CRYPTOCURRENCY OWNERSHIP AND BIASES IN PERCEIVED FINANCIAL LITERACY

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TENENCIA DE CRIPTOMONEDAS Y SESGOS EN LA PERCEPCIÓN DE LA EDUCACIÓN FINANCIERA

(CRYPTOCURRENCY OWNERSHIP AND BIASES IN PERCEIVED FINANCIAL LITERACY)

Resumen ejecutivo

Este informe examina la relación entre la *educación financiera* y la *tenencia de criptomonedas para calibrar hasta qué punto una buena cultura financiera puede contrarrestar inversiones de alto riesgo.* Basándose en una encuesta a 2.121 individuos, identifica los principales factores que predicen la tenencia de criptomonedas, incluyendo la edad, el tamaño de la población, el peso de las transacciones en efectivo, la percepción de innovación bancaria, el nivel de ingresos y la autopercepción del nivel de educación financiera. Se evidencia que:

- La *educación financiera* es un *factor determinante* que reduce la *posesión de criptomonedas.* La educación financiera es tan relevante estadísticamente como la edad en la reducción de la probabilidad de poseer criptomonedas.

- *Cada incremento* unitario *en el nivel de educación financiera (valorado entre 0 y 10) reduce* la probabilidad *de poseer criptomonedas en un 0,2.*

- La existencia de *sesgos en el nivel de educación financiera* (indicando un exceso de confianza respecto a los conocimientos financieros propios) *tiene un efecto sustancial* en la probabilidad de *poseer criptomonedas.* Aquellos con mayores sesgos tienen una probabilidad del 75,3 % más de poseer criptomonedas que aquellos con menores sesgos. Cuando se *corrigen dichos sesgos,* la *educación financiera tiene un efecto negativo (reductor)* del 25,4 % en la probabilidad de *poseer criptomonedas.*

- Las personas con *mayor educación financiera,* así como aquellas con una evaluación *menos sesgada* de sí mismas, tienen *menos probabilidades* de *poseer criptomonedas.*

- Los resultados enfatizan la *necesidad de programas de educación financiera* dirigidos para aumentar el conocimiento de las personas pero también corregir excesos de confianza sobre el conocimiento financiero y mejorar la *toma de decisiones* con respecto a las *criptomonedas y otros activos de alto riesgo.*

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Abstract

This paper examines the relationship between financial literacy and cryptocurrency ownership using machine learning techniques. Based on 2,121 survey responses, it identifies significant predictors of cryptocurrency ownership, including age, population size, cash transaction weight, bank innovation perception, income level, and self-assessed financial literacy. A noteworthy finding is the importance of financial literacy as a determinant of cryptocurrency ownership. Financial literacy is as statistically relevant as other variables, such as age, in reducing the likelihood of holding cryptocurrencies. Employing a neural network model, we find that each unit increase in financial literacy reduces the probability of cryptocurrency ownership by 0.2, which is comparable to the effect of age. A causal forest analysis shows that financial literacy bias (signaling overconfidence regarding financial literacy) has a substantial positive effect on the likelihood of cryptocurrency ownership, with a point estimate of 75.30% and a confidence interval of (+72.6%, +77.8%). Additionally, the bias-corrected financial literacy measure has a negative effect of -25.40% on the likelihood of cryptocurrency ownership. These findings underscore the importance of financial literacy in cryptocurrency ownership. They suggest that individuals with more financial literacy, as well as those with less biased self-assessments, are less likely to hold cryptocurrencies. The results emphasize the need for targeted financial education programs to increase individuals' knowledge and improve their decision-making skills regarding cryptocurrencies.

Key words: cryptocurrencies, financial literacy bias, machine learning, digital asset adoption.

JEL Classification: G21, G24.

1. INTRODUCTION

Cryptocurrencies have emerged as a disruptive force in the financial landscape, capturing the attention of investors and regulators alike. The unprecedented rise of Bitcoin, Ethereum, and other digital currencies has led to a global surge in interest and investments in these alternative assets. However, the associated complexities and risks associated with these assets have raised concerns regarding the need for potential investors interested in cryptocurrencies to possess adequate financial literacy and comprehend the cognitive biases that can influence their decision-making. Prominent international institutions, such as the International Monetary Fund (IMF) and the Bank for International Settlements (BIS), have highlighted the importance of financial literacy in navigating the cryptocurrency ecosystem. The IMF (2022) has stressed the need for individuals to understand the underlying technology, the volatility of digital assets, and the potential for financial losses. Similarly, the BIS (2021) has expressed concerns about investor awareness and knowledge of the risks and regulatory challenges related to cryptocurrencies.

Academic research is increasingly recognizing the importance of financial literacy in shaping individuals' investment decisions and mitigating cognitive biases. Financial literacy, which encompasses knowledge, skills, and attitudes related to financial matters, empowers individuals to make well-informed investment choices. Moreover, cognitive biases, such as overconfidence, herd mentality, and framing effects, can significantly impact decision-making and potentially lead to suboptimal investment outcomes. While the impact of financial literacy and cognitive biases on behavior related to traditional asset classes has been extensively studied, these factors' influence on cryptocurrency ownership remains relatively unexplored. This paper aims to bridge this gap by investigating the relationship between financial literacy, cognitive biases, and cryptocurrency ownership, thereby making a distinct contribution to the existing literature. Examining the relationship between financial literacy and the ownership of cryptocurrencies is particularly relevant, as these assets may be far more complex than traditional financial assets.

Building upon recent studies conducted by Tae Kim, Hanna & Lee (2023) and Fujiki (2020), we examine the relationship between subjective perceptions of financial knowledge and actual financial literacy in the context of cryptocurrency ownership. Tae Kim, Hanna & Lee (2023) conducted a comprehensive survey in the United States and identified a positive link between subjective financial literacy and cryptocurrency ownership, as well as a negative association between objective investment literacy and cryptocurrency investment. Fujiki (2020) focused on the financial literacy of cryptocurrency holders and highlighted a discrepancy between actual and perceived literacy, with individuals often overestimating their financial knowledge.

Inspired by the concerns raised by multinational institutions, our study goes a step further by examining the role of financial literacy and cognitive biases in cryptocurrency ownership using a rich and diverse survey dataset collected in Spain. In doing so, we explore the associations between financial literacy, cognitive biases, and the likelihood of holding cryptocurrencies. Additionally, we employ advanced analytical techniques to disentangle the complex dynamics involved, thereby facilitating a more nuanced understanding of the drivers of cryptocurrency ownership.

By incorporating variables related to digital activity and perception, and by leveraging data collected during a recent period in which awareness of the risks of cryptocurrencies has increased,[1] our study provides novel insights into the effects of financial literacy and cognitive biases on the decision to adopt cryptocurrencies. This deeper understanding will contribute to the broader discussion on the factors influencing cryptocurrency ownership and inform policymakers' and regulators' efforts to promote financial literacy and mitigate risk in this rapidly evolving landscape. By exploring the nuances of financial literacy, cognitive biases, and their implications for cryptocurrency adoption, the study contributes to both the academic literature and the practical domain.

[1] Previous studies (*e.g.,* Fujiki, 2020; Tae Kim, Hanna & Lee, 2023) were conducted during a period in which the cryptocurrency markets only exhibited a growth trend. However, our survey was conducted at the end of 2021, subsequent to a phase of upheaval in the cryptocurrency markets. This allows us to examine the adoption of these digital assets at a crucial juncture, when consumers demonstrated an elevated awareness of the associated risks, particularly with regard to potential losses. This aspect is particularly important because substantial losses act as a catalyst, prompting consumers to actively pursue knowledge pertaining to these assets and their inherent risks.

We aim to provide empirical evidence and insights that can inform regulators and policymakers as well as educational initiatives that aim to increase financial literacy, address cognitive biases, and foster responsible investment behavior in the cryptocurrency markets. Our findings will not only advance our understanding of the cryptocurrency landscape but also offer valuable insights for researchers, practitioners, and policymakers in the fields of finance and investment.

The remainder of the paper is structured as follows. Section 2 provides a review of the relevant literature to benchmark the contributions of this study. The data and methodology are explained in Section 3. Section 4 presents the results. The paper ends with Section 5, which presents the main conclusions.

2. LITERATURE REVIEW

Several distinct factors explain the adoption of cryptocurrencies. This section provides a comprehensive review of the main determinants identified in the existing literature, placing particular emphasis on the role of financial literacy.

2.1. Drivers of cryptocurrency adoption

Studies have shown that the adoption and use of cryptocurrencies is not random. Several socioeconomic factors influence consumers' decision to buy cryptocurrencies (Balutel, Felt *et al.,* 2022; Fujiki, 2020; Hasso, Pelster & Breitmayer, 2019; Karkkainen & Atkinson, 2020). Regardless of the specific jurisdiction considered, it seems that men and young people are more likely to purchase cryptoassets. This pattern is observed in both international data (Auer *et al.,* 2022) and data from distinct geographic regions (*e.g.,* Canada [Balutel, Henry *et al.,* 2022]; Japan [Fujiki, 2020] and Austria [Stix, 2021]). Another factor influencing cryptocurrency adoption is risk-taking behavior. Cryptocurrency holders tend to have a higher risk tolerance than non-holders (Fujiki, 2020; Hackethal *et al.,* 2022; Stix, 2021). In particular, Fujiki (2020) shows that cryptocurrency holders are more impatient, more risk-seeking, and have less self-control than non-holders, while Stix (2021) finds that cryptocurrency holders are more willing to accept investment losses if above-average profits can be expected. In general, cryptocurrency investors are prone to investment biases and hold risky portfolios (Hackethal *et al.,* 2022). In this sense, the increased risk tolerance among young men compared to women and older individuals would explain males' increased willingness to own cryptocurrency.

Furthermore, cryptocurrency adoption seems to be associated with network effects, individual beliefs, and social learning effects. Balutel, Henry *et al.* (2022) find that network effects –the number of current users– and individual effects have a significant positive effect on Bitcoin adoption. In their examination of consumer perceptions of cryptocurrencies, Arli *et al.* (2021) highlight that consumers who understand how cryptocurrencies work are more likely to trust and invest in these assets. Gupta *et al.* (2020) show that social influence is among the strongest predictors of cryptocurrency adoption, while media sentiment is also likely to affect this behavior (Hackethal *et al.,* 2022). In this regard, crowd and media influence may partly explain why some of the main cryptocurrencies exhibit herding behavior (da Gama Silva *et al.,* 2019; Kaiser & Stöckl, 2020; Vidal-Tomás, Ibáñez & Farinós, 2019). Cryptocurrency users are biased toward positive news regarding these assets (Glaser et al., 2014), which increases their propensity to invest in cryptocurrencies during growth periods.

Alongside individual characteristics, empirical studies have also found that the adoption of cryptocurrencies is associated with certain macroeconomic factors. Using country-level data, Bhimani, Hausken & Arif (2022) show that cryptocurrency ownership varies across nations based on country-specific factors related to the level of economic development – human development, regulatory quality, corruption, and economic freedom, among others. These findings are corroborated by Saiedi, Broström & Ruiz (2021), who add that the adoption of cryptocurrency infrastructure is driven by the perceived failings of traditional financial systems. In particular, adoption is higher in countries where residents have low trust in banks and the financial system.

Nevertheless, it is not just individual and country-specific factors that affect cryptocurrency adoption. Another strand of literature has found that cryptocurrency use is also driven by changes in the prices of these digital assets. Auer *et al.* (2022) show that price changes have a causal effect on the adoption of cryptoassets. In particular, an increase in the price of Bitcoin is associated with a significant increase in new Bitcoin users. These authors document that a one-percentage-point increase in the Bitcoin price is associated with a 0.9% increase in new users two months later. Similarly, Kristoufek (2013) identify a relationship between cryptocurrency prices and consumer interest in cryptoassets. Increased consumer attention affects cryptocurrency prices because when cryptocurrency prices are high, an increase in interest pushes them up further. These findings align with results demonstrating that most cryptocurrency users buy cryptocurrencies for investment purposes (Balutel, Felt *et al.,* 2022; Böyükaslan & Ecer, 2021). The rent-seeking behavior of most cryptocurrency users would explain why some cryptocurrencies, such as Bitcoin, are mainly used as speculative investments and not as alternative currencies or mediums of exchange (Baur, Dimpfl & Kuck, 2018; Baur, Hong & Lee 2018; Cheah & Fry, 2015; Liu & Li, 2022; Smaniotto & Neto, 2022).

Finally, other studies have identified additional drivers of the adoption of cryptocurrencies. Foley, Karlsen & Putnins (2019) find that illegal activity accounts for a substantial proportion of Bitcoin use and trading activity. Approximately one-quarter of Bitcoin users are involved in illegal activity. However, the share of Bitcoin activity related to illegal activities declines as mainstream interest in Bitcoin increases and more opaque cryptocurrencies emerge. Saiedi, Broström & Ruiz (2021) find that Bitcoin adoption is partly driven by the usefulness of cryptocurrencies for illicit trade. Furthermore, preliminary evidence suggests that the adoption of cryptocurrencies, which are a type of financial asset, may be affected by changes in inflation and central bank monetary policies. On the one hand, Marmora (2021) shows that trading volumes are strongly related to inflation expectations. As inflation increases, shadow market participants shift away from cash and towards cryptocurrencies to conduct anonymous transactions. On the other hand, Marmora (2022) documents that monetary policy announcements increase attention and trading volume in Bitcoin, but only on days when the public is unusually attentive to inflation. Finally, while it has been argued that cryptocurrencies can impact financial inclusion, Wednesday (2022) concludes that this may not be the case. Rather, cryptocurrencies may exacerbate unequal access to financial services among historically excluded groups.

2.2. Cryptocurrency ownership and financial literacy

The economic importance of financial literacy in relation to financial decision-making is documented in a large and growing empirical literature (Kaiser *et al.,* 2022; Lusardi, 2019; Lusardi & Mitchell, 2014; among others). Financial literacy has been proven to affect both saving and investment behavior. As in other types of investments that involve a certain level of risk, financial literacy plays a role in cryptocurrency adoption. Specifically, individuals' level of education, particularly their financial knowledge, influences the adoption of these types of assets (*e.g.,* Balutel, Felt *et al.,* 2022; Bhimani Hausken y Arif, 2022; Fujiki, 2020; Panos, Karkkainen & Atkinson, 2020; Stix, 2021; Zhao & Zhang, 2021).

However, most prior empirical studies have obtained contradictory results regarding the relationship between cryptocurrency adoption and financial literacy. Some studies have shown that cryptocurrency holders have a higher level of formal education than non-holders. Using data from Austrian consumers, Stix (2021) finds that cryptocurrency holders have more financial knowledge than non-holders. Fujiki (2021) documents that Japanese cryptocurrency holders tend to have greater financial literacy than non-holders. Similarly, Balutel, Henry *et al.* (2022) show that Canadian Bitcoin owners have higher levels of education than non-Bitcoin owners. Similarly, Zhao & Zhang (2021) find that financial literacy and investment experience are positively associated with investment in cryptocurrencies.

Conversely, other studies have found that cryptocurrency holders tend to have less financial education than non-holders. In Balutel, Felt *et al.* (2022), cryptocurrency holders had more knowledge about the Bitcoin network than non-holders but scored lower on questions testing financial literacy. Particularly uninformed users are those who are interested in investing in digital assets (Glaser *et al.,* 2014). Henry *et al.* (2019) show that Bitcoin owners are more likely to have low financial literacy, which suggests that those with high financial literacy are more likely to have heard of Bitcoin but less likely to adopt it. Similarly, Panos, Karkkainen & Atkinson (2020) find that more financially literate individuals are less likely to own cryptocurrencies. However, these authors argue that the relationship between financial literacy and attitudes toward cryptocurrencies is moderated by differences in the perception of the financial risk associated with cryptocurrencies.

These contradictory results could be explained by a mismatch between consumers' subjective perceptions of their financial knowledge and their actual level of financial literacy. This study contributes to the literature on cryptocurrency adoption by examining and quantifying the effect of financial literacy on this behavior, which represents a novel approach in this field. While studies such as Tae Kim, Hanna & Lee (2023) and Fujiki (2020) have explored the relationship between financial literacy and cryptocurrency adoption, our study goes beyond these works by quantitatively assessing the impact of financial literacy on the likelihood of cryptocurrency ownership. By leveraging a rich and diverse survey dataset, we are able to quantify the effects of financial literacy on cryptocurrency adoption. Our study not only investigates the associations between financial literacy, cognitive biases, and the likelihood of holding cryptocurrencies, but also provides empirical evidence regarding the magnitude of these effects. This novel contribution enhances our understanding of the role of financial literacy in the decision to adopt cryptocurrencies. Furthermore, our study extends previous research by incorporating variables related to digital activity, such as digital payments and perceptions of the digital channel. This comprehensive approach allows us to capture the multifaceted influences on cryptocurrency adoption and provides a more accurate assessment of the effects of financial literacy in this context. Employing advanced analytical techniques, including machine learning models such as random forests, classification trees, causal forests, and neural networks, we not only uncover the nuanced dynamics involved but also provide robust estimates of the effects of financial literacy on cryptocurrency adoption. This methodological rigor strengthens the validity of our findings and underscores the importance of considering financial literacy as a key determinant of cryptocurrency adoption.

By examining the discrepancy between subjective (self-assessment) and objective (real assessment) financial literacy, we provide a comprehensive understanding of cryptocurrency adoption, considering both individual beliefs and objective measures of financial literacy. In doing so, we contribute to the existing literature by shedding light on the factors influencing individuals' decisions regarding cryptocurrencies and by providing empirical evidence of the relevance of financial literacy in this context.

The growing body of literature on cryptocurrencies and financial literacy underscores the importance of examining the effect of financial literacy on individuals' decisions regarding cryptocurrencies. Regulatory authorities and policymakers have recognized the importance of promoting financial education in light of the potential risks associated with cryptocurrency investments (IOSCO, 2020). The findings from our study, in conjunction with the existing literature, call for further exploration of the biases between subjective and objective financial literacy to clarify the drivers of cryptocurrency adoption. Our study, with its unique dataset and analytical approaches, not only informs regulatory and educational initiatives but also advances our understanding of the complexities surrounding financial literacy and its influence on cryptocurrency adoption.

3. DATA AND METHODOLOGY

3.1. Data

The data for this study was collected through a survey conducted by IMOP Insights in November and December 2021 specifically for the purposes of this research. The survey was administered to Spanish consumers between the ages of 18 and 70 and aimed to explore their digital preferences and knowledge, with a focus on banking and payment services. To ensure representativeness, age, sex, and location quotas were implemented during the survey process. The sample consisted of 2,121 participants who were surveyed via telephone and online. Participation was voluntary and complied with all legal and sociological requirements. Prior to completing the questionnaire, all participants provided informed consent, which was documented through recorded telephone conversations. The authors anonymized the data prior to analysis to maintain confidentiality.

There are 76 variables in the survey, which, multiplied by the 2,121 respondents, yields 161,196 data points. The variables are described in Table 1, along with their summary statistics.

In particular, to examine the relationship between financial literacy and cryptocurrency ownership, we employ various variables. The level of education completed by each participant (*e.g.,* secondary education, undergraduate education, graduate education, etc.) is taken into account using the variable “education”. This variable reflects the formal level of education, not exclusively in finance, that each individual has attained. The variable “finlit_self” represents the self-assessment of financial literacy level, which indicates subjective financial literacy. It is derived from a question asking individuals to assess their overall knowledge of financial issues. A higher value suggests that the individual believes that he or she possesses a strong understanding of topics related to finance. To capture the objective (real assessment) of each individual’s financial literacy level, we employ the variable “basicfinlit_observed”. This variable is determined by evaluating whether individuals are able to explain correctly fundamental financial concepts financial concepts, such as the difference between a credit card and a debit card or the relationship between returns and risk.

Considering the subjective (self-assessment) and objective (real assessment) levels of financial literacy for each individual, we compute the variable “finlit_bias”. This effectively captures the financial literacy bias by reflecting the discrepancy between subjective (self-assessment) and objective (real assessment) measures of financial literacy. A higher value indicates larger biases in financial literacy for an individual. Finally, we correct for this bias by calculating “finlit_corrected,” which represents each individual’s level of financial literacy after accounting for the financial literacy bias.

Table 1. SUMMARY STATISTICS OF VARIABLES INCLUDED IN THE SURVEY

Variable	Definition	n	mean	sd	median	min	max
Region	The geographic region in which the participant lives	2,121	9.4	5.6	9.0	1.0	18.0
province	The province or state in which the participant lives	2,121	25.6	13.9	28.0	1.0	50.0
Pop_size	The size of the population where the participant lives	2,121	539,104.7	1,015,027.1	91,224.0	49.0	3,334,730.0
Sex	The gender of the participant	2,121	1.5	0.5	1.0	1.0	2.0
Age	The age of the participant	2,121	44.5	14.1	45.0	18.0	70.0
answer_device	The type of device used by the participant to complete the survey	2,121	2.8	1.2	3.0	1.0	4.0
education	The highest level of education completed by the participant	2,121	4.5	1.0	5.0	1.0	6.0
work_status	The employment status of the participant	2,121	1.7	1.1	1.0	1.0	5.0
household_inc	The household income of the participant	2,121	4.4	1.4	5.0	1.0	7.0
account	Whether the participant has a bank account	2,121	1.0	0.0	1.0	1.0	1.0
num_banks	The number of banks at which the participant has an account	2,121	1.7	0.8	1.0	1.0	7.0
num_accounts	The total number of bank accounts held by the participant	2,121	2.2	1.3	2.0	1.0	15.0
num_onlineacc	The number of online bank accounts held by the participant	2,121	0.4	0.8	0.0	0.0	7.0
mainbankweight	The weight of the participant’s main bank in their banking activity	2,121	39.7	58.6	0.0	0.0	999.0
branch_freq	The frequency with which the participant visits a bank branch	2,121	4.1	1.0	4.0	1.0	6.0
branch_freq2years	The frequency with which the participant visited a bank branch two years ago	2,121	3.7	1.2	4.0	1.0	6.0
onlineaccess_freq	The frequency with which the participant accesses their bank account online	2,121	2.1	1.3	2.0	1.0	7.0
onlineaccess_freq2	The frequency with which the participant accessed their bank account online two years ago	2,121	3.1	1.7	3.0	1.0	7.0

Table 1. SUMMARY STATISTICS OF VARIABLES INCLUDED IN THE SURVEY

(continuación)

Variable	Definition	n	mean	sd	median	min	max
cashtrans_weight	The weight of cash transactions in the participant’s banking activity	2,121	30.4	27.4	20.0	0.0	100.0
bizum_user	Whether the participant uses the Bizum mobile payment service	2,121	1.2	0.4	1.0	1.0	2.0
paypal_user	Whether the participant uses the PayPal online payment service	2,121	1.5	0.5	2.0	1.0	2.0
googlepay_user	Whether the participant uses the Google Pay mobile payment service	2,121	1.9	0.3	2.0	1.0	2.0
applepay_user	Whether the participant uses the Apple Pay mobile payment service	2,121	1.9	0.3	2.0	1.0	2.0
amazonpay_user	Whether the participant uses the Amazon Pay online payment service	2,121	1.9	0.3	2.0	1.0	2.0
samsungpay_user	Whether the participant uses the Samsung Pay mobile payment service	2,121	2.0	0.2	2.0	1.0	2.0
verse_user	Whether the participant uses the Verse mobile payment service	2,121	2.0	0.2	2.0	1.0	2.0
vodaf_user	Whether the participant uses the Vodafone mobile payment service	2,121	2.0	0.1	2.0	1.0	2.0
otherpay	Whether the participant uses any other mobile or online payment service	2,121	2.0	0.2	2.0	1.0	2.0
online_balance	The frequency with which the participant checks their bank balance online	2,121	2.8	0.8	3.0	0.0	5.0
online_bills	The frequency with which the participant pays bills online	2,121	3.2	1.3	4.0	0.0	5.0
online_transfer	The frequency with which the participant makes bank transfers online	2,121	3.6	1.2	4.0	0.0	5.0
online_comm	The frequency with which the participant communicates with their bank online	2,121	3.5	1.4	4.0	0.0	5.0
online_contract	Whether the participant signs contracts with their bank online	2,121	1.7	0.5	2.0	0.0	2.0
onlinecontract_timing	The frequency with which the participant signs contracts with their bank online	2,121	0.7	1.3	0.0	0.0	4.0
bank_inno_score	The participant’s perception of their bank’s level of innovation	2,121	7.8	1.6	8.0	0.0	10.0
bank_satisf_score	The participant’s level of satisfaction with their bank	2,121	7.5	2.1	8.0	0.0	10.0
onlineperson_currency	Whether the participant has used online or mobile banking services in a foreign currency	2,121	1.6	0.5	2.0	1.0	2.0
onlineperson_cardlimit	Whether the participant has modified their card’s limit online	2,121	1.2	0.4	1.0	1.0	2.0
onlineperson_openacc	Whether the participant has opened a bank account online	2,121	1.6	0.5	2.0	1.0	2.0
onlineperson_pension	Whether the participant has managed their pension plan online	2,121	1.8	0.4	2.0	1.0	2.0
onlineperson_fund	Whether the participant has managed their investment funds online	2,121	1.8	0.4	2.0	1.0	2.0
digitalloan_oneyear	Whether the participant has applied for a digital loan in the past year	2,121	1.9	0.3	2.0	1.0	2.0
digitalacco_oneyear	Whether the participant has opened a digital bank account in the past year	2,121	1.9	0.3	2.0	1.0	2.0
payapp_oneyear	Whether the participant has used a mobile payment app in the past year	2,121	1.3	0.5	1.0	1.0	2.0
transfapp_oneyear	Whether the participant has used a bank transfer app in the past year	2,121	1.3	0.4	1.0	1.0	2.0
willingrentbuyhouse_online	Whether the participant would rent or buy a house online	2,121	1.7	0.5	2.0	1.0	2.0
safety_mobile	Perception of mobile phone safety	2,121	2.4	1.2	2.0	1.0	6.0
safety_pc	Perception of personal computer safety	2,121	2.1	1.0	2.0	1.0	6.0

Table 1. SUMMARY STATISTICS OF VARIABLES INCLUDED IN THE SURVEY

(continuación)

Variable	Definition	n	mean	sd	median	min	max
safety_onlinebank	Perception of online bank safety	2,121	2.3	1.1	2.0	1.0	6.0
mobilebank_cost	Cost of using mobile banking services	2,121	5.2	1.5	6.0	1.0	7.0
pcbank_cost	Cost of using personal computer banking services	2,121	5.2	1.5	6.0	1.0	7.0
onlinebank_cost	Cost of using online banking services	2,121	5.3	1.5	6.0	1.0	7.0
easy_mobile	Ease of using mobile banking services	2,121	4.0	1.2	4.0	1.0	6.0
easy_pc	Ease of using personal computer banking services	2,121	3.9	1.1	4.0	1.0	6.0
easy_online	Ease of using online banking services	2,121	3.9	1.2	4.0	1.0	6.0
cryptoholder	Ownership of cryptocurrencies	2,121	1.9	0.2	2.0	1.0	2.0
fraud_mail	Experience of receiving fraudulent emails	2,121	1.5	0.5	1.0	1.0	2.0
fraud_call	Experience of receiving fraudulent phone calls	2,121	2.0	0.2	2.0	1.0	2.0
checkweb_true	Checking of web address for authenticity	2,121	1.1	0.3	1.0	1.0	2.0
noaccessfrom_mail	Refraining from accessing links in emails	2,121	1.2	0.4	1.0	1.0	2.0
pc_antivirus	Usage of antivirus software on personal computer	2,121	1.2	0.4	1.0	1.0	2.0
mobile_antivirus	Usage of antivirus software on mobile phone	2,121	1.6	0.5	2.0	1.0	2.0
logoutacc	Logging out of online accounts	2,121	1.2	0.4	1.0	1.0	2.0
finlit_self	Self-assessment level of financial literacy (subjective financial literacy)	2,121	2.6	0.9	3.0	1.0	6.0
diff_debitcredit	Comparison of debit and credit cards in terms of features and benefits	2,121	1.1	0.3	1.0	1.0	2.0
diff_debitcreditone	Comparison of two different debit cards in terms of features and benefits	2,121	3.9	10.0	2.0	0.0	98.0
diff_debitcredittwo	Comparison of two different credit cards in terms of features and benefits	2,121	0.3	0.9	0.0	0.0	5.0
diff_debitcreditthree	Comparison of a debit card and a credit card in terms of features and benefits	2,121	0.0	0.1	0.0	0.0	3.0
riskreturn_know	Knowledge of the relationship between investment risk and return	2,121	1.3	0.7	1.0	1.0	3.0
QR_know	Knowledge of QR codes and their usage	2,121	1.1	0.3	1.0	1.0	3.0
http_https	Knowledge of the difference between HTTP and HTTPS protocols	2,121	1.5	0.6	1.0	1.0	3.0
appinst_know	Knowledge of the risks of installing unauthorized apps	2,121	1.1	0.3	1.0	1.0	3.0
basicfinlit_observed	Observed value of basic financial knowledge (real financial literacy)	2,121	2.5	0.8	3.0	0.0	3.0
finlit_bias	Perception of financial knowledge bias	2,121	0.5	0.8	0.0	0.0	3.0
finlit_corrected	Corrected assessment of financial literacy level taking bias into account	2,121	2.1	1.3	2.0	-2.0	6.0

3.2. Methodology

3.2.1. Utility framework

We aim to empirically determine cryptocurrency ownership and the role of financial literacy therein from an informational standpoint. Most previous studies have employed discrete choice models to examine investor preferences. These models, derived from utility theory, are based on maximizing consumers' utility. Our study builds upon prior research on the utility of investments, taking into account information biases, investment mistakes, and financial literacy (Barber & Odean, 2008; Calvet, Campbell & Sodini, 2007; Gennaioli, Shleifer & Vishny, 2015; and Lusardi & Mitchell, 2007). Accordingly, we consider the following form of the utility function:

$$U = \alpha * CR^{\beta} * FL\gamma * QI\delta * e^{\eta * FLB} * \Omega \qquad [1]$$

where CR represents cryptocurrency holdings by retail investors; FL represents financial literacy; QI represents the quality of information managed by investors; and FLB represents the financial literacy bias, given by the difference between the investor's self-assessed and observed financial literacy. $\alpha, \beta, \gamma, \delta, \eta$ are parameters determining the influence of each variable on utility, and Ω are other factors affecting utility. The exponential term captures the impact of financial literacy bias on utility, with η determining the strength of this relationship. The other parameters ($\alpha, \beta, \gamma, \delta$) represent the respective influences of cryptocurrency ownership, financial literacy, and quality of information on utility.

To derive the first-order conditions, we differentiate the utility function [1] with respect to each variable:

$$\partial U/\partial CR = \alpha * \beta * CR^{(\beta\text{-}1)} * FL^{\gamma} * QI^{\delta} * e^{\eta * FEB} * \Omega = 0 \qquad [2]$$

$$\partial U/\partial FL = \alpha * CR^{\beta} * \gamma * FL^{\gamma\text{-}1} * QI^{\delta} * e^{\eta * FEB} * \Omega = 0 \qquad [3]$$

$$\partial U/\partial QI = \alpha * CR^{\beta} * FL^{\gamma} * \delta * Q^{\delta\text{-}1} * e^{\eta * FEB} * \Omega = 0 \qquad [4]$$

$$\partial U/\partial FEB = \alpha * CR^{\beta} * FL^{\gamma} * Q^{\delta} * \eta * e^{\eta * FEB} * \Omega = 0 \qquad [5]$$

Equation [2] suggests that the optimal level of cryptocurrency holdings (CR) is determined by the parameters $\alpha, \beta,$ and the other factors (Ω) affecting utility. The exponent β captures the sensitivity of utility to changes in cryptocurrency holdings. A positive value of β implies that an increase in holdings leads to higher utility, while a negative value implies the opposite. Equation [3] indicates that the optimal level of financial literacy (FL) is influenced by the parameters $\alpha, \gamma,$ and the other factors (Ω) affecting utility. The exponent γ reflects the impact of financial literacy on utility. A positive value of γ suggests that higher financial literacy increases the satisfaction derived from cryptocurrency ownership. Equation [4] states that the optimal level of the quality of information (QI) is determined by the parameters α, δ, and the other factors (Ω) affecting utility. The exponent δ denotes the impact of information quality on utility. A positive value of δ implies that higher quality information positively affects the satisfaction derived from cryptocurrency ownership. Equation [5] reflects that the optimal level of financial literacy bias (FLB) is influenced by the parameters α, η, and the other factors (Ω) affecting utility.

3.2.2. Machine learning approach

Given the large number of factors that may affect the decisions and utility of a cryptocurrency investor, we use machine learning techniques that are suitable for analyses of large datasets that involve many potential correlates. These techniques are particularly useful for handling large and complex datasets and identifying relationships among multiple variables. In our context, these techniques can provide valuable insight into the reasons for cryptocurrency adoption and its relationship to financial literacy. By leveraging the power of these techniques, we can identify complex patterns and relationships that may be difficult to uncover using traditional statistical methods. Specifically, we employ four different machine learning techniques: random forest, classification trees, causal forest and neural networks. These four techniques are employed because they have been the most prominent ones used in the machine learning literature, and also in contexts similar to ours.[2] Furthermore, for the purpose of comparability and following the standard in the literature, we also employ a parametric econometric model: the logit model.

Random forests are an ensemble of tree predictors in which each tree depends on the values of a random vector sampled independently and with the same distribution for all trees within the forest. Because of the law of large numbers, they tend not to overfit. The algorithm follows four steps:

1. A forest of many trees is growing. Each tree is grown from an independent bootstrap sample derived from the data.

[2] See Albanesi & Vamossy, (2019); Barboza, Kimura & Altman (2017); Carbo-Valverde, Cuadros-Solas Rodríguez-Fernández (2020); Hagenauer & Helbich, (2017); Hothorn *et al.,* (2006); Krauss, Do & Huck (2017); Qi *et al.,* (2020), among others.

2. For each node of the tree, m variables are independently selected at random from M possible variables. Then, based on the selected m variables, the algorithm finds the best split.

3. The algorithm grows each tree to the largest extent possible.

4. These steps are iterated over all trees in the ensemble, and the average vote of all the trees is reported as the random forest prediction.

We use the characteristics and determinants with the largest discriminant power to build a decision tree for each dimension by estimating a *conditional inference tree.* This technique estimates a regression relationship using binary recursive partitioning in a conditional inference framework. To build the trees for each dimension, we follow the methodology developed by Hothorn, Hornik & Zeileis (2006) and Hothorn *et al.* (2006). The algorithm tests the global null hypothesis of independence between each of the input variables and the response and selects the input variable with the strongest association with the response. Subsequently, the algorithm implements a binary split in the selected input variable, and this process is recursively repeated for each of the remaining variables. The classification tree provides insight into the sequencing of consumers' decision-making processes, which helps explain how people adopt cryptoassets. Notably, these classification trees do not require any linearity assumptions, which is crucial considering the nonlinear relationships that may exist among the drivers of cryptocurrency adoption.

Because machine learning models are not designed to estimate causal effects, a new field of study has recently emerged: *causal machine learning.* Over the last few years, different causal machine learning algorithms have been developed, combining the advances in machine learning with the theory of causal inference (Athey & Imbens, 2016; Wager & Athey, 2018; Athey & Wager, 2019). The objective of causal machine learning techniques is not to replace machine learning methods but to complement them by estimating causal effects. The main advantage of causal machine learning is that it can be used after the modeling phase to confirm the relationships between variables and the target or outcome. In our context, we use this method to examine the causal effect of the features with the largest predictive power on cryptocurrency ownership. In technical terms, the causal forest algorithm is a forest-based method for treatment effect estimation that allows for tractable asymptotic theory and valid statistical inference. It is an extension of Breiman's random forest algorithm. Methodologically, causal forests maintain the fundamental structure of random forests –including recursive partitioning, subsampling, and random split selection– but instead of averaging over the trees, they estimate heterogeneous treatment effects to establish causality. Then, unlike a regular decision tree, the causal tree uses a splitting rule that explicitly balances two objectives: first, finding the splits at which treatment effects differ most, and second, estimating the treatment effects with the greatest possible accuracy. In order to obtain consistent estimates of the treatment effects (the features that may affect cryptocurrency adoption), it splits the training data into two subsamples: a splitting subsample and an estimating subsample. The splitting subsample is used to perform the splits and thus grow the tree, and the estimating subsample is used for making predictions. All observations in the estimating subsample are dropped down the previously grown tree until they fall into a terminal node. Thus, the prediction of the treatment effects is given by the difference in the average outcomes between the treated and untreated observations of the estimating subsample in the terminal nodes. Using this empirical methodology, we can examine the causal effect of those features with the largest predictive power on cryptocurrency ownership. All analyses are conducted using the R package grf.

Neural networks have unique advantages for the analysis of cryptocurrency ownership and its relationship with financial literacy. Given the complex and dynamic nature of financial markets, intricate non-linear relationships may exist between financial literacy and cryptocurrency ownership, and neural networks are able to capture these relationships. Unlike traditional statistical models, neural networks can learn from and adapt to large and high-dimensional datasets, making them well suited for handling the vast amount of information available in the cryptocurrency domain (Smith Johnson & Brown, 2022). This adaptability allows neural networks to uncover hidden and nuanced relationships that might be challenging to capture using conventional statistical methods. Moreover, the effectiveness of neural networks has been demonstrated in various finance-related studies. For instance, they have been successfully employed to predict investment decisions and assess the impact of financial literacy on portfolio choices (Jones, Johnson, & Williams, 2019; Brown, Smith & Johnson, 2020). By incorporating neural networks into our analysis, we can uncover novel insights that other methods might overlook, thereby enhancing our understanding of the relationship between financial literacy and cryptocurrency ownership.

By leveraging the strengths of neural networks alongside other methods such as random forests, causal forests, classification trees, and logistic regression, we can obtain a more comprehensive and nuanced understanding of the relationship between financial literacy and cryptocurrency ownership (Smith, Johnson & Brown, 2022; Johnson *et al.,* 2021).

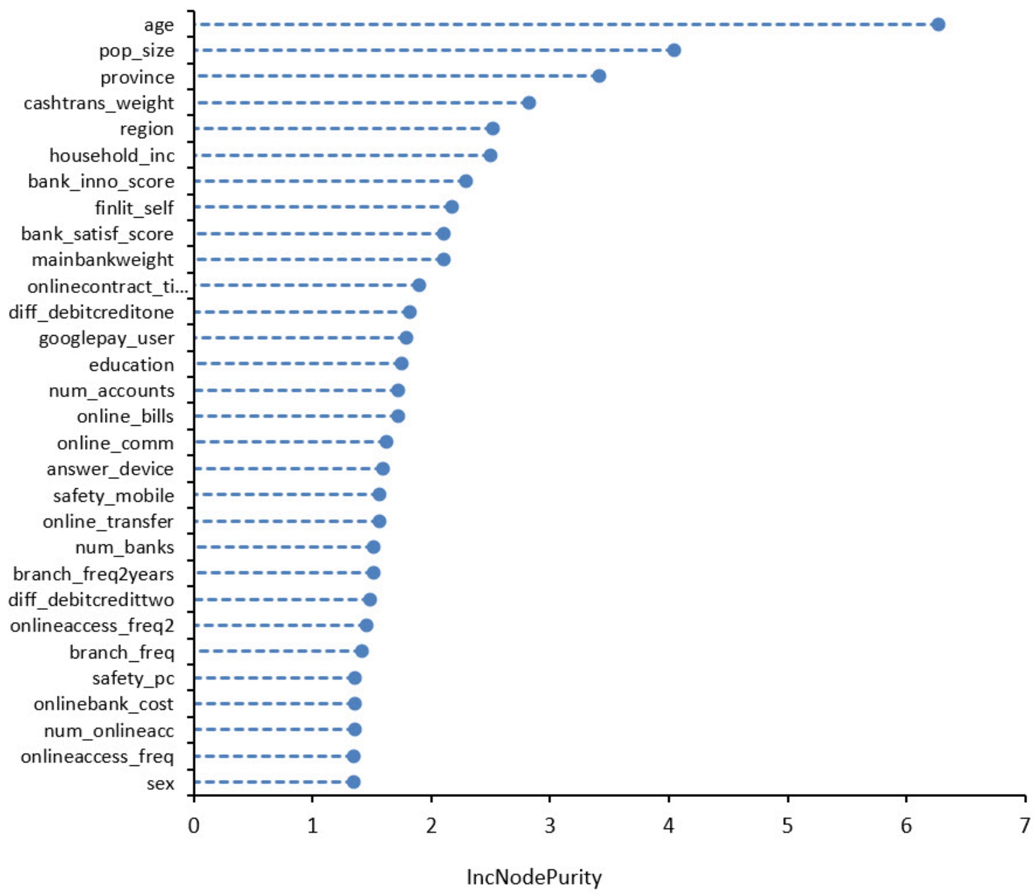
Finally, since previous studies have primarily employed discrete choice models to examine consumer behavior, we also employ logit models to examine cryptocurrency adoption. We employ a multinomial logit regression for the ownership (value 1) or non-holding (value 0) of cryptocurrencies. For consistency, we employ the same set of variables used in the machine learning methods for the regression analysis.

4. RESULTS

4.1. Random forest: Variable importance

In the random forest analysis, the variable importance measure known as IncNodePurity provides insight into the relative contributions of different variables in predicting cryptocurrency ownership. The IncNodePurity

FIGURE 1. VARIABLE IMPORTANCE. BASELINE RANDOM FOREST MODEL



scores (Figure 1) for each variable reflect the improvement in the purity (homogeneity) of the target variable achieved by splitting the data based on that feature.

The out-of-bag (OOB) performance of the random forest model, as indicated by an accuracy of 0.02%, suggests that the model performs well in predicting cryptocurrency ownership on unseen data. The OOB performance is an estimate of how well the model generalizes to new, unseen instances based on the data that was not included in the training process. It indicates that the model can capture the underlying patterns and relationships in the data effectively, allowing it to make accurate predictions of cryptocurrency ownership for new observations that were not part of the training set.

As for the results, first, it is noteworthy that the variable with the highest IncNodePurity score is age, with a score of 6.27. This result emphasizes the significant role of age in predicting cryptocurrency ownership. Different age groups may exhibit varying levels of interest in or familiarity with cryptocurrencies and incorporating age as a predictor improves the model's accuracy in capturing these differences. The variable of population size (Pop_size) follows closely, with an IncNodePurity score of 4.04. This result indicates that considering population size significantly improves the model's ability to accurately predict cryptocurrency ownership. A larger population size might suggest a larger pool of potential cryptocurrency investors, which could have a substantial effect on the prediction outcomes. A herding behavior toward cryptocurrency ownership is more likely to happen in larger cities. Household income (household_inc) has an IncNodePurity score of 2.49, indicating its significance as a predictor. Higher household income levels contribute to the model's improved ability to predict cryptocurrency ownership. Individuals with higher incomes may have more financial resources available to invest in cryptocurrencies, which may impact their holdings.

The weight assigned to cash transactions (cashtrans_weight) has an IncNodePurity score of 2.81, implying its importance in predicting cryptocurrency ownership. This variable reflects individuals' preferences and priorities in relation to financial transactions, and considering this variable enhances the model's ability to capture the influence of these preferences on cryptocurrency ownership. Bank innovation score (bank_inno_score) has an IncNodePurity score of 2.29, highlighting its relevance as a predictor. A higher bank innovation score indicates a greater level of innovation in banking services or products, which may impact individuals' openness to exploring alternative financial assets such as cryptocurrencies. Incorporating this variable improves the model's accuracy in capturing this relationship.

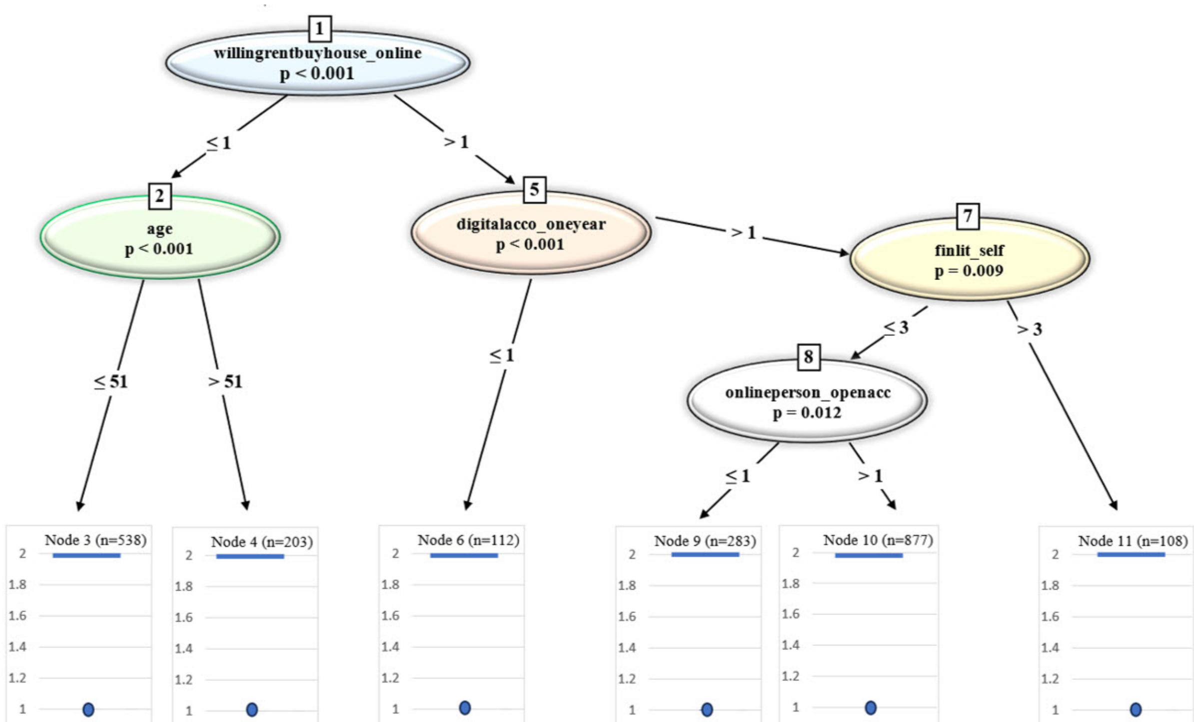
Lastly, individuals' self-perceived financial knowledge or literacy (finlit_self) has an IncNodePurity score of 2.17. This result suggests that self-perceived financial knowledge is a meaningful predictor of cryptocurrency holding. Individuals who perceive themselves as more financially knowledgeable may exhibit different behaviors and inclinations in relation to cryptocurrency investments, which the model captures more accurately by considering this variable.

4.2. Conditional inference trees

Figures 2 and 3 plot the conditional inference tree explaining cryptocurrency ownership. While Figure 2 provides the results from the baseline regression, Figure 3 includes financial literacy bias. A comparison of these figures clarifies the relevance of financial literacy bias in the sequencing of customers' decision-making processes regarding cryptocurrency ownership. In conducting this comparison, we focus on the conditional inference tree that accounts for potential biases in the level of financial literacy.

At the root of the classification tree (Figure 3), the analysis splits the data based on the variable "willingrentbuyhouse_online," which captures individuals' willingness to rent or buy a house via the Internet. This variable serves as an initial differentiator in the classification process. If the value of "willingrentbuyhouse_online" is less than or equal to 1, indicating a lower willingness to rent or buy a house online, the analysis proceeds to evaluate the "age" variable. This variable represents the age of the individuals being analyzed.

FIGURE 2. CONDITIONAL INFERENCE TREE EXPLAINING CRYPTOCURRENCY OWNERSHIP – BASELINE MODEL

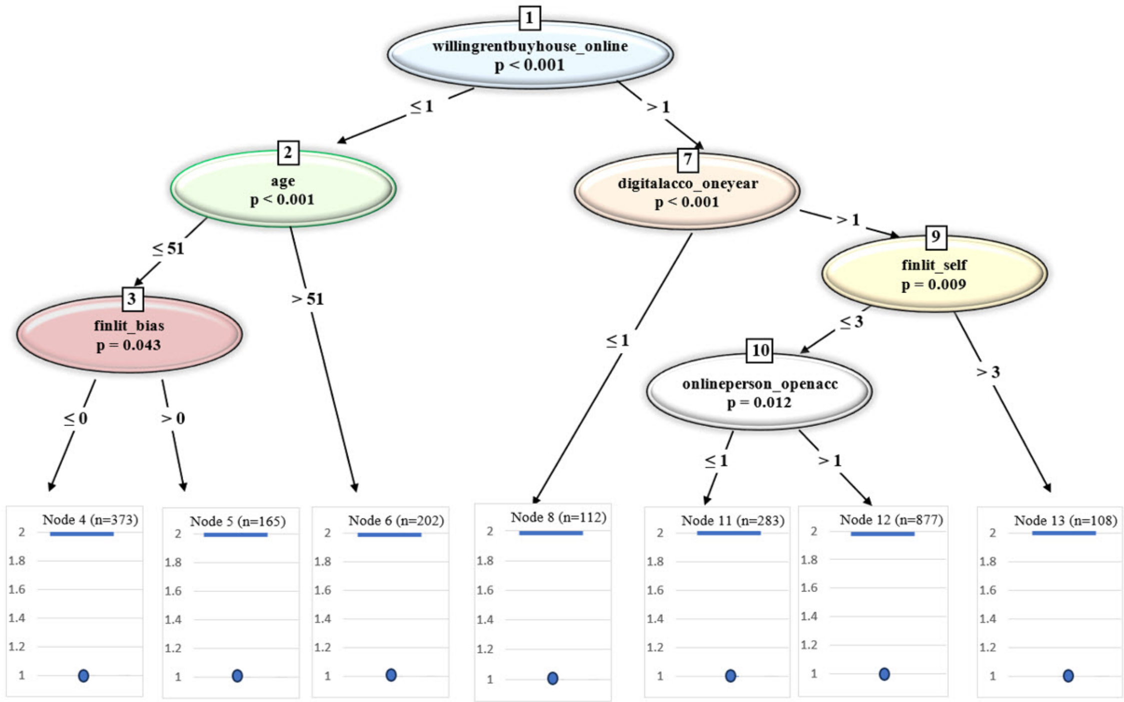


Within the age evaluation, if the individual's age is less than or equal to 51, the tree splits again based on the variable "finlit_bias." This variable measures the bias related to financial literacy, capturing discrepancies between individuals' self-perceived and objectively assessed financial literacy. Conversely, if the individual's age is greater than 51, no further splitting occurs, and the predicted probability of cryptocurrency ownership is determined without considering financial literacy bias.

On the other hand, if the value of "willingrentbuyhouse_online" is greater than 1, indicating a higher willingness to rent or buy a house online, the analysis considers the "digitalacco_oneyear" variable. These variable captures whether an individual has held a digital account within the past year and represents their engagement with digital financial services. Within the "digitalacco_oneyear" evaluation, the tree branches based on the value of "finlit_self," which represents an individual's self-perceived financial knowledge and thus reflects their subjective assessment of their own financial literacy. If "finlit_self" is less than or equal to 3, suggesting lower self-perceived financial knowledge, the subsequent splitting occurs based on the "onlineperson_openacc" variable. This variable represents the number of online personal accounts held by the individual. Conversely, if "finlit_self" is greater than 3, indicating higher self-perceived financial knowledge, no further splitting occurs based on the "onlineperson_openacc" variable.

Each split within the classification tree represents a different combination of variables and their associated values, resulting in specific predicted probabilities of cryptocurrency ownership for the corresponding subsets of data. By examining the entire classification tree, including the variables "finlit_self" and "finlit_bias," we can gain insight into the hierarchical decision process and identify which variables influence the predicted probabilities of cryptocurrency ownership. These variables, specifically related to financial literacy, provide valuable information regarding how individuals' perceptions of and biases regarding their financial knowledge influence their likelihood of holding cryptocurrencies.

FIGURE 3. CONDITIONAL INFERENCE TREE EXPLAINING CRYPTOCURRENCY OWNERSHIP – INCLUDING FINANCIAL LITERACY BIAS



4.3. Causal forests: Treatment effects

Because we aim to investigate the relationship between financial literacy, cognitive biases, and the adoption of cryptocurrencies, we explicitly examine the causal effect of the difference between subjective and objective financial literacy on cryptocurrency ownership. The causal forest analysis examines the impact of these variables related to financial literacy on the likelihood of holding cryptocurrencies while controlling for confounding factors. The results are shown in Table 2. These results allow for exploring causal relationships and considering confounding factors. They provide insight into the factors influencing the likelihood of cryptocurrency ownership and clarify the role of financial literacy and biases in shaping investment decisions.

The analysis reveals that self-assessment of financial literacy has a small positive effect of 0.40% on the likelihood of holding cryptocurrencies. However, the effect is not statistically significant, as the confidence interval is (-0.3%, +0.6%). Hence, we cannot conclude that self-assessed financial literacy has a significant effect on cryptocurrency ownership. In contrast, the presence of a financial literacy bias has a substantial positive effect on the likelihood of cryptocurrency ownership, with a point estimate of 75.30% and a confidence interval of (+72.6%, +77.8%). This suggests that individuals with a bias, reflecting a difference between self-assessed financial literacy and observed financial literacy, are significantly more likely to own cryptocurrencies. This result is consistent with previous research that has identified overconfidence bias as a driver of risky investment behavior (Barber & Odean, 2001).

Lastly, we observe a negative effect of -25.40% when considering the bias-corrected financial literacy measure. The confidence interval (-27.0%, -23.6%) indicates that this effect is statistically significant. This result suggests that individuals with higher observed financial literacy, after correcting for biases, are significantly less likely to own cryptocurrencies. These findings emphasize the importance of accounting for biases in financial literacy assessments and highlight the complex relationship between financial literacy, cognitive biases, and the likelihood of cryptocurrency ownership. Cognitive biases can play a key role in investment decision-making, including in decisions related to cryptocurrency ownership. Two cognitive biases that are particularly relevant in the context of these results are overconfidence bias and confirmation bias. Overconfidence bias occurs when people overestimate their abilities or knowledge, leading them to make overly optimistic predictions and take excessive risks (Barber & Odean, 2001). This bias could explain the strong effect of financial literacy bias on the probability of cryptocurrency ownership identified in our analysis. People who overestimate their financial literacy may be more likely to invest in cryptocurrencies because they believe they have the knowledge and skills needed to successfully navigate this complex and rapidly changing market. Confirmation bias, on the other hand, occurs when people seek out and interpret information in a way that confirms their existing beliefs or opinions (Kahneman, 2011). In the context of cryptocurrency investment behavior, confirmation bias may cause individuals to selectively focus on information that supports their decision to invest in cryptocurrencies while disregarding or downplaying information suggesting that cryptocurrency may not be a wise investment choice. Overall, these cognitive biases can lead to suboptimal investment decisions and financial outcomes. However, they are also common among investors and can be difficult to overcome. Recognizing these biases and understanding their potential impact on investment decisions is an important step towards making more informed and rational investment choices.

Table 2. AVERAGE TREATMENT EFFECTS. FINANCIAL LITERACY AND CRYPTOCURRENCY OWNERSHIP

	Average treatment effect on the probability of cryptocurrency ownership		
	Point estimate	**C.I.**	**Significant**
Cost increase	0.40%	(-0.3%, +0.6%)	No
Rate change cost	75.30%	(+72.6%, +77.8%)	Yes
Competition	-25.40%	(-27.0%, -23.6%)	Yes

The finding that individuals with stronger financial literacy biases are more likely to hold cryptocurrencies suggests that people who overestimate their financial skills are more likely to invest in these assets. This result could be attributed to the fact that overconfidence in one's abilities can result in riskier investment behaviors (Barber & Odean, 2001). Moreover, people with stronger financial literacy biases may be more likely to believe that they can outperform the market, which is a common misconception among retail investors (Ben-David, Palvia & Spatt, 2018).

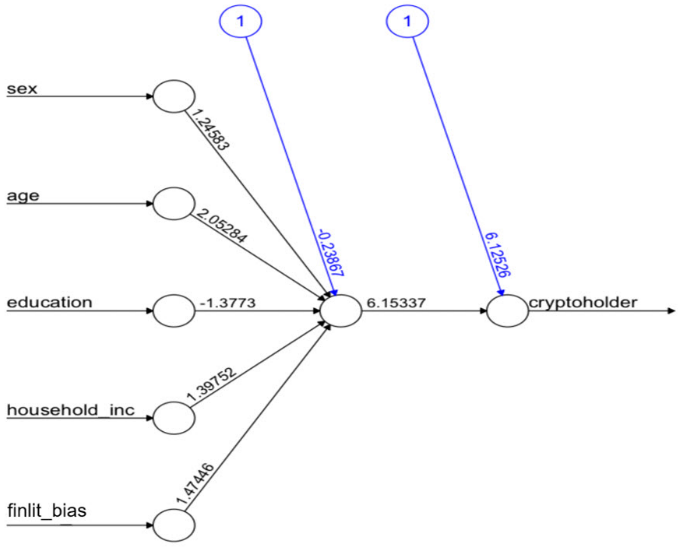
4.4. Neural network results

The neural network model (Figure 4) provides insight into an individual's probability of cryptocurrency ownership and offers numerical interpretations of the coefficients that shed light on the magnitude and significance of the factors influencing this probability. The neural network model utilized in this study has been shown to be the best-fitting among alternative models and provides robust insight into the probability of being a cryptocurrency owner. By selecting the top five predictors based on importance, namely gender, age, education, household income, and financial literacy bias, the model effectively captures the key factors influencing cryptocurrency ownership. The high McFadden's pseudo-R-squared value of 0.92 reflects the model's high goodness of fit. This high value suggests that the selected predictors collectively capture a significant portion of the underlying relationships and patterns influencing cryptocurrency ownership. The coefficients of these predictors clarify the magnitude and statistical significance of their impact on the likelihood of being a cryptocurrency owner.

The coefficient for the "sex" variable is 1.24, suggesting that being male has a positive impact on the predicted log-odds of being a cryptocurrency owner. To interpret this coefficient in terms of probability, we can exponentiate it is using the exponential function (exp(1.24)). By exponentiating the coefficient (exp(1.24)), we find that the odds of being a cryptocurrency owner are approximately 3.48 times higher for males compared to females. In terms of probability, this means that males are approximately 77% more likely than females to own cryptocurrencies.

The coefficient for the "age" variable is 2.05, indicating that for each unit increase in age, the predicted log-odds of being a cryptocurrency owner increase by approximately 2.05. Exponentiating this coefficient (exp(2.05)),

FIGURE 4. NEURAL NETWORK REPRESENTING CRYPTOCURRENCY OWNERSHIP



we find that the odds of being a cryptocurrency owner increase by a factor of approximately 7.79 for every year of increase in age. This result implies that, on average, the probability of being a cryptocurrency owner increases by around 88.5% for each additional year of age.

The coefficient for the "education" variable is -1.37, suggesting that higher levels of education negatively impact the predicted log-odds of being a cryptocurrency owner. Exponentiating this coefficient (exp(-1.37)), we find that the odds of owning cryptocurrencies decrease by a factor of approximately 0.252 for every unit increase in education. This implies that, on average, individuals with higher education levels are approximately 74.8% less likely than individuals with lower education levels to own cryptocurrencies.

The coefficient for the "household_inc" variable is 1.39, indicating that an increase in household income is associated with higher predicted log-odds of being a cryptocurrency owner. Exponentiating this coefficient (exp(1.39)), we find that the odds of owning cryptocurrencies increase by a factor of approximately 4.04 for each unit increase in household income. This result implies that, on average, individuals with higher income levels are approximately 76.9% more likely than individuals with lower income levels to own cryptocurrencies.

The coefficient for the "finlit_bias" variable is 1.47, suggesting that stronger financial literacy bias is associated with an increase in the predicted log-odds of being a cryptocurrency owner. Exponentiating this coefficient (exp(1.47)), we find that the odds of owning cryptocurrencies increase by a factor of approximately 4.37 for every unit increase in financial literacy bias. This result implies that, on average, individuals with a larger discrepancy between their self-assessed and observed financial literacy are approximately 76.9% more likely than individuals with a weaker financial literacy bias to own cryptocurrencies. This latter finding underlines the relevance of cognitive biases related to financial literacy in explaining investment choices in the cryptocurrency markets.

4.5. Logit results and comparison of model performance metrics

Finally, for robustness purposes, we employ logit estimation as a parametric econometric approach. The results are presented in Table 3; for simplicity, only the most relevant coefficients are included. Panel A of the logit model examines the relationship between several variables and the likelihood of cryptocurrency ownership. The results indicate the following statistically significant effects: Gender (sex) has a coefficient of 1.411037 ($p < 0.001$), suggesting that being male increases the log-odds of cryptocurrency ownership. Age has a coefficient of 0.053826 ($p < 0.001$), indicating that for each one-unit increase in age, the log-odds of owning cryptocurrencies increases.

The finding that age is a significant predictor of cryptocurrency ownership is consistent with prior research. For example, Kristoufek (2015) found that younger people were more likely to invest in cryptocurrencies. This may be because younger people are generally more technologically proficient and more comfortable with new technologies than older people. Similarly, individuals with higher self-assessed financial literacy (finlit_self) have higher log-odds of owning cryptocurrencies, as evidenced by the coefficient of 0.457052 (p < 0.001).

Panel B explores the influence of additional variables on the likelihood of cryptocurrency ownership. The results reveal significant effects of gender (sex), with a coefficient of 1.372632 (p < 0.001), indicating a higher log-odds of owning cryptocurrencies for males. Age also has a significant effect, with a coefficient of 0.054009 (p < 0.001), suggesting that an increase in age corresponds to an increased likelihood of owning cryptocurrencies. Notably, the presence of a financial literacy bias (finlit_bias) significantly affects the log-odds of cryptocurrency ownership, as indicated by the coefficient of -1.23778 (p < 0.001).

Table 3. LOGIT MODEL ON CRYPTOCURRENCY OWNERSHIP

Panel A.

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.112855	0.564834	0.200	0.842
sex	1.411037	0.244375	5.774	7.74e-09 ***
age	0.053826	0.007917	6.799	1.05e-11***
finlit_self	0.457052	0.108340	4.219	2.46e-05 ***

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.
AIC: 758.39.
Number of Fisher Scoring iterations: 6.

Panel B.

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.123635	0.602844	0.218	0.802
sex	1.372632	0.266289	5.120	6.19e-09 ***
age	0.054009	0.005082	6.783	1.01e-11***
finlit_bias	-1.23778	0.113881	4.037	1.97e-05 ***

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.
AIC: 728.12.
Number of Fisher Scoring iterations: 6.

Finally, we present model performance metrics, which we use to compare the machine learning approaches and the logistic regression model. We use accuracy, precision, recall, F1 score, and Macro F1 Score. These metrics provide an overview of the performance of each model in predicting cryptocurrency ownership. Accuracy measures the overall correctness of the predictions by calculating the ratio of correctly classified instances to the total number of instances. It provides a general assessment of model performance but may be influenced by class imbalance. Precision quantifies the proportion of correctly predicted positive instances out of all instances predicted to be positive. It focuses on the accuracy of positive predictions and is useful when the cost of false positives is high. Recall, also known as sensitivity or true positive rate, measures the proportion of actual positive instances that are correctly predicted as positive. It highlights the model's ability to identify positive cases correctly and is particularly relevant when the cost of false negatives is high. The F1 score combines precision and recall into a single metric that balances both aspects. It is the harmonic mean of precision and recall, providing a comprehensive measure of the model's performance in both positive and negative instances. The Macro F1 score calculates the average F1 score across all classes, weighting each class equally. It is particularly useful when the dataset is imbalanced or when the aim is to evaluate overall model performance across different classes. The results are presented in Table 4.

Table 4. MODEL PERFORMANCE METRICS

(Percentage)

Model	Accuracy	Precision	Recall	F1 Score	Macro F1 Score
Random Forest	91	88	90	86	88
Causal Forest	90	87	86	84	89
Neural Network	86	80	82	84	80
Logistic Regression	76	58	44	46	43

The random forest model achieved the highest accuracy, 91%, indicating a high percentage of correct predictions overall. The causal forest model also performed well, with an accuracy of 90%. Both models demonstrated good precision, recall, and F1 scores, suggesting balanced performance in capturing positive instances. The neural network model had an accuracy of 86% and demonstrated moderate precision, recall, and F1 scores. It shows potential in predicting cryptocurrency holding, although it may have slightly worse performance than the random forest and causal forest models. The logistic regression model had the lowest accuracy at 76% and lower precision, recall, and F1 scores than the other models. This result may indicate limitations on this model's ability to capture the complex relationships between the predictors and the outcome variable. The Macro F1 scores provide an assessment of overall model performance across all classes. The causal forest model achieved the highest Macro F1 score, 89%, indicating its ability to perform well across different classes.

5. CONCLUSION

This paper examined the relationships between financial literacy, cognitive biases, and the ownership of cryptocurrencies. Our findings reveal that financial literacy plays a significant role in the decision to own cryptocurrencies, even when accounting for other factors such as age, income, and digital activity. The results demonstrate that individuals with more financial literacy are less likely to own cryptocurrencies, indicating a potential need for improved financial literacy to promote informed decision-making in relation to this emerging (digital) asset class.

Furthermore, we identify the presence of cognitive biases, particularly overconfidence, as a considerable influence on cryptocurrency ownership. Individuals whose self-perceived financial knowledge differs from their actual level of financial literacy (financial literacy bias) are more likely to own cryptocurrencies. This finding emphasizes the importance of addressing biases and promoting realistic self-assessments of financial literacy in mitigating the risks associated with cryptocurrency investment.

While our study contributes to the existing literature on financial literacy and cryptocurrency adoption, it has some limitations. The cross-sectional nature of our data prevents us from establishing more direct causal relationships. Future research employing a longitudinal design could provide stronger evidence in this respect. Additionally, our study focuses on a specific region and population. Further investigations in different contexts would increase the generalizability of our findings.

Despite these limitations, our paper suggests several avenues for future research. First, the underlying mechanisms through which financial literacy influences cryptocurrency ownership and the potential mediators and moderators of this relationship could be examined with deeper detail. Second, the interaction between financial literacy and other individual or contextual factors could be investigated. Third, objective measures of financial literacy and experimental manipulations could be employed to address the limitations of self-reported data. Fourth, the role of institutional and regulatory factors in shaping individuals' cryptocurrency investment decisions could be explored in order to provide insight into the broader socioeconomic and legal contexts that influence this domain. Lastly, given the significance of the cryptocurrency markets and their volatility, ongoing research is needed to stay abreast of the developments in this domain. Further exploration of specific types of cryptocurrencies, technological advancements, regulatory developments, and market dynamics will contribute to a comprehensive understanding of the decision to own cryptocurrencies.

By promoting financial literacy and addressing biases, policymakers, educators, and individuals can make more informed decisions in the cryptocurrency space. Future research building upon our findings and addressing the identified limitations will contribute to a deeper understanding of the factors influencing cryptocurrency adoption and inform strategies for promoting responsible participation in this asset class.

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