emerged, based on empirical analyses carried out through experiments or questionnaires (see, for example, the works of Durand *et al.*, 2013; Nicholson *et al.*, 2005). Effectively, human judgment is limited by emotional and cognitive factors (Straub & Welpe, 2014) and psychological characteristics shape investor behavior (Hans *et al.*, 2024).

Recent empirical works shed light on the behavioral dynamics within cryptocurrency markets, revealing notable trends that underscore the influence of psychological aspects on market movements. Abnormal price oscillations can be attributed, to some degree, to overreactions to news events (Nguyen *et al.*, 2020). This is particularly pronounced in the cryptocurrency sphere due to the significant presence of inexperienced investors, suggesting heightened susceptibility to irrational behavior compared to traditional asset markets (Fruehwirt *et al.*, 2021). These retail investors tend to be heavily influenced by sentiments expressed through social media platforms (Naeem *et al.*, 2021). Similarly, collective optimism among investors exerts a strong influence on cryptocurrency trading activities (Rehman *et al.*, 2020). Moreover, individuals often fail to consider the unique features of cryptocurrencies and instead engage in herding behavior, driven by an unrealistic belief that prices will continue to rise unabated (Bouri *et al.*, 2019), and leading to impulsive investments in crypto-assets, based purely on social trends and fads (Kaiser & Stöckl, 2020), and resembling, in certain cases, to a gambling behavior (Oksanen *et al.*, 2022).

An examination of evidence related to conventional theory indicates that it is far from providing a comprehensive framework to understand individual investment choices, with many researchers focusing beyond the expected utility assumption (Starmer, 2020). This expanding literature integrates psychological elements intrinsic to financial decisions, providing a more accurate reflection of reality (García, 2013) with research focused on elucidating individual-level behaviors, investigating how psychological aspects influence decision-making processes (Lim *et al.*, 2013).

Although the classic model of decision under risk assumes that individuals are generally risk averse (Glaser *et al.*, 2004), inconsistent attitudes toward risk are long standing, as observed by Fisher & Statman (1997): individuals who are risk averse buy insurance, but paradoxically purchase lottery tickets exhibiting risk-seeking behavior; and similarly, frequenters of casinos often take more risks with money won while gambling than with their own money, illustrating a distorted cognitive perception between funds that are fundamentally equal.

Economics and psychology have devoted substantial efforts to examining attitudes toward risk, and the capacity for rational decision-making (Heckman *et al.*, 2021), with risk propensity being considered a powerful explanatory variable of how individuals make decisions in risky situations (Hung & Tangpong, 2017). Research has indicated that individuals vary in their risk propensity (Farmer, 1993; MacCrimmon & Wehrung, 1990; Stewart & Roth, 2001).

Furthermore, reasons for the observed deviations that individuals exhibit in relation to the logical way they should act have been attributed to their personal traits. Personality has been identified as an important explaining variable for differences in cognitive processing when making judgments (Furnham & Boo, 2011), and risk propensity is considered a personal characteristic linked to personality (Filbeck *et al.*, 2005; Kowert, P. A. & Hermann, 1997).

Moreover, personality influences beliefs which can ultimately be conducive to certain kinds of biases (Ramos, 2019), perceived in situations where human cognition engenders representations systematically distorted compared to some aspect of objective reality (Haselton *et al.*, 2016). According to Cloninger (2009), the study of personality encompasses two approaches: idiographic and nomothetic. The idiographic viewpoint delves into individual details, akin to a scientific biography, emphasizing personal history. Conversely, the nomothetic approach focuses on groups of people, highlighting comparisons among individuals, being useful for practical decisions. Exemplified by models like the Five-Factor Model (Benet-Martínez & John, 1998), such research employs quantitative measures to study individual differences and make comparative analysis, providing evidence for the generality of concepts. The five-factor model (FFM) is the most widely accepted framework for understanding personality traits (Lo, 2005) and, as such, we have adopted it for this study.

The theoretical relationship between personality and investment behavior has been the focus of an expanding body of literature (Durand *et al.*, 2008), with studies on personality differences among individuals employing different psychometric scales to assess the connection between specific personality traits and financial behavior across different domains (Lo *et al.*, 2005). For instance, Pompian and Longo (2004) utilized the Myers-Briggs type indicator (MBTI), and Lather *et al.* (2020) employed Cattell's sixteen personality factors and some demographic questions to demonstrate that personality traits are related to some cognitive biases exhibited by investors. Similarly, Hunter & Kemp (2004) used two subscales from Costa & McCrae's (1998) personality inventory to show that e-commerce investors are more open to experience, influencing risk preferences and, consequently, investment decisions. However, consensus on personality traits tends toward the five-factor model (Judge, 2002).

The FFM conceptualizes personality as a constellation of distinct traits and characteristics, delineated across five principal domains: extraversion (or surgency); agreeableness; conscientiousness (or dependability); neuroticism (vs. emotional stability); and openness to experience, intellect, or culture (Goldberg, 1992). This largely acclaimed framework is extensively utilized in personality research, offering a comprehensive understanding of individual differences (Jain *et al.*, 2023). Furthermore, a number of studies have provided empirical evidence on the association among these personality dimensions, risk propensity, and investment decision-making, as an early research by Durand *et al.* (2008) demonstrates. Their investigation with a small sample of investors uncovers a positive connection between neuroticism and trade frequency, while extraverted individuals exhibit the inverse. Also, drawing upon individual-level data from the British Household Survey, Brown and Taylor (2014) observed that some particular personality dimensions wield considerable influence over household financial decisions, impacting levels of unsecured debt and financial assets held.

4.3 Conceptual framework and hypotheses development

This research develops a theoretical framework relating the FFM to risk propensity and attitudes toward cryptocurrencies, while controlling for age, gender, education, and income. Existing studies suggest a link between these traits and attitudes toward cryptocurrencies (Luo *et al.*, 2024). Risk propensity, often used interchangeably with terms like risk preference, risk tolerance, and risk taking, is regarded as a personal trait linked to personality (Filbeck *et al.*, 2005; Frey *et al.*, 2017; Kowert, P. A. & Hermann, 1997; Weber *et al.*, 2002). Some research points out that risk propensity is context-dependent (MacCrimmon & Wehrung, 1990; Slovic, 1972). For instance, an individual willing to take financial risks may avoid physically risky recreational activities, while someone comfortable with business risks may display caution in personal matters (MacCrimmon & Wehrung, 1985). In this study, we focus on analyzing individual risk attitudes specifically within the domain of personal finance.

Extant research presents mixed findings on the relationship between openness to experience and investment intention in general, with some studies finding positive correlations (Sarwar *et al.*, 2020; Tauni *et al.*, 2017), while others show no connection (Durand *et al.*, 2008; Jain *et al.*, 2023). Regarding risk propensity, although Durand *et al.*

(2008) and Nga and Ken Yien (2013) did not find a relationship, openness to experience is often linked to higher risk-taking (Becker *et al.*, 2012; Nicholson *et al.*, 2005). Therefore, in the context of investment in cryptocurrencies, we hypothesize:

H1a: Openness to experience is positively related to attitude toward cryptocurrencies.

H1b: Openness to experience is positively related to risk propensity.

While some studies have found no relationship between conscientiousness and stock trading frequency (Tauni *et al.*, 2017), the amount of unsecured debt and financial assets held (Brown & Taylor, 2014), or general investment intention (Jain *et al.*, 2023), the work of Sarwar *et al.* (2020) reported a positive association between conscientiousness and investments in secure assets. Additionally, although Brown and Taylor (2014) and Durand *et al.* (2008) find no connection, a substantial number of studies (Aren & Hamamci, 2020; Becker *et al.*, 2012; Nga & Yien, 2013; Nicholson *et al.*, 2005) report a negative relationship between conscientiousness and risk propensity. Adjusting to cryptocurrencies, we hypothesize:

H2a: Conscientiousness is positively related to attitude toward cryptocurrencies.

H2b: Conscientiousness is negatively related to to risk propensity.

Extraversion is positively associated with investment intentions in stock markets (Jain *et al.*, 2023), cryptocurrencies (Luo *et al.*, 2024) and frequent trading (Tauni *et al.*, 2017). However, no relationship was found with risky investment intention (Aren & Hamamci, 2020) or the holding of risky assets (Brown & Taylor, 2014; Oehler *et al.*, 2018). In contrast, Durand *et al.* (2008) finds a positive correlation with the exposure to stocks by individual investors, and Nicholson *et al.* (2005) show that higher extraversion correlates with greater risk propensity. Thus, we hypothesize:

H3a: Extraversion is positively related to attitude toward cryptocurrencies.

H3b: Extraversion is positively related to risk propensity.

Some studies found no relationship between agreeableness and general investment intention (Jain *et al.*, 2023) or risky investment attitude (Aren & Hamamci, 2020). Nevertheless, Sarwar *et al.* (2020) identified a positive connection with investment intentions in secure assets, and Tauni *et al.* (2017) linked agreeableness to higher trading frequency. On the other hand, other authors (Durand *et al.*, 2008; Aren & Hamamci, 2020; Becker *et al.*, 2012; Nicholson *et al.*, 2005) found a negative relationship between agreeableness and risk propensity. Hence, again extrapolating to cryptocurrencies, our hypotheses are:

H4a: Agreeableness is positively related to attitude toward cryptocurrencies.

H4b: Agreeableness is negatively related to risk propensity.

Jain *et al.* (2023) and Sarwar *et al.* (2020) observed that neuroticism negatively correlates with investment intentions, a result also echoed by Aren & Hamamci (2020) regarding risky investment intention, not excluding investment in cryptocurrencies intention. Moreover, several studies (Aren & Hamamci, 2020; Becker *et al.*, 2012; Nicholson *et al.*, 2005; Oehler *et al.*, 2018) associate negatively neuroticism and risk propensity, thus supporting:

H5a: Neuroticism is negatively related to attitude toward cryptocurrencies.

H5b: Neuroticism is negatively related to risk propensity.

Moreover, given the high volatility of the cryptocurrency market (Kallinterakis & Wang, 2019), their vulnerable trading platforms (Chow, 2022; Shen, 2022) and fraud currently identified (Mirtaheri *et al.*, 2021), we hypothesize:

H6: Risk propensity is positively related to attitude toward cryptocurrencies.

Finally, demographic factors like age, gender, income, and education also shape financial risk-taking behavior (Grable, 2000), and are included as control variables in our analysis. The conceptual model for this study is presented in Figure 4.1.

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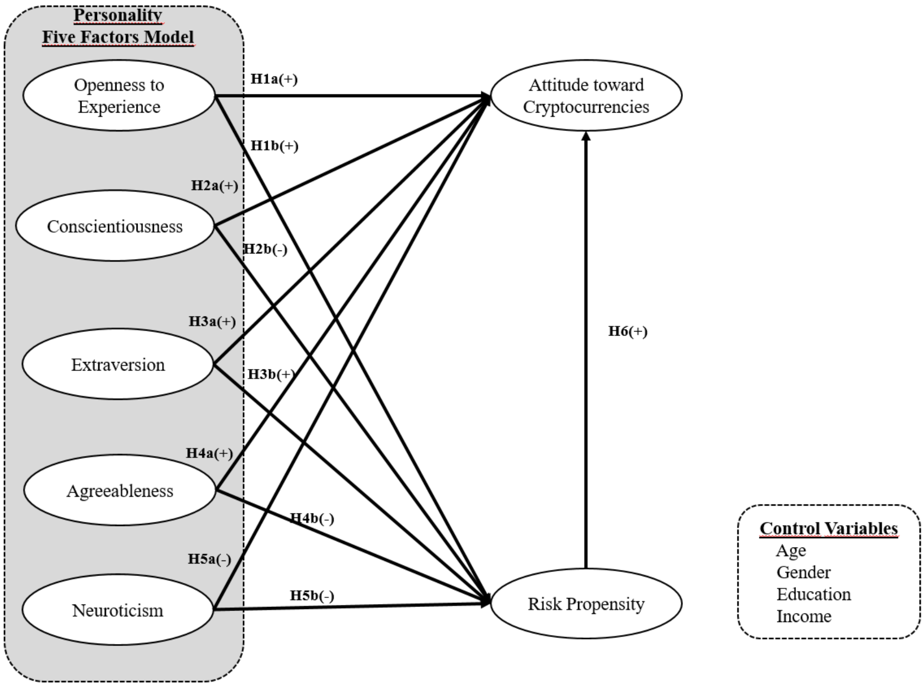

Figure 4.1 Conceptual model

4.4 Materials and methods

4.4.1 Data Collection

This study employed a survey method using an online questionnaire distributed via social networks and cryptocurrency-related groups on Facebook, Instagram, and LinkedIn. Convenience sampling was used for accessibility (Bryman & Bell, 2011). The survey targeted adults aged 18 and older, capitalizing on the broad public discourse surrounding investment practices (Keller & Siegrist, 2006). The survey was available from May 1st to August 31st, 2023, via LimeSurvey, yielding 826 responses.

4.4.2 Questionnaire Design

Emphasis was given on concise and clear statements to minimize misinterpretation and measurement errors (Alwin, 2007; Rowley, 2014). Demographic questions were placed last to maintain engagement (Shaughnessy *et al.*, 2012). Closed-ended questions captured nominal data like gender, while for numerical variables such as age and income use used free-response or pre-defined ranges.

The survey, initially in English, was translated into Portuguese and back-translated to ensure consistency (Chapman & Carter, 1979). A pretest (Reynolds *et al.*, 1993) involving 24 participants refined the questionnaire. Ethical guidelines were strictly followed – including informed consent – ensuring anonymity, confidentiality, and compliance with research standards (Aldridge & Levine, 2001; Bryman & Bell, 2011). The research was approved by the University's Ethics Committee, under the number 04/2023.

4.4.3 Measures

We considered the need for a questionnaire not excessively lengthy, as overly long surveys can lead to respondent fatigue and boredom (Burisch, 1984) and discourage the completion of the questionnaire. To measure *personality traits,* we applied the Big Five Inventory (Benet-Martínez & John, 1998; John & Srivastava, 1999), but some of the items were dropped on the purification process. *Risk propensity* was measured using the financial subscale the DOSPERT - Domain-Specific Risk-Attitude Scale (Weber *et al.*, 2002), namely a Portuguese version (Vieira, 2016). *Attitude toward cryptocurrencies*, the dependent variable, was assessed with four self-assessment questions based on Aydemir & Aren (2017) and Dodds *et al.* (1991). Control variables were directly measured.

4.4.4 Non-response and common-method bias

In an open-ended survey, nonresponse bias is not a concern. Nevertheless, following Armstrong & Overton (1977) we found no significant differences between early respondents (first three months) and late respondents (last month).

Yet, common-method bias (CMB) can occur when the same method is used for multiple measurements (Burton-Jones, 2009). The most effective way to address this bias is during the research design phase (Montabon *et al.*, 2018). Following established guidelines (Podsakoff *et al.*, 2003; Podsakoff *et al*., 2024), we implemented several measures to reduce the risk of CMB. For example, we assured respondents of anonymity and confidentiality, informed them there were no right or wrong answers, and designed the survey to prevent access to the theoretical model. Besides these precautions, we conducted Harman's one-factor test (Malhotra *et al.*, 2006). If CMB were present, a single factor would emerge (Podsakoff & Organ, 1986). Our analysis identified nine components, explaining 64.8% of the variance, with the first factor accounting for just 13.1%. We also tested for CMB by using the marker variable test (Lindell & Whitney, 2001). We computed the matrix correlation of this variable with all the other variables in the conceptual model, which shows an average of 0.088. Taking the second smallest correlation ($r_M = -0.018$), a CMB-adjusted correlation matrix was calculated. The comparison between the original and adjusted matrices exhibited no significant differences ($\Delta r = -0.017$), maintaining the significance levels of the existing correlations. Hence, CMB was not a concern.

4.5 Results

The descriptive statistics of the survey results are presented in Table 4.1, based on a total of 826 responses, collected in Brazil and Portugal. Participants' ages range from 18 to a maximum of 85, with a mean age of 35.85 and a median age of 32, and the distribution follows a classical pyramid format. Gender distribution within the sample is balanced, with approximately 57% of respondents identifying as men. In terms of education levels, the majority of participants (approximately 78%) fall within the upper secondary to postgraduation of specialization courses education range. Only a small fraction (0.8%) of respondents have completed primary or lower secondary education. Conversely, a significant proportion (21%) of respondents have attained levels of high education, such as master's or doctorate degrees.

Table 4.1 Descriptive statistics

		N	%
Age	18 - 25	297	36.0
	26 - 30	85	10.3
	31 - 40	166	20.1
	41 - 50	116	14.0
	51 - 60	84	10.2
	> 60	78	9.4

		N	%
Annual Gross Income	0 to 14.000 Euros	261	32%
	14.001 to 21.000 Euros	113	14%
	21.001 to 28.000 Euros	74	9%
	28.001 to 35.000 Euros	65	8%
	35.001 to 42.000 Euros	56	7%
	above 42.000 euros	257	31%
	Total	826	100%

		N	%
Educational Level	Primary	2	0.2%
	Lower Secondary	5	0.6%
	Upper Secondary	155	18.8%
	Professional	34	4.1%
	Bachelor's	233	28.2%
	Postgraduation or specialization	223	27.0%
	Master's	125	15.1%
	Doctorate	49	5.9%

Gender	Male	475	57.5%
	Female	351	42.5%
Total number of respondents		826	

This study employs partial least squares structural equation modeling (PLS-SEM) using SmartPLS version 4. SEM is a robust, widely used multivariate technique in empirical research, particularly for validating instruments and analyzing relationships between constructs (Fornell & Larcker, 1981). It is well-suited for examining constructs such as attitude while allowing flexibility in equation specification (Monecke & Leisch, 2012).

PLS-SEM is a non-parametric tool designed to maximize variance explained by latent constructs, like risk tolerance, and is particularly useful in behavioral finance research (Avkiran & Ringle, 2018). It operates through two components: the measurement model and the structural model (Hair *et al.*, 2019). Measurement model connects observed variables to latent constructs, while the structural model captures relationships between constructs, providing insights into underlying mechanisms.

4.5.1 Measurement model

We initially analyzed the items used to measure latent variables, discarding those with low loadings to enhance reliability. The overall measurement model was then evaluated for item reliability, composite reliability, and average variance extracted (AVE) for each latent variable (Bagozzi & Yi, 1988). As suggested by Hair *et al.* (2017), items below 0.60 were excluded, ensuring convergent validity (Table 4.2).

As Cronbach's alpha tends to underestimate reliability, composite reliability is a more suitable measure, where values between 0.70 and 0.90 are ideal (Hair *et al.*, 2017). The results indicate that all variables are in the recommended range. AVE values for all the variables also surpassed the 0.50 threshold (Fornell & Larcker, 1981) (Table 2).

Table 4.2 Measurement scales

Scale items	Standardized loadings
ATTITUDE TOWARD CRYPTOCURRENCIES (α = 0.87; CR = 0.88 ; AVE = 0.66)	
(Scale: 1 = 'Totally disagree'; 4 = 'Neither agree nor disagree'; 7 = 'Totally agree')	
While making investment decision, I generally prefer risky alternatives	0.601
If I were going to make an investment, I would consider cryptocurrencies	0.838
The likelihood of buying cryptocurrencies is high	0.882
My willingness to buy cryptocurrencies is high	0.881
OPENNESS TO EXPERIENCE (α = 0.78; CR = 0.84; AVE = 0.52)	
(Scale: 1 = 'Totally disagree'; 4 = 'Neither agree nor disagree'; 7 = 'Totally agree')	
Is original, comes up with new ideas	0.725
Is inventive	0.844
Has an active imagination	0.692
Is ingenious, a deep thinker	0.679
Likes to reflect, play with ideas	0.648
CONSCIENTIOUSNESS (α = 0.76; CR = 0.84; AVE = 0.57)	
(Scale: 1 = 'Totally disagree'; 4 = 'Neither agree nor disagree'; 7 = 'Totally agree')	
Does a thorough job	0.778
Tends to be lazy	0.808
Is easily distracted	0.700
Tends to be disorganized	0.731
EXTRAVERSION (α = 0.76; CR = 0.84; AVE = 0.58	
(Scale: 1 = 'Totally disagree'; 4 = 'Neither agree nor disagree'; 7 = 'Totally agree')	
Is talkative	0.740
Is reserved	0.693
Is sometimes shy, inhibited	0.773
Tends to be quiet	0.820
AGREEABLENESS (α = 0.80; CR = 0.88; AVE = 0.71	
(Scale: 1 = 'Totally disagree'; 4 = 'Neither agree nor disagree'; 7 = 'Totally agree')	
Likes to cooperate with others	0.887
Is helpful and unselfish with others	0.845
Is considerate and kind to almost everyone	0.791
NEUROTICISM (α = 0.75 CR = 0.82; AVE = 0.53)	
(Scale: 1 = 'Totally disagree'; 4 = 'Neither agree nor disagree'; 7 = 'Totally agree')	
Is relaxed, handles stress well	0.882
Remains calm in tense situations	0.750
Can be tense	0.619
Gets nervous easily	0.640
RISK PROPENSITY (α = 0.69; CR = 0.81; AVE = 0.52)	
(Scale: 1 = 'very improbable'; 4 = 'I'm not sure'; 7 = 'very probable')	
Gamble a whole day's salary in a high-stakes poker game	0.765
Gamble a whole day's salary on the result of a sporting event (e.g., football)	0.756
Gamble a week's salary at the casino	0.665
Invest 5% of my annual salary in a very speculative stock	0.681

Discriminant validity checks if constructs are distinct. Ideally, the square root of a construct's AVE score should exceed its correlations with the other constructs (Fornell & Larcker, 1981). Table 4.3 confirms that all constructs meet this criterion. A second method, comparing heterotrait-monotrait method correlations, also supported discriminant validity (Henseler *et al.*, 2015) because all the values are lower than the threshold of 0.85. These results confirm that our measurement system is reliable and consistent.

Table 4.3. Discriminant validity

	1	2	3	4	5	6	7	8	9	10	11
1. Age	**n.a.**	*0.119*	*0.226*	*0.324*	*0.090*	*0.459*	*0.011*	*0.561*	*0.125*	*0.069*	*0.189*
2. Agreeableness	0.116	**0.842**	*0.171*	*0.125*	*0.326*	*0.089*	*0.249*	*0.063*	*0.168*	*0.411*	*0.168*
3. Attitude toward cryptocurrencies	-0.204	-0.149	**0.809**	*0.170*	*0.063*	*0.180*	*0.186*	*0.156*	*0.116*	*0.055*	*0.392*
4. Conscientiousness	0.289	0.105	-0.145	**0.756**	*0.151*	*0.257*	*0.100*	*0.243*	*0.298*	*0.132*	*0.216*
5. Extraversion	-0.013	0.286	-0.044	0.091	**0.758**	*0.058*	*0.147*	*0.060*	*0.221*	*0.244*	*0.090*
6. Education	0.459	0.088	-0.160	0.228	0.025	**n.a.**	*0.001*	*0.483*	*0.108*	*0.064*	*0.101*
7. Gender	-0.011	0.218	-0.182	0.067	0.129	0.001	**n.a.**	*0.148*	*0.240*	*0.064*	*0.136*
8. Income	0.561	0.060	-0.103	0.214	-0.005	0.483	-0.148	**n.a.**	*0.127*	*0.039*	*0.155*
9. Neuroticism	-0.077	-0.114	-0.112	-0.125	-0.083	-0.063	0.233	-0.080	**0.730**	*0.232*	*0.106*
10. Openness to Experience	0.038	0.317	0.046	0.023	0.162	0.035	-0.041	0.005	-0.147	**0.721**	*0.080*
11. Risk propensity	-0.169	-0.127	0.319	-0.164	0.057	-0.090	-0.119	-0.126	-0.097	0.026	**0.718**

Notes: the diagonal values in bold show the square roots of the AVE; the values below the principal diagonal are the correlation values; the values above the principal diagonal are the heterotrait-monotrait (HTMT) ratios; n.a. = not applicable.

4.5.2 Structural model

The structural model reveals causal relationships and linear equations among latent variables, with a global goodness-of-fit (GoF) measure of 0.270, classifying it slightly above medium (Wetzels *et al.*, 2009). The R^2 for our model is 0.17, also above the medium level of significance (Cohen, 1988). As a final fit measure, we assessed the standardized root mean square residual (SRMR), finding a value of 0.07, below the recommended limit of 0.08 (Hu & Bentler, 1998). All these results indicate a good model fit.

Collinearity, evaluated by variance inflation factor (VIF), showed values between 1.097 and 1.678, below the threshold of 5, confirming the accuracy of path coefficient estimates (Hair *et al*., 2017).

We used bootstrapping with 5,000 samples to assess direct and mediating effects (Table 4.4). The analysis of the direct effects shows that openness to experience trait is neither related to the attitude toward cryptocurrencies (β=0.066, n.s.) nor with the risk propensity (β=0.048, n.s.), and hence H1a and H1b are not supported. Similarly, extraversion is not related with attitude toward cryptocurrencies (β=-0.032, n.s.) nor with the risk propensity (β=0.103, n.s.), not supporting also H3a and H3b. On the other hand, the relationship between conscientiousness and attitude toward cryptocurrencies was not significant (β=-0.048, n.s.), although this personality trait is negatively related to risk propensity (β=-0.172, $p<0.001$). Therefore, H2a is not supported, but H2b is supported. Similarly, agreeableness is related to attitude toward cryptocurrency (β=-0.092, $p<0.05$), but the sign is negative, not supporting H4a. This personality characteristic is negatively linked to risk propensity (β=-0.168, $p<0.001$), meaning that H4b finds support. Neuroticism is also negatively related to attitudes toward cryptocurrencies (β=-0.087, $p<0.05$) and risk propensity (β=-0.122, $p<0.001$), supporting both H5a and H5b. Notwithstanding, conscientiousness shows an indirect negative relationship, mediated by risk propensity (β=-0.044, $p<0.001$) and agreeableness shows a similar indirect negative relationship, (β=-0.043, $p<0.01$). On the other hand, neuroticism also shows a negative indirect relationship with attitude towards cryptocurrencies via risk propensity (β=-0.031, $p<0.01$).

Risk propensity positively is also positively related with attitude toward cryptocurrencies (β=0.255, p<0.001), supporting H6. As for controls, being younger (β=-0.129, p<0.001) and also being male (β=-0.197, p<0.001) leads to having a positive attitude towards cryptocurrencies. Similarly, people with lower education (β=-0.098, p<0.005) also had more positive attitude toward cryptocurrencies.

Table 4.4 Structural model results

	Hyp	Standardized estimate (t-value)	Result
Direct effects			
Openness to Experience → Attitude toward cryptocurrencies	H1a	0.066 (1.257)	Not supported
Openness to Experience → Risk propensity	H1b	0.048 (0.756)	Not supported
Conscientiousness → Attitude toward cryptocurrencies	H2a	-0.048 (1.464)	Not supported
Conscientiousness → Risk propensity	H2b	-0.172*** (5.004)	Supported
Extraversion → Attitude toward cryptocurrencies	H3a	-0.032 (0.765)	Not supported
Extraversion → Risk propensity	H3b	0.103 (1.882)	Not supported
Agreeableness → Attitude toward cryptocurrencies	H4a	-0.092* (2.341)	Not supported (a)
Agreeableness → Risk propensity	H4b	-0.168*** (4.043)	Supported
Neuroticism → Attitude toward cryptocurrencies	H5a	-0.087* (2.334)	Supported
Neuroticism → Risk propensity	H5b	-0.122** (3.244)	Supported
Risk propensity → Attitude toward cryptocurrencies	H6	0.255*** (7.325)	Supported
Indirect effects			
Openness to Experience → Risk propensity → Attitude toward cryptocurrencies	H1a	0.012 (0.760)	Not supported
Conscientiousness → Risk propensity → Attitude toward cryptocurrencies	H2a	-0.044*** (4.131)	Not supported (a)
Extraversion → Risk propensity → Attitude toward cryptocurrencies	H3a	0.026 (1.847)	Not supported
Agreeableness → Risk propensity → Attitude toward cryptocurrencies	H4a	-0.043** (3.267)	Not supported (a)
Neuroticism → Risk propensity → Attitude toward cryptocurrencies	H5a	-0.031** (3.032)	Supported
Control variables			
Age → Attitude toward cryptocurrencies		-0.129*** (3.304)	
Gender → Attitude toward cryptocurrencies		-0.197** (2.617)	
Education → Attitude toward cryptocurrencies		-0.082* (2.083)	
Income → Attitude toward cryptocurrencies		0.035 (0.823)	

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$ (a) = Relationship is significant, but in the opposite direction

4.6 Discussion

Our findings show an inverse relationship between agreeableness and attitude toward cryptocurrency. While this differs from its positive link to trading frequency (Tauni *et al.*, 2017), it aligns with the arguments of Durand *et al.* (2008) that found a similar effect on stock exposure. We also evaluate that this result is also comparable with Sarwar *et al.* (2020) since he found a positive relationship between this personality trait and the intention to invest in conservative assets, such as real estate, hence indicating that cryptocurrencies are on the opposite end, constituting high-risk assets. In addition, we identified a negative association between neuroticism and the attitude toward cryptocurrencies~~,~~ following the findings of Jain *et al.* (2023) (investment intention in general), Sarwar *et al.* (2020) (secure investment) and Aren & Hamamci, (2020) (risky investment), further demonstrating that this factor is related to the aversion of investing, no matter the asset class and risk involved.

While the other three factors showed no significant direct relationship with attitudes toward cryptocurrencies, a different pattern emerges when considering indirect effects. Conscientiousness plays a crucial role, exhibiting a negative relationship mediated by risk propensity. This finding is notable for two reasons: first, it reveals the mediating influence one independent variable can exert on another, broadening our understanding of potential predictors for the dependent variable; second, it challenges the very limited literature on the topic, which suggests a positive relationship between conscientiousness and cryptocurrency attitudes (Luo *et al.*, 2024), highlighting the need for further research.

Concerning the relationship with risk propensity, we find that three personality traits do influence risk propensity. The negative link with conscientiousness indicates that people who are careful, attentive, meticulous, and organized are less prone to take financial risks. The negative association with agreeableness shows that those who are unselfish with others and more cooperative are less inclined to assume higher risks. Finally, the negative connection with neuroticism points that individuals who are stressed and incapable of remaining calm in tense situations exhibit a lower tendency to take risks. All these results are totally in line with Aren and Hamamci (2020), Becker *et al.* (2012) and Nicholson *et al.* (2005), and also agree with Durand *et al.* (2008) (agreeableness), Oehler *et al.* (2018) (neuroticism), and Nga & Ken Yien (2013) (conscientiousness). On the other hand, (1) openness and (2) extraversion factors show no association with risk propensity, in accordance with previous studies (Durand *et al.*, 2008; Nga & Yien, 2013; Aren & Hamamci, 2020; Brown & Taylor, 2014; Oehler *et al.*, 2018).

Regarding the demographic variables, we find that the higher the age of people, the less inclined they are to invest in cryptocurrencies. We conjecture this happens not only due to the lower tolerance older individuals have in relation to financial risks (Lewellen *et al.*, 1977) but also to the fact that crypto assets are traded only through internet applications, the adoption of which has been much slower among older generations compared to the population average (Bergström, 2017). Concerning gender, the cryptomarket reflects a pattern observed in other financial assets, further confirming extensive research in psychology and economics showing that men are generally more inclined toward risky choices (Faff *et al.*, 2011; Sila *et al.*, 2016), as is the case of cryptocurrencies. When it comes to education, the attitude toward cryptocurrencies is in line with the literature (Shaw, 1996): our study indicates that those with higher levels of education are less prone to invest in cryptocurrencies, suggesting they are more informed about the risky nature of this market.

Finally, we find that risk propensity and attitude toward cryptocurrencies are positively related. Therefore, the more inclined individuals are to take risks, the more favorable they are to investing in cryptocurrencies (Özçelik & Kurt, 2024), confirming the perception of these assets as highly insecure, due to the many perils they face, related to abrupt price changes, incipient regulation, and frequent occurrence of fraud.

In summary, our study offers new insights into the influence of personality traits on risk propensity and explores how these traits, along with age, gender, and education, shape investment attitudes toward cryptocurrencies – an area still largely unexplored. Some contradictory results were expected, despite the consensus among researchers on the role of personality in financial decision-making. Nevertheless, there is no unanimity on how each specific personality trait affects behavior. Further research is certainly needed, especially in the context of cryptocurrencies.

4.7 Conclusions

4.7.1 Theoretical implications

Our investigation significantly expands the scope of analysis regarding the influence of personality traits on financial decision-making, particularly within the domain of cryptocurrencies, a novel and not yet fully understood financial instrument. Specifically, our findings indicate that personality dimensions such as agreeableness, conscientiousness, and neuroticism are inversely related to the intention to invest in crypto-assets. This contributes to the advancement of knowledge in this field, highlighting the critical role of personal characteristics in investment behavior.

Furthermore, we confirm that individuals with higher risk propensity are more likely to invest in cryptocurrencies, which aligns with the inherent risks associated with this unconventional asset class. Importantly, our study also elucidates how risk propensity serves as a mediating factor, linking personality traits and financial decision-making. This mediation is particularly evident between conscientiousness and individuals' attitudes toward cryptocurrencies, suggesting that risk propensity significantly influences the investment choices of those with certain personality profiles. Unlike previous studies that have separately analyzed the impacts of risk propensity and personality traits on financial decision-making, our research explores the interconnected relationships among these factors in the general public. This approach was pivotal to reveal the mediating role of risk propensity and offer new insights into the complex dynamics that drive investment behavior in the cryptomarket.

4.7.2 Practical implications

This research provides valuable insights into decision-making and risk management within the crypto market, and several important implications can be highlighted. For policy-makers, our findings emphasize the need to account for psychological factors in crafting investor education initiatives. The insights from this research can guide public policies and programs to promote responsible investment behavior, thus enhancing systemic stability. They offer, for example, regulators valuable perspectives on protecting investors under the Markets in Financial Instruments Regulation (MFIR) and the Markets in Financial Instruments Directive II (MiFID II), which regulate EU investment services and financial markets.

Additionally, these findings highlight the importance of tailoring educational campaigns to different demographic profiles. For instance, older individuals might require initiatives focusing on simplifying technology use and addressing their risk aversion. Similarly, campaigns targeting highly educated groups could focus on nuanced discussions about risk mitigation and market volatility to bridge the gap between informed caution and market participation.

Private stakeholders can also benefit from our analysis to better understand the influence of personality, risk propensity, and factors like age, gender and education on the attitude toward cryptocurrencies. This comprehension is essential for designing informed campaigns that prioritize investor protection, encouraging trading platforms to foster prudent investment practices. Notably, financial advisors and fintech firms could leverage insights into personality traits, such as the inverse relationships between agreeableness, conscientiousness, and investment attitudes, to personalize investment strategies and provide tailored recommendations to clients.

For retail investors, the study underscores the importance of recognizing how their personal characteristics shape their investment attitudes. By being aware of these aspects, investors can better structure their financial strategies, improving overall decision-making in the cryptocurrency market. Lastly, risk propensity's role as a mediating factor underscores the need for investors to actively evaluate their tolerance for risk before entering this high-volatility market.

4.7.3 Limitations and future research

Our study investigated the influence of personality traits, as defined by the five-factor model, and risk propensity on individuals' attitudes toward cryptocurrencies, while controlling for demographic variables. However, limitations should be noted. First, after data was collected, some relevant facts have occurred – such as the rise of futures markets for some cryptocurrencies and the collapse of the FTX trading platform – which may have altered public perceptions.

Second, our research focused on the broad dimensions of personality, each encompassing several facets. Future studies would benefit from exploring new features introduced in the cryptomarket, as well as deepening the relationships between more specific personality facets and individual decision-making.

Third, while this study accounted for personality traits and risk propensity, future research could expand the scope of inquiry to include further constructs and provide additional understanding of the determinants of cryptocurrency investment behavior.

Forth, this study relies on self-reported data regarding cryptocurrency purchasing behavior. There was no possibility to verify the actual investment in cryptocurrencies made by respondents. The decision to conduct the survey anonymously was intended to maximize respondent participation, but it precluded the possibility of follow-up research.

Future research could compare survey responses with actual investment decisions, what could increase the reliability of the data.

Finally, this study employed a quantitative research methodology. Incorporating a qualitative or mixed-methods approach in future research could offer a more comprehensive understanding of the motivations underlying the investment in cryptocurrencies. In particular, mixed-methods research may provide deeper insights into motivational dynamics by facilitating participant self-reflection, potentially uncovering novel perspectives

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Disclosure of interest

The authors report there are no competing interests to declare.

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Chapter 5: Overconfidence and Online Banking as Drivers of Behavioral Intentions in the Cryptomarket [8]

Abstract

Purpose – Cryptocurrencies are a rapidly evolving category of digital assets characterized by their lack of fundamental valuation benchmarks and substantial risks for retail participants. Overconfidence, a well-documented cognitive bias in traditional financial markets, can lead individuals to underestimate risks, potentially driving increased engagement in such volatile markets. Additionally, technological skills and familiarity with digital financial platforms are considered to facilitate the broader adoption of internet-based innovations. This study examines how overconfidence and online banking usage contribute to explaining behavioral intention and actual participation in the cryptomarket.

Design/methodology/approach – The research adopts a confirmatory design, employing an open online questionnaire targeted at the general population. Data analysis is conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique.

Findings – This study highlights the significant role of overconfidence in cryptocurrency markets, particularly in influencing investment intentions and actions in a high-risk environment. Also, the findings confirm the mediating role of behavioral intention in

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linking individual characteristics to actual behaviors. In addition, the parallel with online banking suggests that cryptocurrencies represent a natural extension of digital financial engagement, facilitated by existing familiarity with internet-based platforms.

Originality/value – Our results provide unique implications for understanding the intersection of personal traits, demographic factors, and financial behaviors in the emerging digital asset market. This research contributes to the behavioral literature by deepening the understanding of how overconfidence and digital familiarity influence decision-making in the underexplored cryptomarket. The investigation also provides valuable insights into the demographic segmentation of cryptocurrency retail users, informing about behavioral patterns.

Keywords: Investor behavior, decision-making, risk management, cryptocurrencies, innovation adoption.

5.1 Introduction

This paper investigates the influence of overconfidence and familiarity with internet-based financial technologies, such as online banking, on individuals' intentions to invest in cryptocurrencies and their actual participation in the cryptomarket. With the cryptomarket rapidly evolving into a global financial ecosystem, understanding these behavioral and technological drivers is critical. The study addresses significant gaps in the literature, regarding why individuals are drawn to this volatile, high-risk market.

Cryptocurrencies, emerging from Nakamoto's (2008) white paper, were designed to form a decentralized digital payment system, operating beyond traditional regulatory frameworks. As digital representations of value, cryptocurrencies leverage cryptographic techniques and rely on distributed networks instead of central entities (Mendoza-Tello *et al*., 2019). The revolutionary concept of a peer-to-peer financial network and the ability to be rapidly exchanged for fiat currencies, grant cryptocurrencies the necessary condition to be a truly global financial asset, with a high potential to be a factor of disruption (Hu *et al*., 2019).

However, despite their promise, the cryptomarket faces profound challenges. It is growing exponentially (Liu *et al*., 2022), with thousands of cryptocurrencies currently available and new ones emerging every day but while this rapid proliferation creates numerous opportunities it simultaneously poses significant challenges (Arias-Oliva *et al*., 2019). In spite of its fast growth, the industry remains in an early developmental phase, operating within a loosely regulated environment (Bouri *et al*., 2019). Such conditions expose the sector to risks of fraud and mismanagement, which can harm not only individual users but also significantly extend to a broader context, as demonstrated by the collapse of the TerraUSD stablecoin, and the bankruptcy of FTX, one of the world's largest cryptocurrency exchanges (Chow, 2022; Fletcher, 2023; Shen, 2022; Yaffe-Bellany, 2023). Furthermore, cybercrimes resulting in significant financial losses from exchanges are well-documented (Bischoping, 2016; Nguyen *et al*., 2020; van Hardeveld *et al*., 2017). These incidents intensify concerns regarding security (Demiralay & Bayracı, 2021) and exacerbate the already volatile nature of the market (Caporale *et al*., 2020; Marella *et al*., 2020). Indeed, cryptocurrencies exhibit extreme levels of volatility (Phillip *et al*., 2019), making them high-risk assets (Anastasiou *et al*., 2021; Ben & Xiaoqiong, 2019).

In such a context, the elements that motivate individuals to invest in cryptocurrencies are not fully understood, leaving this market largely unexplored. A key behavioral factor that may influence these decisions is overconfidence. Overconfidence leads individuals to overestimate their abilities and market knowledge, often resulting in excessive trading and suboptimal returns (Odean, 1998; Pompian, 2006). While this bias has been extensively studied in traditional financial markets (DeBondt *et al.*, 2008). Existing research highlights that understanding the role of overconfidence in cryptocurrency investment is a relevant gap in the literature (Almeida & Gonçalves, 2023; Shrotryia & Kalra, 2022).

In addition, the combination of technological innovation and financial ingenuity underscores the transformative potential of cryptocurrencies in reshaping global financial markets. They embody the concept of disruptive innovation, by introducing radically new functionalities (Nagy *et al.*, 2016). On the technological front, investing in cryptocurrencies parallels the adoption of previous financial innovations, such as online banking. At the time of its introduction, online banking triggered a revolution on how consumers interacted with financial institutions, leveraging internet technology to create a virtual platform for conducting transactions (Shih & Fang, 2006).

Over time, online banking gained global prominence and fundamentally reshaped the financial services industry (Santouridis & Kyritsi, 2014). In addition, the advent of the internet not only catalyzed the growth of new industries but also transformed the business models of many existing ones, including the financial sector (Hernández-Murillo *et al.*, 2010). However, consumer attitudes toward internet-based financial services are often ambivalent, reflecting a complex interplay between the unfamiliarity of the internet as a channel and the intricacies of financial services (Eriksson *et al.*, 2005).

Indeed, the adoption of new technologies has been a recurring source of disruption in financial services, fundamentally transforming the sector (Anagnostopoulos, 2018). Cryptocurrency trading represents the latest evolution of this trend, blending financial and technological innovation. Nevertheless, studies examining the relationship between online banking usage and the intention to invest in cryptocurrencies remain scarce (Auer & Tercero-Lucas, 2022).

As per the aforementioned, this study seeks to answer the following research question: How do overconfidence and familiarity with internet-based financial technologies, such as online banking, influence individuals' intentions to invest in cryptocurrencies and their actual participation in the cryptomarket?

The findings offer important insights into the interplay of psychological, technological, and behavioral factors shaping investment decisions in this emerging domain. This research contributes to a more nuanced understanding of cryptocurrency adoption by emphasizing the critical role of overconfidence within these volatile markets. Specifically, the study investigates how overconfidence influences both investment intentions and actual investment behaviors among individuals navigating the inherent risks associated with cryptocurrencies. Furthermore, the findings corroborate the mediating effect of behavioral intention, confirming its crucial role in translating individual characteristics into observable investment actions. Drawing parallels with online banking, the study suggests that cryptocurrencies represent a natural progression of digital financial engagement. This is facilitated by individuals' existing familiarity with and comfort in utilizing internet-based platforms for financial transactions.

The remainder of this paper is structured as follows: Section 2 reviews the literature on the cryptomarket, overconfidence, and online banking. Section 3 outlines the conceptual framework and hypotheses. Section 4 details the methodology, including data collection and measurement design. Section 5 presents the results of the measurement and structural models. Finally, Sections 6 and 7 discuss the findings and contributions, along with their implications, limitations, and directions for future research.

5.2 Literature review

5.2.1 Investment in cryptocurrencies

Cryptocurrencies have emerged as disruptive financial instruments, building a bridge between technological innovation and investment opportunities in a way that few other assets have achieved. While they are increasingly recognized as components of diversified portfolios, their distinctiveness lies not only in their digital nature but in their ability to challenge traditional notions of value and financial structure (Bouri *et al*., 2019; Fang *et al*., 2022; Trucíos *et al*., 2020). This dual identity as both an innovative technology and a high-risk financial asset underscores the urgent need to understand the behavioral and technological drivers behind cryptocurrency adoption, addressing the gaps identified in the academic literature.

Unlike traditional financial markets, the cryptomarket is primarily driven by individual investors—many of whom lack prior financial expertise—creating a unique environment characterized by high volatility, speculation, and a susceptibility to behavioral biases such as overconfidence, contrasting with traditional markets dominated by institutional investors with sophisticated tools and strategies (Fruehwirt *et al*., 2021; Nguyen *et al*., 2020; Zhang *et al*., 2019).

The prevalence of novice investors, drawn by the allure of rapid profits despite limited understanding of asset pricing and market mechanisms profits (Chu *et al*., 2020; Katsiampa, 2019; Mirtaheri *et al*., 2021), raises questions about the influence of psychological factors. Investors in the cryptomarket frequently lack expertise, are prone to behavioral biases, and can be swayed by what immediately grabs their attention, leading to impulsive decisions (Kallinterakis & Wang, 2019; Subramaniam & Chakraborty, 2020).

Overconfidence, a key behavioral factor, can lead individuals to overestimate their knowledge and trading abilities, often resulting in excessive risk-taking and suboptimal outcomes. While this bias has been extensively studied in traditional financial markets (Odean, 1998; Pompian, 2006), its role in the cryptomarket—a domain marked by high uncertainty and novelty—remains underexplored. Our study builds on existing literature (Almeida & Gonçalves, 2023; Shrotryia & Kalra, 2022) by delving into how overconfidence influences both the intention to invest in cryptocurrencies and actual participation, shedding light on why individuals are drawn to this volatile market.

Adding to the complexity is the technological dimension. Cryptocurrencies, as synthetic assets, represent the latest stage in the evolution of financial innovation, and their impact may be comparable with that of online banking in transforming consumer behavior and financial services (Shih & Fang, 2006). However, while the adoption of online banking was widely studied, the connection between familiarity with such technologies and the propensity to invest in cryptocurrencies has received limited attention (Auer & Tercero-Lucas, 2022). This study addresses this gap by investigating how technological familiarity interacts with behavioral traits, potentially influencing individuals to venture into the cryptomarket.

Moreover, the cryptomarket itself is a complex technological ecosystem comprising diverse participants, including issuers, clients, miners, and exchanges, all operating within a decentralized, global framework (Aspris *et al*., 2021; Cukierman, 2020; Fang *et al*., 2022; Hu *et al*., 2019). This network introduces unprecedented opportunities for cross-border transactions and financial inclusivity, but it also amplifies risks, particularly for inexperienced investors who may lack the tools to navigate this incipiently regulated landscape (Bouri *et al*., 2019). By situating the cryptomarket within the broader context of financial innovation, this study emphasizes the need for a deeper understanding of how behavioral and technological factors shape participation in this high-risk environment.

Ultimately, the study contributes to a growing body of knowledge aimed at bridging the gap between behavioral finance and technological adoption. By exploring the intersections of overconfidence, familiarity with internet-based financial technologies, and cryptocurrency investment, this research not only addresses critical gaps in the literature but also provides valuable insights into the mechanisms driving participation in this rapidly evolving market. In doing so, it offers a foundation for informed strategies that can support both investors and regulators in navigating the challenges and opportunities posed by cryptocurrencies.

5.2.2 Overconfidence

The study of cryptomarkets from a behavioral finance perspective has increasingly focused on identifying cognitive biases among investors. Although the literature on deviations from rational investment decisions in cryptocurrency markets remains limited, researchers have uncovered several irrational patterns. For example, some investors abandon their own strategies to imitate others' decisions (Ballis & Drakos, 2020). Emotional factors have also been linked to trading volumes and price volatility, with studies revealing that investors often react to market trends with unwarranted confidence, believing prices will continue to rise indefinitely (Ahn & Kim, 2021; Bouri *et al*., 2019).

One critical bias to explore in this context is overconfidence, which refers to an individual's excessive belief in their ability to make optimal decisions. Overconfident investors tend to exaggerate the accuracy of their knowledge, leading to flawed judgments and suboptimal actions (Baker & Nofsinger, 2002; Barber & Odean, 1999; Schaefer *et al*., 2004). This cognitive bias quite often results in investors overestimating the true value of an asset, further complicating rational decision-making (Biais *et al*., 2005), making this phenomenon particularly relevant in cryptocurrency markets, where the concept of fundamental value is not yet well-defined due to the market's unique characteristics (Enoksen *et al*., 2020; Gronwald, 2021).

Overconfidence has been identified as one of the most influential factors driving irrational behavior in financial decision-making, often leading individuals to overestimate the accuracy of their judgments (Debondt & Thaler, 1995; Hirshleifer, 2001). This bias exemplifies the limitations of human information-processing capabilities and serves as a cornerstone for understanding behavioral deviations in decision-making (Hoffrage, 2017). Its effects are observed across various professions and contexts (Broihanne *et al*., 2014; Hilary & Hsu, 2011).

Overconfident individuals often undervalue risks and overrate their ability to outperform the market (DeBondt *et al*., 2008). Such attitudes frequently lead to increased trading activity (Deaves *et al*., 2009; Glaser & Weber, 2007; Graham *et al*., 2009), and results in poor investment outcomes (Baker & Nofsinger, 2002; Odean, 1998). The manifestations of overconfidence are multifaceted with diverse measurement approaches. Broadly, this bias can be categorized into three key dimensions: (a) overestimation, where individuals overrate their performance or likelihood of success; (b) overplacement, or the "better-than-average" effect, where individuals believe their abilities surpass those of others; and (c) overprecision, characterized by excessive certainty in the accuracy of one’s knowledge (Benoit & Dubra, 2011; Moore & Healy, 2008; Moore & Schatz, 2017).

5.2.3 Online banking and internet-based technologies

The acceptance of new technologies has been extensively studied, attracting significant attention from scholars across various disciplines (Peng & Mu, 2011). Numerous models have been developed to predict technology adoption, with research focusing on diverse topics such as e-commerce, wireless technologies, instant messaging, and online banking. These studies typically examine usage or intention to use as key dependent variables (Abushanab *et al*., 2010).

Innovations, by their nature, are often perceived as risky and initially adopted by those who can tolerate higher levels of uncertainty (Rogers, 2003). While potential benefits may be recognized by all users, there is no assurance that adoption will yield the expected outcomes (Agarwal & Prasad, 1998). Innovation adoption behavior can be analyzed through two major constructs: (a) attributes of the innovation, where perceived risk – defined as the potential for unfavorable outcomes – plays a pivotal role; and (b) personal-social characteristics such as age, gender, and education, which offered a valuable framework for understanding the adoption of internet-based banking and e-commerce services (Branca, 2008; Forsythe & Shi, 2003).

Online banking, as a transformative information system, has revolutionized how individuals manage their financial transactions (Shih & Fang, 2006). Its adoption is closely tied to prior internet usage (Szopiński, 2016) and can be defined as the application of information and communication technology by customers to perform various banking tasks (Alzaidi & Qamar, 2018). Online banking encompasses terms like electronic banking, internet banking, and e-banking, allowing users to conduct a range of financial activities, such as bill payments and fund transfers, through electronic means (Martins *et al*., 2014).

The diffusion of innovations follows a trajectory shaped by market-wide dynamics, individual attributes, and product-specific features (Xue *et al*., 2011). Moreover, although findings and methodologies vary across countries, research has frequently emphasized demographic characteristics as crucial determinants of online banking adoption (Jenkins *et al*., 2022), as well as retail electronic purchasing (Burroughs & Sabherwal, 2002). Additionally, gender and age have been shown to moderate intentions in mobile stock trading (Tai & Ku, 2013). Consistently, demographics are considered to significantly influence technology perception and adoption (Venkatesh & Agarwal, 2006).

Besides, the adoption of new technologies, products, or services is often influenced by individuals' intentions toward that object, and these intentions, in turn, are shaped by the attitudes of the subjects (Jarvenpaa *et al*., 1999). However, some authors focus only on behavioral intention, as the dependent variable. For instance, Lee-Partridge and Ho (2003) highlight operational risk - the potential for money loss due to security breaches – as a significant barrier to online stock trading intentions. Similarly, Lee (2009) identifies security and financial risks as detrimental factors to internet banking adoption intentions, while Liao *et al*. (2016) conducted a survey on virtual forums to explore consumer and firm-level characteristics, finding that vulnerability issues significantly impact internet banking usage intentions. In addition, Zhao *et al*. (2010) employed a mixed-methods approach to develop a model incorporating risk, trust, and bank competence. Their findings emphasize the critical role of risk in explaining intentions to use internet banking.

Furthermore, to address behavioral intention towards online banking, some scholars have developed unique models. For instance, Yousafzai and Yani-de-Soriano (2012) proposed a customer-specific acceptance model incorporating technology readiness – a concept introduced by Parasuraman (2000) – which reflects the personal predisposition to embrace new technologies. Technology readiness is shaped by a positive view of technology and inhibited by discomfort or distrust. Other authors have adapted models from different sources to select specific factors that fit within the context of e-commerce (Barkhi *et al*., 2008) and online banking (Safeena *et al*., 2014), underscoring the critical role of security in internet-based transactions.

The factors influencing online banking adoption are multifaceted. Alzaidi and Qamar, (2018) identify 44 elements, highlighting prior IT knowledge as a critical enabler. However, emerging markets face unique challenges, such as the absence of clear legal frameworks, which significantly hinder internet banking adoption (Gikandi & Bloor, 2010; Sukkar & Hasan, 2005). This complex interplay of risks, personal traits, and contextual factors underscores the nuanced nature of technology perception and adoption in the digital age.

5.3 Conceptual framework and hypotheses development

This study follows the same reasoning of prior research, developing a framework to address specific research questions (e.g. Barkhi *et al*., 2008; Safeena *et al*., 2014; Santouridis & Kyritsi, 2014). The framework proposed here examines individual intentions toward cryptocurrencies, their influence on the engagement in cryptomarket transactions, and the potential role of overconfidence and prior adoption of a technology-based financial platform, specifically online banking. We also extend beyond some previous studies (e.g. Abushanab *et al*., 2010; Lee, 2009; Liao *et al*., 2016; Tai & Ku, 2013; Zhao *et al*., 2010) that have focused solely on behavioral intention. This research incorporates both intention and actual behavior into the analysis. Additionally, we include age, gender and education as control variables.

5.3.1 Hypotheses

Cryptocurrencies have moved outside their initial purpose of being a decentralized medium of exchange, becoming speculative assets that attract investors seeking potential financial gains (Gagarina *et al*., 2019; Hashemi Joo *et al*., 2020). The unique characteristics of the cryptocurrency market – limited responsiveness to global events (Schaub & Phares, 2020), significant volatility compared to sovereign currencies (Phillip *et al*., 2019), and high intra-market interconnectedness (Andrada-Félix *et al*., 2020) – make it a particularly unstable and risky environment. Such conditions are ideal for examining the role of overconfidence, a cognitive bias where individuals overvalue their knowledge and ability to make accurate decisions. In financial markets, overconfident investors tend to underestimate risks and engage in riskier behaviors, often leading to suboptimal outcomes (Baker & Nofsinger, 2002; DeBondt *et al*., 2008; Schaefer *et al*., 2004). Although the topic has not yet been extensively investigated in the cryptomarket, there is some initial indication that cryptocurrency investors exhibit significantly higher levels of overconfidence than non-crypto-investors (Iamin, 2025). It is then plausible to expect that overconfident investors are more likely to perceive their skills as sufficient to navigate the risks and volatility inherent in this market. Therefore, we hypothesize that:

H1: Overconfidence positively influences individual investment in cryptocurrencies.

Furthermore, the intention to engage in cryptocurrency-related activities may also be shaped by overconfidence. It not only leads individuals to underestimate uncertainties and overvalue their abilities, as it has been documented in currency trading (Oberlechner & Osler, 2012), but has also a positive and significant influence on individual investment intention in stock markets (Jain *et al*., 2023). In the context of cryptocurrencies, this bias may foster greater enthusiasm and intention to invest, even when market conditions suggest caution. Therefore, it should be expected that individuals with heightened confidence are more likely to be inclined toward such investments despite their potential risks, and, by analogy, we propose the following hypothesis:

H2: Overconfidence positively influences the intention toward cryptocurrencies.

The existing literature on the adoption of new technologies, products, and services consistently demonstrates that actual behavior is primarily driven by adoption intentions (Jarvenpaa *et al*., 1999; Tan & Teo, 2000). Early research, both in laboratory and field settings, revealed a significant correlation between intentions and usage of computer-based systems (Davis *et al*., 1989; Davis, 1989). In addition, Hill *et al*. (1987), using a questionnaire administered to undergraduate students, found that the intention to use computers strongly predicted enrollment in computer-related courses. Similarly, Taylor and Todd (1995), testing three competing models of information technology usage, concluded that behavioral intention is the most critical determinant of IT adoption, with a significant path between intention and behavior across all models. Consistently, intention has been identified as a proximal cause of behavior (Lee *et al*., 2005). More recent findings by Martins *et al*. (2014) highlight that behavioral intention is the primary factor explaining actual engagement in internet banking. Based on these insights, this study proposes the following hypothesis:

H3: The intention toward cryptocurrencies positively influences the investment in cryptocurrencies.

Moreover, personal innovativeness in information technology, defined as an individual's tendency to adopt new technologies earlier than others (Rogers, 2003), has been found to positively influence the adoption of internet banking (Yiu *et al*., 2007), Extrapolating from this, it is reasonable to anticipate a similar impact on cryptocurrency investment behavior. However, the emergence of novel technologies, such as online banking, often carries an inherent perception of risk. While their potential benefits may be acknowledged, there is no assurance that their adoption will necessarily yield positive outcomes (Agarwal & Prasad, 1998). Consequently, individuals with a higher tolerance for uncertainty are more likely to embrace these innovations (Rogers, 2003), leading us to the assumption that overconfident individuals are more likely to invest in cryptocurrencies, in a relationship moderated by the predisposition to use new technologies, captured by a proxy that is online banking. This assumption is further explored in the following two hypotheses of our study.

The perceived risks of operational, security, and financial issues have been identified as significant barriers to online banking adoption (Lee-Partridge & Ho, 2003; M. C. Lee, 2009; Liao *et al*., 2016; Zhao *et al*., 2010). Thus, it is expected that individuals who view online banking as low-risk are more likely to adopt the technology, with confidence in its use serving as a critical determinant (Tan & Teo, 2000). Furthermore, Parasuraman (2000) and Ratchford and Barnhart (2012) posit optimism as a contributing factor to adopt technology. In parallel, some scholars contend that overconfidence may emerge from optimism (ul Abdin *et al*., 2022). Overoptimism by managers, for example, can lead to an excessive appraisal in their capability to compete (Lowe & Ziedonis, 2006). Building upon that, we hypothesize:

H4: Overconfidence positively influences online banking usage.

Technological skills play a crucial role in driving cryptocurrency adoption (Sobhanifard & Sadatfarizani, 2019). Additionally, the literature identifies online banking usage as a key precursor to the development of business on internet-based platforms (Szopiński, 2016). Early studies on the adoption of new technological systems emphasize the significant influence of individuals' prior experience, knowledge, and involvement in related areas (DeLone, 1988; Igbaria *et al*., 1989). Similarly, internet usage has been shown to facilitate behaviors such as electronic purchasing by retail consumers (Burroughs & Sabherwal, 2002) and the adoption of internet banking (Tan & Teo, 2000). In a related framework, the concept of technology readiness developed by Parasuraman (2000) highlights that a favorable perception of technology systems is a critical driver for embracing new technologies. Drawing on these insights, online banking usage can be viewed as a proxy for innovativeness and technology readiness, suggesting its potential to impact on the engagement with cryptocurrency transactions by retail investors. Based on this reasoning, we propose the following hypothesis:

H5: Online banking usage positively influences cryptocurrency investment.

According to the research hypotheses, Figure 5.1 depicts the research framework.

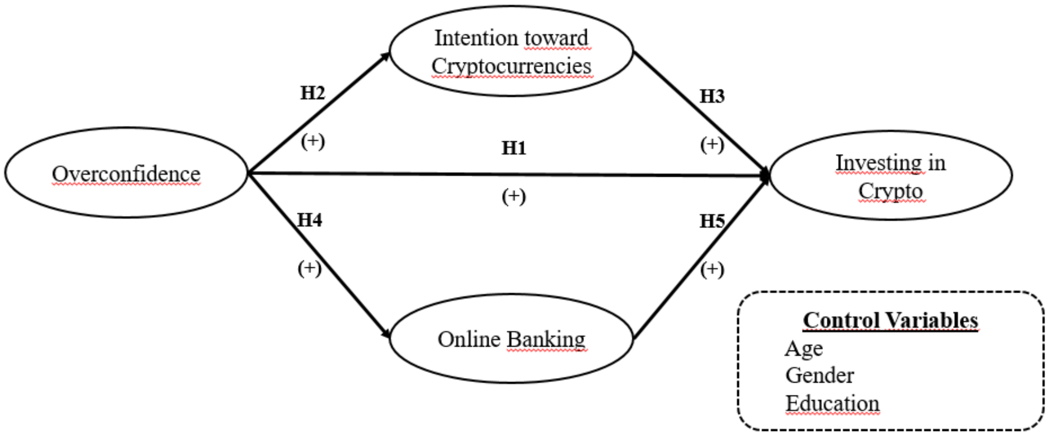

Figure 5.1 Research framework

5.4 Methodology

5.4.1 Data Collection

This study employed a survey-based approach for data collection. Leveraging the connectivity provided by digital communication channels, data was gathered using an online questionnaire. Invitations to participate in the survey were disseminated via social networks and cryptocurrency-focused discussion groups on platforms such as Facebook, Instagram, and LinkedIn, targeting a broad adult population. The questionnaire was accessible for three months, from May 1st to August 31st, 2023, through the LimeSurvey platform, resulting in a total of 826 responses.

5.4.2 Questionnaire Design

The online questionnaire was structured considering no direct interaction between researchers and respondents, thus clarity and ease of completion were emphasized (Lavrakas, 2004). In addition, concise and straightforward language was used to avoid the risk of ambiguity or misinterpretation that could lead to measurement errors (Alwin, 2007; Rowley, 2014).

To enhance respondent engagement and improve response rates, the questionnaire was strategically organized. The most engaging and relevant questions were presented at the beginning, while demographic inquiries were reserved for the end (Shaughnessy *et al*., 2012). This sequencing aimed to maintain interest throughout the survey, thereby improving data quality and completeness.

Since most of the scales utilized in this research were originally in English, they were translated into Portuguese and subsequently back-translated to identify and address any inconsistencies or conceptual inaccuracies (Chapman & Carter, 1979). To ensure that the questions would be interpreted consistently by participants, accounting for potential linguistic and cultural nuances (Reynolds *et al*., 1993), the questionnaire underwent pretesting with 24 participants – an appropriate sample size within the recommended range of 12 to 25 cases (Sheatsley, 1983).

Ethical principles were rigorously upheld throughout the research process. Key considerations included informed consent, participant confidentiality, and obtaining necessary permissions and approvals (Aldridge & Levine, 2001; Bryman & Bell, 2011). These measures reflect a strong commitment to maintaining the integrity of the research and protecting participants' rights and well-being.

5.4.3 Measures

Behavioral intention, defined as the subjective probability of an individual performing a given behavior, is best measured along a bipolar continuum reflecting the possible behaviors toward some action (Fishbein & Ajzen, 1975). For this study, items related to behavioral *intention toward cryptocurrencies* were adapted from Aydemir and Aren (2017) and Dodds *et al*. (1991). These included statements such as, “If I were to make an investment, I would consider cryptocurrencies,” rated on a 7-point Likert scale ranging from 1 (totally disagree) to 7 (totally agree). On the other hand, the measure of *investing in cryptocurrency* was assessed using a single yes/no question.

Overconfidence was conceptualized using the "better-than-average" effect, also referred to as overplacement (Guenther & Alicke, 2010; Larrick *et al*., 2007). Overplacement involves overestimating one’s abilities relative to others and can be assessed by comparing perceived and actual performance (Hirshleifer, 2015; Olsson, 2014). To measure this construct, we employed a toolkit developed by the Organization for Economic Cooperation and Development (OECD, 2018), which is widely recognized and used in over 40 countries, including the G-20 nations. This instrument evaluates financial literacy while capturing behaviors and intentions. For instance, one question asked participants, “How would you rate your overall knowledge about financial matters compared with other adults?” Overconfidence was then measured by comparing participants’ self-assessed financial knowledge with their actual performance (individual score minus the average group score) on financial literacy questions, following the methodology outlined by Hirshleifer (2015) and Olsson (2014).

Online banking usage was assessed through two sets of items addressing basic and advanced activities. Basic activities included account management and payments, while advanced activities encompassed investments. Responses were collected on a 7-point Likert scale ranging from 1 (very rarely) to 7 (very often). These variables were subsequently combined into a higher-order construct labeled Online Banking for the analysis.

Control variables were measured directly using specific question formats. Gender and education were captured through closed-ended questions, while age was collected via a numerical, open-response field with a pre-defined range. Latent constructs, on the other hand, were measured using multi-item scales to ensure reliability and validity.

5.4.4 Non-response and common-method bias

While nonresponse bias is generally not a concern in open-ended surveys, we followed (Armstrong & Overton, 1977) to assess potential differences between early and late respondents. By comparing responses received within the first three months to those received in the last month, we found no significant differences. Therefore, nonresponse bias is not a significant issue in our study. We also applied the MCAR test (Little, 1988). We found a p-value of 0,859 and so concluded that missing data are completely at random.

Common method bias (CMB) arises when the same method or parts of the same method are used for multiple measurements (Burton-Jones, 2009). To prevent common method bias, it's crucial to plan carefully during the initial research design stage (Montabon *et al*., 2018). In line with the literature, we followed several specific strategies to mitigate its occurrence (Podsakoff *et al*., 2003; Podsakoff *et al*., 2024), implementing, among others, the following measures: respondents were informed that there were no right or wrong answers and assured anonymity and confidentiality; they did not have access to the theoretical model; questions were placed in a different order from that in the conceptual model; and the response scales included both extreme values and a midpoint. After implementing these procedures, we conducted Harman's one-factor test (Malhotra *et al*., 2006) to ensure that our efforts were successful to avoid common method bias. In this test, all variables of interest are entered into a factor analysis, with the expectation that, if common method bias is present, either a single factor will emerge or one factor will account for the majority of the covariance (Podsakoff & Organ, 1986). Our analysis revealed six components, explaining 62.6% of the variance, with the first factor accounting for 20.4%.

We also assessed the potential presence of CMB by employing the marker variable technique (Lindell & Whitney, 2001). This involved calculating the correlation matrix of a marker variable with all other variables in the conceptual model. The average correlation between the marker variable and the other variables was found to be 0.079. By selecting the second smallest correlation ($r_M = -0.035$), we computed a CMB-adjusted correlation matrix. A comparison of the original and adjusted correlation matrices revealed no substantial differences ($\Delta r = -0.03$). Consequently, the significance levels of the original correlations remained unaffected, and common method bias is not a concern in this study.

5.5 Results

The descriptive statistics of the survey, based on 826 responses, are presented in Table 5.1. Of the respondents, 224 have invested in cryptocurrencies, while 602 have not.

The age of participants ranges from 18 to 85, with a mean of 35.85 and a median of 32 years. The age distribution exhibits a classic pyramid shape, indicating a younger demographic. Regarding gender, the sample is relatively balanced, with approximately 57% of respondents identifying as male. In terms of education, the majority of participants (78%) have completed upper secondary to postgraduate or specialization course education. A small percentage (0.8%) have only completed primary or lower secondary education, while a proportion of 21% have attained other higher education levels like master's or doctoral degrees.

This study employs partial least squares structural equation modeling (PLS-SEM) to analyze the survey data. As a non-parametric statistical tool, it aims to maximize the explained variance of latent constructs, offering numerous applications in the field of behavioral finance (Avkiran & Ringle, 2018).

Table 5.1 Sample profile

Characteristics	N	%
Respondents' Age		
18-25	297	36.0
26-30	85	10.3
31-40	166	20.1
41-50	116	14.0
51-60	84	10.2
>60	78	9.4
Respondents' Gender		
Male	475	57.5
Female	351	42.5
Respondent's Educational Level		
Primary	2	0.2
Lower Secondary	5	0.6
Upper Secondary	155	18.8
Professional education	34	4.1
Bachelor's Degree	233	28.2
Postgraduate or specialization course	223	27.0
Master's Degree	125	15.1
Doctorate	49	5.9
Investors in Cryptocurrencies		
Yes	224	27.1
No	602	72.9
Total	***826***	***100.0***

The PLS-SEM technique comprises two interconnected components: the measurement model and the structural model (Hair *et al*., 2019). The measurement model defines the relationship between observed variables and latent constructs, where each construct is represented by a set of indicators. This approach captures the multidimensional nature of constructs. The structural model, on the other hand, depicts the relationships between latent constructs, revealing the underlying mechanisms that drive the observed phenomena.

5.5.1 Measurement model

To assess the internal structure of the model, several key metrics were examined, including individual item reliability, reliability for the composite of measures of latent variables, and average variance extracted from the set of measures of each latent variable (Bagozzi & Yi, 1988). Regarding the composites, Cronbach's alpha is sensitive to the number of items in the scale and generally tends to underestimate their internal consistency reliability, being technically more appropriate to employ the composite reliability measure (CR), for which values greater than 0.70 are sufficient (Hair *et al.*, 2017). The results indicate that all variables are above the recommended minimum. Additionally, the average variance extracted (AVE) values for all variables exceeded the 0.50 threshold, (Fornell & Larcker, 1981). Detailed results are presented in Appendix.

The discriminant validity of the measurement model was assessed to ensure the distinctness of the constructs. Firstly, the square root of each construct's Average Variance Extracted (AVE) was compared to its correlations with other constructs, as suggested by Fornell and Larcker (1981). All constructs met this criterion. Secondly, the heterotrait-monotrait (HTMT) ratio was calculated, and the maximum value was 0.433, way below the 0.850 threshold (Henseler *et al.*, 2015). This method further supported the discriminant validity of the model. The results for both methods are presented in Table 5.2.

Table 5.2 Discriminant validity

	1	2	3	4	5	6	7
1. Overconfidence	**n.a.**	*0.102*	*0.130*	*0.114*	*0.045*	*0.138*	*0.026*
2. Intention toward Cryptocurrency	0.099	**0.927**	*0.074*	*0.398*	*0.201*	*0.088*	*0.178*
3. Online Banking	0.115	0.050	**0.747**	*0.203*	*0.172*	*0.207*	*0.215*
4. Investing in Cryptocurrency	0.114	0.385	0.190	**n.a.**	*0.101*	*0.287*	*0.019*
5. Age	-0.045	-0.189	0.160	-0.101	**n.a.**	*0.020*	*0.433*
6. Gender	-0.138	-0.086	-0.195	-0.287	-0.020	**n.a.**	*0.001*
7. Education	0.026	-0.167	0.196	-0.019	0.433	0.001	**n.a.**

Notes: the diagonal values in bold show the square roots of the AVE; the values below the principal diagonal are the correlation values; the values above the principal diagonal are the heterotrait-monotrait (HTMT) ratios; n.a. = not applicable.

5.5.2 Structural model

The structural model analysis revealed significant causal relationships among the variables. The goodness-of-fit (GoF) index of 0.26 indicates a slightly above-medium fit (Wetzels *et al*., 2009). Moreover, the R^2 value of 0.235, quite close to the threshold of a large effect (Cohen, 1988) and well above the recommended minimum of 0.10 (Falk & Miller, 1992), further supports the model's adequate fit.

Collinearity assessment, conducted through variance inflation factor (VIF) analysis, yielded values ranging from 1.000 to 1.276, well below the critical threshold of 5. This finding confirms the reliability of the estimated path coefficients (Hair *et al*., 2017).

We used bootstrapping technique to assess direct and mediating effects (Table 5.3) and tested our model in two progressive phases, in terms of causal relationships. In the first one we considered only hypotheses 1, 2 and 4. In this case, the relationship between overconfidence and investing in cryptocurrencies is significant (β=0.031, $p<0.05$) and supports H1. The effects of overconfidence on the intention toward cryptocurrencies and on online banking are also positive and strong (β=0.149, $p<0.001$ and β=0.113, $p<0.001$ respectively), thus supporting H2 and H4. We then step to the second stage and connect intention toward cryptocurrencies and online banking with the variable investing in cryptocurrencies, the relationship between overconfidence and investing in cryptocurrencies no longer works. This shows that overconfidence has an impact on investment, but because it has other aspects behind it. The effect of intention toward cryptocurrencies and online banking over investing in cryptocurrencies is significant ($\beta=0.155$, $p<0.001$ and $\beta=0.057$, $p<0.001$ respectively), therefore H3 and H5 are supported.

The analysis of the indirect effects shows that the effect of overconfidence on investing in cryptocurrencies is fully mediated by the variables intention toward cryptocurrencies ($\beta=0.015$, $p<0.01$) and online banking ($\beta=0.007$, $p<0.05$).

Finally, the results for the control variables indicates that age ($\beta=-0.052$, $p<0.001$ and $\beta=-0.035$, $p<0.05$) and gender ($\beta=-0.252$, $p<0.001$ and $\beta=-0.207$, $p<0.001$) have a significant impact on investing in cryptocurrencies in both stages of the model, while education shows no significant effect in any case.

Table 5.3 Structural model results

	Hyp.	Model 1		Model 2	
		Standardized estimate (t-value)	Standard Deviation	Standardized estimate (t-value)	Standard Deviation
Direct effects					
Overconfidence → Investing in Cryptocurrencies	H1	0.031* (2.212)	0.014	0.013 (0.906)	0.014
Overconfidence → Intention toward Cryptocurrencies	H2	0.149*** (4.642)	0.031	0.099** (2.982)	0.033
Intention toward Cryptocurrencies → Investing in Cryptocurrencies	H3			0.155*** (10.170)	0.015
Overconfidence → Online Banking	H4	0.113*** (3.271)	0.035	0.115*** (3.336)	0.035
Online Banking → Investing in Cryptocurrencies	H5			0.057*** (3.779)	0.015
Indirect effects					
Overconfidence → Intention toward Crypto → Investing in Cryptocurrencies				0.015** (2.808)	0.005
Overconfidence → Online Banking → Investing in Cryptocurrencies				0.007* (2.409)	0.003
Control variables					
Age → Investing in Cryptocurrencies		-0.052*** (3.554)	0.014	-0.035* (2.559)	0.014
Gender → Investing in Cryptocurrencies		-0.252*** (8.945)	0.028	-0.207*** (7.764)	0.027
Education → Investing in Cryptocurrencies		0.013 (0.825)	0.016	0.021 (1.450)	0.014
R^2 Investing in Cryptocurrencies		0.100		0.246	
R^2 Intention toward Cryptocurrencies		0.021		0.017	
R^2 Online Banking		0.012		0.013	

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

5.6 Discussion

The study highlights intriguing insights into the dynamics of overconfidence, intention, and technological adoption as they pertain to cryptocurrency investment. These results not only affirm existing theoretical constructs but also reveal nuanced relationships between psychological traits, behavioral intentions, and investment actions, providing fertile ground for comparison with the extant literature.

In the first stage of our analysis, we identified a relationship between overconfidence and the investment in cryptocurrencies. This finding is aligned with the perception of the cryptomarket as a speculative arena (Gagarina *et al*., 2019), marked by extremely high levels of volatility (Anastasiou *et al*., 2021; Ben & Xiaoqiong, 2019), where optimistic investors trade when prices increase (Naeem *et al*., 2020), and the understanding of overconfidence as a cognitive bias that leads to underestimate uncertainty (DeBondt *et al*., 2008; Oberlechner & Osler, 2012). Overconfident investors appraise in excess their ability, underestimate the risks and overrate the rewards associated with cryptocurrencies, leading to impulsive investment decisions, in a market predominantly volatile (Phillip *et al*., 2019)

However, in the second stage the mediation analysis revealed that overconfidence's impact on cryptocurrency investment is fully mediated by the intention toward cryptocurrencies. This suggests that overconfident individuals are more likely to form positive intentions toward cryptocurrencies, that ultimately leads to increased investment in cryptocurrencies. In line with the notion that risk plays a critical role in shaping individuals' engagement with transactions on the internet, and the general perception of internet transactions as a risky activity, influencing consumers' behavioral intention (Donthu & Garcia, 1999; Tan, 1999), overconfidence was found to have a direct, positive influence on individuals' intentions to invest in cryptocurrencies.

The intention to invest in cryptocurrencies was found to have a significant positive impact on actual investment behavior, both directly and indirectly, through mediating effects. Thus, the role of behavioral intention in relation with cryptomarket investments sheds light on a layered decision-making process. While overconfidence initially appears to directly influence investment, its significance becomes more clear when mediated by an individual's intention to invest. This aligns with established research, which consistently identifies behavioral intention as a critical predictor of actual behavior across various domains (Jarvenpaa *et al*., 1999; Tan & Teo, 2000), and consistently confirms the strong link between intentions and behavior, as demonstrated by studies across various contexts, including controlled laboratory experiments and real-world settings (Davis *et al*., 1989; Davis, 1989; Hill *et al*., 1987; Lee *et al*., 2005; Martins *et al*., 2014; Taylor & Todd, 1995).

The findings also corroborate that online banking usage positively influences cryptocurrency investment. Individuals who use online banking are more likely to invest in cryptocurrencies. This finding suggests that online banking usage may serve as a precursor to cryptocurrency investment, as it requires a certain level of technological literacy and comfort with online financial transactions. This result is consistent with previous studies by Szopiński (2016) and Sobhanifard and Sadatfarizani (2019), who argue that technological skills and familiarity with digital financial platforms facilitates broader adoption of internet-based innovations. It also aligns with the extant literature that emphasizes the significant influence of individuals' prior experience, knowledge, and involvement in related areas on the adoption of new technological systems (DeLone, 1988; Igbaria *et al*., 1989). The role of technology readiness (Parasuraman, 2000) and personal innovativeness (Yiu *et al*., 2007) is particularly evident here, as online banking users display the abilities and receptiveness necessary to navigate the complexities of cryptocurrency platforms.

Moreover, individuals exhibiting overconfidence were more likely to utilize online banking services. This is consistent with previous research indicating that new technologies, like online banking, are often perceived as risky, with potential negative consequences (Agarwal & Prasad, 1998). Confirming Rogers (2003), such technologies tend to be adopted by those who can handle higher levels of uncertainty. Only individuals who view online banking as a low-risk endeavor are likely to adopt it, and, consequently, confidence in using this service is a significant factor influencing its adoption (Tan & Teo, 2000). This finding also provides further support to the arguments of ul Abdin *et al*. (2022), Lowe and Ziedonis (2006), Parasuraman (2000) and Ratchford and Barnhart (2012), who posit that optimism and overconfidence go hand in hand, at the bottom of an excessive appraisal of individual abilities, being contributing factors to adopt new technologies. The relationship between overconfidence and technology adoption, reveals a critical insight to understand why individuals gravitate toward both online banking and cryptocurrencies, which, as internet-based technologies, require an appetite for uncertainty and innovation (Donthu & Garcia, 1999; Rogers, 2003; Tan, 1999).

The analysis of demographic factors provides additional insights into the cryptomarket dynamics. Control variables reveal significant demographic influences on cryptocurrency investment, particularly age and gender. Younger individuals and men are more likely to invest, which is consistent with prior findings by Naeem *et al*., (2021) and Oksanen *et al*. (2022), who link cryptocurrency trading with younger, tech-savvy males. This demographic profile parallels the adoption patterns of online banking, where age and gender also emerge as significant predictors (Jiménez & Díaz, 2019; Safeena *et al*., 2014). Our results further reinforce the perception of cryptocurrencies as a technology-driven and innovative asset class, appealing to younger individuals with higher technological literacy. Interestingly, education does not exhibit a significant impact on cryptocurrency investment. This suggests that cryptocurrency participation is less about formal education and more about individual traits and exposure to technology.

The overall model fit was found to be satisfactory, indicating that the proposed theoretical framework provides a good explanation of the relationships between the variables. The significant connections between overconfidence, intention, online banking usage, and cryptocurrency investment highlight the complex interplay of psychological, technological, and behavioral factors influencing individual investment decisions in this emerging market.

5.7 Conclusions

5.7.1 General conclusions

This research answers to the question on how overconfidence and online banking, influence individuals' intentions to invest in cryptocurrencies and their actual participation in the cryptomarket. The findings highlight the pivotal role of online banking usage, which emerges as a precursor to cryptocurrency investment by fostering technological literacy and comfort with digital financial transactions. These results align with prior studies emphasizing the influence of technological readiness and personal innovativeness on the adoption of new systems.

Overconfidence also significantly impacts cryptocurrency investment, with the mediation analysis revealing that its effect operates through individuals' intentions to invest, highlighting a layered decision-making process in this domain. The study further underscores a critical link between overconfidence and the adoption of online banking, suggesting that overconfident individuals, with their optimism and ability to handle uncertainty, are more likely to embrace technologies perceived as risky. Additionally, demographic factors such as age and gender influence cryptocurrency investment, with younger, tech-savvy males being more inclined to participate, while education appears less relevant. These insights contribute to understanding the behavioral and technological drivers behind cryptocurrency adoption, offering valuable implications for both academic research and practical applications in finance and technology.

5.7.2 Theoretical implications

This study contributes to the understanding of how overconfidence operates across financial and technological contexts. In line with DeBondt *et al.*, (2008), the findings underscore the role of overconfidence, particularly in risky and volatile markets like cryptocurrencies. This study answers a research gap (Almeida & Gonçalves, 2023; Shrotryia & Kalra, 2022) that was the analysis of overconfidence as a determinant of the investment in cryptocurrencies. Moreover, the mediating role of intention supports widely used behavioral models, reaffirming the importance of behavioral intention in translating personal characteristics into action.

The parallels drawn between online banking usage and cryptocurrency investment drawn upon technological adoption concepts (Parasuraman, 2000; Rogers, 2003), highlight that familiarity with online financial platforms facilitates cryptocurrency adoption. In this context, cryptocurrencies can be seen as a further step in digital financial engagement. The role of online banking as a mediator between overconfidence and investment in cryptocurrencies is particularly interesting, as this is, to the best of our knowledge, the first study to explore this relationship (Auer & Tercero-Lucas, 2022).

Finally, the results provided by the demographics pondering offer additional theoretical implications. Younger individuals and males are more likely to engage in cryptocurrency investment, underscoring the gendered and generational dynamics of this activity. Concurrently, the stronger inclination of males toward cryptocurrency investment reflects broader patterns of risk-seeking behavior. In contrast, the lack of significance for education in influencing cryptocurrency investment challenges assumptions about the role of knowledge in shaping investment decisions, further suggesting that cryptocurrency adoption may be driven more by sentiment and risk attitudes than by formal education. Together, these findings highlight the demographic segmentation of cryptocurrency investors and open avenues for exploring how these characteristics intersect with personal traits to shape financial behaviors.

5.7.3 Practical implications

The findings of this study have important implications for policymakers, market participants and regulators, by pointing to some critical determinants of the eventual entrance in the cryptomarket by individual users. Whether cryptocurrencies are seen as virtual currencies, as originally intended by their creators, or as digital investments, it is clear that we are witnessing only their beginning. No doubt cryptocurrency brokerage on virtual platforms will become commonplace for many individuals.

As cryptocurrency trading becomes more widespread globally, it is essential to understand the factors driving its adoption. By addressing these factors and implementing appropriate measures, we can work to foster a more secure market for everyone. Understanding the role of overconfidence can help to mitigate the risks associated with cryptocurrency investment. Policy-makers should prepare financial literacy programs, designed to educate investors about the potential pitfalls of overconfidence and the importance of making informed investment decisions. Platforms dedicated to cryptocurrency transactions should be required by regulators to address cognitive biases, such as overconfidence, through risk-awareness initiatives. Simultaneously, understanding the demographic tilt toward younger males can benefit institutions on the offer side, allowing them to tailor marketing strategies accordingly.

5.7.4 Limitations and future research

While the study makes significant contributions, it also has limitations, including its reliance on self-reported data and convenience sampling. These constraints might affect the generalizability of the findings, particularly given the rapidly evolving nature of the cryptocurrency market. Despite the limitations, the study provides a strong basis for future investigation by revealing and highlighting important elements to influence individual engagement in the technology-driven cryptocurrency trading. Future research could explore longitudinal data to assess how market dynamics and user profiles evolve over time, particularly in response to regulatory changes or security advancements. Additionally, exploring the role of social influence and network effects on cryptocurrency investment would provide more insights into the underlying forces that are shaping this emerging market.

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Appendix 5.1

Table 5.4 Measurement scales

CONSTRUCT/ scale items	Standardized loadings
INTENTION TOWARD CRYPTOCURRENCIES (α = 0.92; CR = 0.95; AVE = 0.86) (Scale: 1 = 'Totally disagree'; 4 = 'Neither agree nor disagree'; 7 = 'Totally agree')	
If I were going to make an investment, I would consider cryptocurrencies	0.896
The likelihood of buying cryptocurrencies is high	0.947
My willingness to buy cryptocurrencies is high	0.937
ONLINE BANKING (α = 0.84; CR = 0.88; AVE = 0.56) Please indicate how often you performed the activities listed below in the last month. (Scale: 1 = 'Very rarely; 4 = 'Sometimes'; 7 = 'very often')	
BASIC BANKING (α = 0.89; CR = 0.93; AVE = 0.82)	
I used internet banking or other applications to manage my bank account	0.870
I used internet banking or other applications to transfer and remit money	0.941
I used internet banking or other applications to make payments	0.904
SOPHISTICATED BANKING (α = 0.90; CR = 0.94; AVE = 0.84)	
I made investments or placed investment orders through internet banking or other financial investment applications	0.777
Check the status of financial applications through internet banking or other financial investment applications	0.789
I looked for financial investment alternatives through internet banking or other financial investment applications	0.735
INVESTING IN CRYPTOCURRENCIES Have you ever invested in cryptocurrencies?	

OVERCONFIDENCE

A - How would you rate your knowledge of the financial market compared to other adults in your country?
(Scale: 1 = 'Extremely low'; 4 = 'On average'; 7 = 'Extremely high')

The following questions are more like a quiz. The questions are not designed to surprise you, so if you don't have the correct answer, choose the one that makes the most sense.

B1 - A person has 1,000 euros in a demand deposit account, which he hopes to use within a year. If the inflation rate in that same year is 10%, in a year from now she will be able to buy:
More products than she could buy today.
The same amount of products as she could buy today.
Fewer products than she could buy today.
I don't know.

B2 - You lend 25 euros to a friend one night and he gives you 25 euros back the next day. How much interest did he pay on this loan?
Zero.
50 euros.
I don't know.

B3 - Imagine that someone deposits 100 Euros into a savings account, exempt from fees and taxes, with an interest rate of 2% per year on the account balance. This person no longer makes deposits into this account and does not withdraw money. How much would be in the account at the end of the first year, since interest payments are deposited annually into the same account?
98 euros.
100 euros
102 euros.
120 euros.
I don't know.

B4 - And how much would there be in the account at the end of five years [remembering that there are no commissions or taxes and interest is deposited annually into the same account]?
More than 110 euros.
Exactly 110 euros.
Less than 110 euros.
Impossible to say from the information given.
I don't know.

Please say whether the following statements are true or false:

B5 - An investment with a high return is likely to be high risk
B6 - High inflation means the cost of living is rising rapidly
B7 - It is generally possible to reduce the risk of investing in the stock market by buying shares in different companies.

Overconfidence = A - Σ (B1,…, B7)

Chapter 6: Research Conclusions

This research delves into the realm of cryptocurrency investment, a new financial landscape marked by complex dynamics, impregnated with abrupt movements in price, and within a yet incipient framework, where investors are exposed to a myriad of risks. There are many questions waiting to be answered in this domain. This work addresses a significant gap in the literature by providing a comprehensive examination of the behavioral, demographic, and psychological dimensions influencing cryptocurrency investment. It is important because it offers valuable insights for investors seeking to navigate the complexities of this market, regulators aiming to develop appropriate frameworks, and financial institutions considering incorporating cryptocurrencies into their offerings.

The emergence of cryptocurrencies has been interpreted through diverse lenses. Some posit that their creation represents a direct response to the 2008 global financial crisis, signifying a decline in trust in the established international monetary system (Rosales, 2019; Trucíos *et al.*, 2020). Others argue that cryptocurrencies reflect libertarian philosophies, embodying a desire for a decentralized, self-regulating financial paradigm independent of nation-state control and central authorities (Dallyn, 2017; Spithoven, 2019). This perspective is echoed by the European Central Bank (2012), which early on recognized the link between cryptocurrencies and criticisms of the prevailing fiat money system and governmental interventions. Whether cryptocurrencies will ultimately fulfill these libertarian aspirations and change the international monetary architecture in such direction we do not know. What we know for sure is that the cryptomarket is unique (Huang *et al.*, 2022), growing exponentially (Liu *et al.*, 2022) but still immature (Bouri *et al*., 2019). Characterized by a lack of intrinsic value and the absence of backing by either private entities or governments, this market demonstrates significant inefficiencies, and research suggests that considerable uncertainty persists regarding the determinants of cryptocurrency price fluctuations (Fidrmuc *et al*., 2020; Fil & Kristoufek, 2020; King & Koutmos, 2021; Palamalai *et al*., 2021; Shen *et al*., 2020).

Indeed, the increasing prominence of cryptocurrencies in the global financial landscape, the wild volatility levels they constantly exhibit, and its underdeveloped regulatory framework underscore the need for a comprehensive research on the topic, particularly about investors behavior.

At its core, by employing a multidisciplinary approach and rigorous empirical analysis, this research provided pioneering information to answer fundamental questions about why individuals invest in cryptocurrencies and the factors that shape their decisions. It delved into the psychology of cryptocurrency investors, examining the cognitive bias of overconfidence, the individual propensity to risk, and the influence of personality traits. Our work drew on perspectives from behavioral finance and technology innovation studies to illuminate the complex interplay of factors driving cryptocurrency investment, and offer valuable perspectives for academics, practitioners, and policymakers alike.

6.1 Main Conclusions

The main goal of this thesis is to answer the following research question: What are the key behavioral, demographic, and psychological factors shaping the personal intention to invest in cryptocurrencies, and how do they interact to influence actual behavior? We sought to answer this question by defining other, more specific questions, divided into four different research works. This thesis integrates insights from a systematic literature review and three subsequent empirical studies to provide a comprehensive understanding of the factors influencing cryptocurrency investment, spanning demographic, psychological, and behavioral dimensions. By synthesizing the results of these interconnected investigations, the overarching conclusions not only validate existing theoretical frameworks but also reveal novel insights into the interplay of personal characteristics, the propensity to take risks, and technological readiness in shaping intentions and behaviors toward cryptocurrencies, offering a multifaceted perspective on the emerging and volatile cryptomarket.

One of the central findings of this research is the nuanced portrayal of cryptocurrency investors, highlighting their distinct behavioral and psychological traits. The studies demonstrate that overconfidence and risk propensity are not only prevalent among cryptocurrency investors but also serve as significant predictors of their engagement in this market. Overconfidence is particularly striking, emerging as a defining characteristic that differentiates cryptocurrency investors from non-investors. This trait, detected by an inflated self-assessment of financial competence, leads individuals to underestimate risks and make impulsive decisions, fostering a sense of invulnerability that encourages speculative behaviors. Overconfidence emerges as a central element driving investment behavior, aligning with the speculative nature of the cryptomarket, where volatility and uncertainty are prevalent. This bias influences investment decisions directly and indirectly, mediated by behavioral intentions. Overconfidence influences cryptocurrency investment primarily through its effect on the intention to invest. The mediating role of intention highlights a layered decision-making process, where psychological traits shape attitudes and subsequent actions.

Moreover, our study points to demographic factors such as age, gender, and income, as significant predictors of cryptocurrency investment. The findings consistently show that younger individuals are more inclined to engage in this market, a pattern likely influenced by their greater familiarity with technology and higher risk tolerance. Gender differences are also evident, with men demonstrating a greater propensity to invest in cryptocurrencies compared to women. This aligns with broader research in behavioral finance, which links men to higher risk-taking tendencies and overconfidence. Income plays a somewhat paradoxical role in cryptocurrency investment. While individuals in the lower-income brackets are more likely to invest, this behavior may reflect the aspirational appeal of cryptocurrencies as a means of achieving financial growth. Interestingly, financial knowledge and education did not prove to be a significant factor in cryptocurrency investment, indicating that some individuals start trading with crypto assets without sufficient preparation, leading us to think that participation in this market is less about literacy and more about personal traits, bias, and risk appetite.

The joint analysis of age and financial market experience provided critical insights into the evolving nature of overconfidence and risk propensity. Older and more experienced investors exhibit heightened overconfidence but reduced risk propensity. Therefore, age and experience play nuanced roles in shaping investment behaviors, interacting in complex ways with overconfidence and risk propensity. The research reveals that younger individuals are more likely to invest in cryptocurrencies, driven by their greater familiarity with technology and higher risk tolerance. On the other hand, age exhibits a negative association with risk propensity, suggesting that as individuals mature, they become more cautious in their financial decisions. Experience, particularly in financial markets, influences overconfidence in a contrasting manner. The findings indicate that greater market experience correlates with heightened levels of overconfidence, reflecting a self-reinforcing cycle where past successes bolster individuals' belief in their abilities. This dynamic highlights the dual-edged nature of experience, which can enhance financial competence while also fostering cognitive biases that lead to overestimation of skills.

The interplay between age, financial experience, risk propensity and overconfidence underscores the complexity of investment behavior. It suggests that while younger and inexperienced investors may exhibit high risk propensity and less overconfidence, seasoned investors may paradoxically display high overconfidence and low risk propensity. This duality reflects the evolving nature of financial decision-making, where psychological traits and life experiences interact to shape individual choices. While confidence in financial skills grows with experience, an increased awareness of the need for financial security tempers risk-taking behavior. This interplay has significant implications for understanding investment behavior across the life cycle and call for financial education measures and adequate policymaking. They emphasize the need for targeted interventions that address the psychological and experiential dimensions of investment behavior, promoting a balanced approach that mitigates cognitive biases while fostering informed risk-taking. This is particularly crucial in the context of cryptocurrencies, where the high-risk nature of the market necessitates a nuanced understanding of investor psychology and behavior. Younger individuals, with limited experience but higher risk tolerance, dominate the cryptomarket. In contrast, older investors, despite their confidence, adopt a more conservative approach, prioritizing financial stability.

In addition, cross-country comparisons reveal an intriguing dynamics. The findings suggest that differences in national and economic contexts, such as those between Brazil and Portugal, play a significant role in shaping attitudes and behaviors toward cryptocurrencies. In our case, these cultural and economic influences manifest in varying levels of overconfidence and risk-taking, with Portuguese investors generally exhibiting higher overconfidence and risk propensity than their Brazilian counterparts. The difference in overconfidence intensity may be rooted in historical factors, illustrated by the Brazilian rich history of cultural exchange, marked by extensive interracial mixing and immigration. The difference in propensity to take risks may be due to diverging economic conditions between the two countries. Employment rates and inflation are typically higher in Brazil in comparison to Portugal and may impact negatively the risk taking attitude. In countries with stable economies, people may feel more secure and apt to take higher risks, whereas, in less stable environments, risk aversion might be more dominant. These findings underscore the importance of considering cultural and economic factors in behavioral finance research, as they significantly influence investor psychology and decision-making.

The inclusion of personality traits, employing the Five Factor Model, added depth to our analysis, revealing the inverse relationships of agreeableness, conscientiousness, and neuroticism with risk propensity and crypto investment attitudes, indicating that individuals who are cooperative, meticulous, or stress-prone are less likely to take financial risks. In addition, the negative association of these traits with risk-taking and the intention to invest in cryptocurrencies aligns with previous research linking these traits to conservative investment preferences, emphasizing the cautious and risk-averse nature of individuals who score high on these dimensions, and reinforces the perception of cryptocurrencies as a high-risk asset class, appealing to those with a higher tolerance for uncertainty and innovation.

Interestingly, the relationship between personality traits and investment attitudes is not always direct. In particular, conscientiousness influences cryptocurrency attitudes indirectly through its effect on risk propensity, highlighting the mediating role of psychological constructs in financial decision-making. This underscores the complexity of human behavior, where multiple factors interact to shape individual choices. On top of that, the study reveals that risk propensity strongly predicts cryptocurrency investment, reinforcing the notion that these assets attract individuals who are comfortable with uncertainty and volatility. This is further supported by the demographic profiles of cryptocurrency investors, who are predominantly younger and male, reflecting their higher risk tolerance and willingness to explore innovative financial instruments.

Another important contribution of this thesis is the exploration of technological adoption. Prior adoption of internet-based financial tools, as evidenced by online banking usage, is a significant factor influencing cryptocurrency investment. The positive relationship between the use of online banking and cryptocurrency investment reveals the interconnectedness of technological familiarity and financial behaviors in a world living the fintech moment. Individuals who are comfortable with online banking are more likely to explore cryptocurrencies, reflecting their openness to technological innovation and willingness to navigate complex digital platforms. This highlights the importance of technological literacy in modern investment behaviors, particularly in the context of internet-based innovations such as cryptocurrencies. Our research also indicates a broader pattern of technology readiness and personal innovativeness among cryptocurrency investors, by showing that individuals exhibiting overconfidence are more likely to utilize online banking services. This is consistent with previous research indicating that new technologies are often perceived as risky, with potential negative consequences. The relationship between overconfidence and technology adoption reveals a critical insight to understand what sort of individuals gravitate toward both online banking and cryptocurrencies, which, as internet-based technologies, require an appetite for uncertainty and innovation. Overconfidence enable them to embrace new financial technologies, despite the risks and uncertainties involved.

In conclusion, this thesis provides a broad analysis of the behavioral and technological elements shaping cryptocurrency investment. By integrating theoretical and empirical investigation, it offers a multifaceted understanding of the complex cryptomarket environment. As the cryptomarket continues to attract participants who may not fully grasp its complexities, our research highlights its behavioral and technology-driven nature, highlighting the need for further education and awareness among investors.

6.2 Theoretical Implications

This research makes important theoretical contributions to the field of finance in a number of ways. First, we provide a foundational mapping of the cryptomarket's research landscape, highlighting its inefficiencies, incipient regulatory framework and susceptibility to fraud. While emphasizing the fact that, unlike traditional assets, cryptocurrencies lack intrinsic value, and their acceptance and price are a result of public consensus, we shed light on the investors irrational behavior in the market.

The empirical investigation into overconfidence, risk propensity, and demographic variables expands behavioral finance theories by demonstrating how cognitive biases influence investment behavior, contributing to a more nuanced understanding of the under-researched cryptomarket. The indication that overconfidence plays a pivotal role in driving investment intentions, reinforces the notion that psychological biases persist even in modern financial ecosystems. The focus on overconfidence is particularly relevant given the intangible nature of cryptocurrencies and their reliance on public perception. Moreover, our study enhances cross-national perspectives in financial decision-making, by exploring investor behavior in Brazil and Portugal.

In adding the analysis of personality traits, our work further refines theoretical models, uncovering the inverse relationship between specific personality dimensions – agreeableness, conscientiousness, and neuroticism – and investment intention. It contributes to the extant literature by connecting personality psychology with investment in cryptocurrencies and revealing that certain personality traits favor engagement in the cryptomarket. Furthermore, it highlights the mediating role of risk propensity, particularly in the link between conscientiousness and investment attitudes, offering a novel perspective on how individual differences shape financial decision-making.

Our work also extends the theoretical discourse, examining the interaction between overconfidence and technological adoption. The novel finding that online banking experience facilitates cryptocurrency adoption highlights the increasing convergence of finance and technology. The analysis of investment in cryptocurrencies under the view of digital finance, contributes to illuminate the rationale of technological factors influencing participation in the cryptomarket.

Finally, the demographic findings, particularly the higher inclination of younger males towards cryptocurrency investment, contribute to broadening our comprehension of investor profiles in the cryptomarket. Moreover, the unexpected result that education level does not significantly impact cryptocurrency investment challenges prevailing assumptions about the role of financial literacy, suggesting that behavioral and psychological factors may play a more critical role than formal knowledge in driving investment decisions. These insights provide a valuable addition to existing theoretical frameworks, advancing the understanding of how demographic variables intersect with behavioral finance principles.

6.3 Practical Implications

Our investigation offers a range of practical implications for various stakeholders in the cryptocurrency market. For policymakers and regulators, the findings emphasize the necessity of incorporating psychological insights into the design of investor education initiatives. These programs should not only focus on the technical aspects of cryptocurrencies but also address cognitive biases, such as overconfidence, and promote responsible investment behavior. Furthermore, the research suggests tailoring educational campaigns to different demographic profiles. For instance, younger males, who are often more drawn to cryptocurrency investments, may benefit from targeted information about the high volatility and potential risks associated with this asset class. Regulators should also consider mandating cryptocurrency trading platforms to implement risk-awareness initiatives that address cognitive biases and promote investor protection over profit. This could include requirements for platforms to provide information about risks and encouraging prudent investment practices.

Private sector stakeholders can also leverage these insights to improve their practices. Financial advisors can use this knowledge to tailor investment recommendations to individual clients, taking into account their risk tolerance and psychological profile. Fintech firms can design user-friendly platforms that incorporate educational resources and tools to help investors make informed decisions. Cryptocurrency exchanges can implement measures to mitigate the impact of overconfidence, such as providing risk disclosures and promoting responsible trading practices.

Perhaps most importantly, individual investors need to be aware of how their own psychological characteristics can influence their investment decisions. Recognizing the impact of overconfidence and risk propensity is crucial for making sound financial choices in the volatile cryptocurrency market. Investors should actively evaluate their risk tolerance before entering this market and develop well-defined investment strategies based on their actual abilities and experience, rather than on sentiment. Learning about investor psychology and the tendency to perceive oneself as better-than-average can help individuals make more rational decisions.

6.4 Limitations and future research

This thesis, exploring cryptocurrencies within the investment sphere, acknowledges several limitations that pave the way for future research. A primary constraint lies in the inherent complexity of the cryptocurrency ecosystem. While the included studies offered valuable insights into specific facets, the broader landscape encompasses a multitude of interconnected elements, including technological underpinnings, regulatory frameworks, economic implications, and social dynamics, offering magnificent opportunities for future research.

Specifically, while the literature review provided a structured overview of cryptocurrency research, it necessarily focused on a defined set of keywords and databases. This approach, while systematic, excluded research published outside of these parameters. Future studies could explore alternative search strategies, including, for example, blockchain, distributed ledger methodology or the role of cryptocurrencies as a source of financing, as is the case of initial coin offers (ICO).

The empirical studies presented in this thesis also encountered limitations. The reliance on self-reported data limits the ability to verify actual behavior. Future research could explore innovative methods for data collection, such as incorporating behavioral data from blockchain transactions or collaborating with cryptocurrency exchanges (while respecting privacy), to enhance the validity of findings. Furthermore, the cross-sectional nature of empirical studies provides a snapshot in time, potentially overlooking the dynamic interplay between individual characteristics, market fluctuations, and evolving regulatory landscapes. Longitudinal studies, tracking individuals and their investment behavior over time, would offer valuable insights into the long-term trends and drivers of cryptocurrency adoption.

The focus on specific aspects of investor behavior, such as overplacement or the influence of personality traits, while contributing valuable knowledge, also suggests avenues for future research. Exploring other psychological factors, such as trust or fear of missing out, could provide a more nuanced understanding of investment decision-making in the cryptocurrency market. Additionally, investigating the role of social influence, including peer effects and online communities, could shed light on the diffusion of cryptocurrency adoption and the formation of market trends.

Finally, the impacts resulting from the rapid pace of technological advances, the emergence of new ecosystems interrelated with the cryptocurrency space, and the direction that regulation will take – more restrictive or more permissive – necessitates continuous research. Future studies could prioritize investigating the effects of decentralized finance (DeFi), as well as of the evolving regulatory landscape, not only locally, but also at the international level.

By addressing these limitations and pursuing these research directions, future studies can contribute to a more comprehensive and nuanced understanding of the complex and ever-changing world of cryptocurrencies.

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