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Disentangling the "crypto fever": An exploratory study of the psychological characteristics of cryptocurrency owners

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A B S T R A C T

Cryptocurrencies are innovative digital assets that became significantly popular in recent years. Despite their popularity, literature about cryptocurrencies is still lacking. Specifically, little is known about the psychological profile of cryptocurrency owners. The present paper aims to investigate the role of financial literacy, self-efficacy, risk tolerance, and impulsivity in cryptocurrency ownership in a representative sample of 1,153 Italian consumers. In particular, a Latent Profile Analysis was performed on cross-sectional data to identify different psychological profiles of consumers, and test which of these profiles is more likely to hold cryptocurrencies. Results indicate the presence of six different psychological profiles and that the psychological profile that best describes those who hold cryptocurrencies is characterized by high levels of financial literacy, risk tolerance, and self-efficacy in investment domains. Instead, a configuration of low financial literacy and high self-efficacy, risk appetite, and impulsivity scores is mostly associated with having owned cryptocurrencies in the past. These findings would suggest that psychological characteristics play a key role in cryptocurrency ownership.

Introduction

Cryptocurrencies are an innovative digital currency, decentralized and based on a peer-to-peer network. Through blockchain technology, individuals can keep and transact cryptocurrencies using a shared digital ledger. Moreover, blockchain enables to encrypt these virtual currencies to secure and monitor transactions between individuals (Corbet et al., 2019). Thanks to the decentralized network of cryptocurrencies, digital coins – or tokens – can be exchanged on trading platforms at every moment of the day and without any intermediaries (Delfabbro et al., 2021). Consumers can buy cryptocurrencies either directly or indirectly: the former via online exchange platforms, while the latter through structured retail products (Hackethal et al., 2022).

Since their creation in 2009, cryptocurrencies progressively received more and more attention from consumers and became widespread in 2017 (Hasso et al., 2019). In recent years, the market capitalization of cryptocurrencies vertiginously increased, establishing them as a new financial asset. In 2021, at its highest, the cryptocurrency market has grown to over three trillion of dollars (Lau, 2021). However, cryptocurrencies are frequently subject to strong drawdowns. For instance, in 2022 the market for digital tokens has experienced a loss of approximately 70% of the value reached in 2021, after the failure of the Terra-Luna ecosystem and the crack of FTX, one of the biggest cryptocurrency exchanges (CoinMarketCap, 2022).

Recent estimates report that over six thousand cryptocurrencies are quoted on the market (Steinmetz et al., 2021). Even the share of population holding cryptocurrencies is gradually increasing. A study of fifteen countries found that around 9% of respondents held digital tokens and 14% of them intended to own them in the future. Cryptocurrency owners accounted for about 7% in Australia and the UK and 9% of the total population in the US and Germany (Panos et al., 2020). Similar findings are reported by Laboure and Reid (2020), who showed that the number of individuals holding cryptocurrencies was approximately 7% in Germany, the USA and Italy, 6% in France and 4% in the UK. Other data are also congruent with these findings (Steinmetz et al., 2021).

Although cryptocurrencies were created as an alternative to fiat money and traditional banking (Auer and Tercero-Lucas, 2022) they are often used as financial assets rather than actual currencies (Baur et al., 2018; Corbet et al., 2019). Specifically, various studies (e.g., Fry and

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Cheah, 2016) suggest that cryptocurrencies, due to their high volatility, are primarily used for speculative trading. Indeed, according to Blau (2017), cryptocurrency trading is one of the main factors influencing the price of tokens. Investing and trading are two distinct financial behaviors and assume different strategies, as the latter is focused on a short-term horizon and involves higher amounts of risk. Moreover, since the cryptocurrency market is young, less liquid, and with low participation of institutional investors, Gurdgiev and O'Loughlin (2020) suggested that cryptocurrencies are more influenced by investors' sentiment in contrast to other financial assets. A recent study (Ante, 2023) also highlighted how social media activity could influence the price and returns of cryptocurrencies, thus suggesting potential risks of market manipulations.

Given the great interest in cryptocurrencies and the recent happenings that shook the world of digital tokens (Mark and De Vynck, 2022), there is a strong need for systematic research in the field. Although studies on cryptocurrencies increased in parallel with the interest of retail investors (Sousa et al., 2022), literature is still scarce. In particular, little is known about the characteristics of cryptocurrency owners and the reasons why they hold these assets (Hackethal et al., 2022).

The financial literature has specifically investigated behavioral and decision biases related to cryptocurrency investments (see Almeida and Gonçalves, 2023 for a review). For instance, Bouri et al. (2019) found that investors in cryptocurrency markets tend to show herding behavior, especially when uncertainty increases. Moreover, various studies (e.g., Chen et al., 2020; Gurdgiev and O'Loughlin, 2020) outlined a strong association between the price of cryptocurrencies and investors' sentiment.

On the other side, psychological research focused mainly on the relationship between cryptocurrency trading and gambling behaviors (see Johnson et al., 2023 for a review). Different studies (e.g., Delfabbro et al., 2021; Mills and Nower, 2019) highlighted a strong association between problem gambling and trading frequency, trade size, and price checking of cryptocurrencies. Moreover, it seems that the severity of problem gambling is higher for cryptocurrency traders than for stock market investors and non-investors (Kim et al., 2020; Oksanen et al., 2022). Literature focused also on the relationship between trading cryptocurrencies and mental health (Johnson et al., 2023). For instance, Mills and Nower (2019) found that anxiety and depression are associated with high levels of cryptocurrency trading. Similarly, a recent study (Oksanen et al., 2022) showed that cryptocurrency traders report generally higher levels of psychological distress, perceived stress and loneliness in comparison to stock investors and non-investors.

Even if behavioral sciences shed light on the problematic use of trading cryptocurrencies, there is still a gap in literature regarding the psychological characteristics of individuals holding cryptocurrencies. The purpose of this study is to identify cryptocurrency owners in terms of psychological profiles.

Theoretical background

In this section, we summarize the literature about the psychological factors associated with investing and trading behaviors, focusing especially on cryptocurrency ownership. When talking about financial market participation, financial literacy is one of the main determinants that have been studied, as it is strictly associated with the decision to invest (Hsiao and Tsai, 2018; van Rooij et al., 2011). The concept of financial literacy can be defined as a "combination of knowledge, skills and attitudes required for proper financial behavior" (OECD, 2013). As for investment decision-making, it seems that financially literate individuals generally hold better-diversified portfolios (e.g., Guiso and Jappelli, 2008) and tend to invest in riskier assets (Bannier and Neubert, 2016; Zhu and Xiao, 2022). Regarding the role of financial literacy in predicting cryptocurrency ownership, there is still no agreement yet. For instance, Steinmetz et al. (2021) found that self-assessed knowledge about cryptocurrencies and blockchain was a strong predictor of cryptocurrency adoption. Similarly, it seems that perceived financial literacy is associated with the intention to hold cryptocurrencies (Gupta et al., 2021). Arli et al. (2020) showed that self-reported knowledge about cryptocurrencies is positively related to trust in cryptocurrencies and negatively associated with anxiety to invest in this financial product.

On the contrary, Panos et al. (2020) revealed that financially literate individuals are less likely to own cryptocurrencies and less intentioned to buy them in the future. A recent study on a sample of investors (Zhao and Zhang, 2021) reported that cryptocurrency owners had generally lower levels of objective financial literacy and, at the same time, higher levels of perceived financial literacy. Furthermore, results from a logistic regression showed that objective financial literacy was not able to predict cryptocurrency possession, while subjective financial literacy was positively associated with holding digital tokens. A similar trend was suggested by Arias-Olivas et al. (2019), who discover that financial literacy was incapable of explaining the intention to adopt cryptocurrencies among Spanish consumers. Kim et al. (2023) recently stated that objective and perceived financial literacy were differently associated with cryptocurrency ownership, thus highlighting a divergence between actual and self-assessed knowledge in financial domains. Indeed, while objective financial literacy was negatively related to cryptocurrency ownership, they also found that when perceived literacy increased by one unit, the probability of investing in cryptocurrency increased by 80.6%. A strong and positive association between overconfidence and cryptocurrency investing was also underlined by the authors. This finding is consistent with Nyhus et al. (2023), who reported that overconfident consumers were more inclined to invest in crypto assets. Conversely, Fujiki (2020), using data from the Japanese population, highlighted that cryptocurrency owners display higher objective financial literacy in comparison with non-owners. These findings are in line with Stix (2021). The lack of conclusive results emphasizes the need for further investigation into the phenomenon.

Besides financial literacy, literature shows that financial self-efficacy occurs in shaping investment decision-making as well (Allgood and Walstad, 2016; Henager and Cude, 2016; Mishra et al., 2023). By financial self-efficacy, we mean people's belief in their capability to achieve financial goals (Forbes and Kara, 2010). In other words, financial self-efficacy reflects individuals' confidence in their financial skills and knowledge. Various studies (e.g., Cupák et al., 2021) found that people with greater confidence in their financial skills were also more willing to invest in higher-risk assets. However, scholars point out that there may be a mismatch between actual and perceived financial skills (Allgood and Walstad, 2016; Yeh and Ling, 2022), as some individuals might be excessively confident in their competencies. Overconfidence could negatively affect decisions and behaviors in financial markets. Indeed, overconfidence is associated with low diversification (Goetzmann and Kumar, 2008) and excessive trading activity (Statman et al., 2006). As for cryptocurrencies, Sudzina et al. (2021) found that cryptocurrency adopters display personality traits typically associated with overconfidence: lower agreeableness and higher extraversion.

Attitudes towards risk also play a key role in investment decisions. Indeed, risk tolerant individuals are more likely to participate in capital markets (Dohmen et al., 2011) and to invest in riskier assets (Keller and Siegrist, 2006). As mentioned above, cryptocurrencies are extremely volatile and risky. Thus, risk tolerance could be expected to have a significant role in the ownership of cryptocurrencies. Zhao and Zhang (2021) reported that those owning digital tokens are more inclined to take risks. Moreover, individuals holding risky portfolios are more likely to hold cryptocurrencies. This finding is consistent with Hackethal et al. (2022), who showed that cryptocurrency owners have a major number of single stocks in their portfolios and are more active traders than non-owners. Similarly, Stix (2021) found that cryptocurrency holders are more prone to assume risks and invest in risky financial assets. Likewise, the willingness to purchase cryptocurrencies has also been associated with risk appetite.

Concerning the relationship between impulsivity and financial behaviors, a recent study (Rey-Ares et al., 2021) reported that individuals with higher levels of self-control (i.e., low levels of impulsivity) are more likely to invest. Likewise, Sekścińska et al. (2021) found that higher self-control is related to a greater likelihood to invest although it is also associated with low-risk financial investments. On the other side, high impulsivity has been linked with trading activity and investment biases, such as overconfidence (Uhr et al., 2021). As for cryptocurrencies, recent findings also showed higher levels of impulsivity among those who frequently exchange digital tokens (Sonkurt and Altinöz, 2021). Furthermore, it seems that cryptocurrency adopters generally lack self-control (Sudzina et al., 2021). Kim et al. (2020) reported that persons holding cryptocurrencies show higher novelty-seeking behaviors in comparison to stock investors and non-investors.

While previous studies have highlighted the role that these psychological variables play in cryptocurrency adoption through a variable-centered approach, the current study aims to embrace a person-centered approach. While the former is able to identify how a specific psychological factor affects the decision to own cryptocurrency in the entire sample on average, the second one jointly considers more psychological variables together and identifies how a specific configuration of such factors is associated with the outcome. In other words, adopting a person-centered approach to analyze the different psychological factors here considered (financial literacy, investment self-efficacy, financial risk attitudes, and impulsivity) challenges “the assumption that all individuals are drawn from a single population and consider the possibility that the sample might include multiple subpopulations characterized by different sets of parameters” (Morin et al., 2018, p. 805).

The result is a classification system that groups individuals into distinct psychological profiles or patterns depending on how the different psychological variables coexist. In particular, the person-centered approach allows us to identify different combinations of psychological factors that are detectable in our sample and verify whether one or more of these configurations are associated with the decision to own cryptocurrencies. We believe that a person-centered approach is a key method to use when studying psychological variables. Indeed, individuals’ behavior is not determined by just one psychological factor but by a set of more aspects interacting together.

Considering these assumptions, the current study aims to identify different psychological profiles related to financial domains (i.e., psychological profiles based on scores of financial literacy, investment self-efficacy, financial risk attitudes, and impulsivity) and verify how these profiles are associated with cryptocurrency ownership.

Methods

Fig. 1 depicts the research workflow employed in the present study. Once the research question was defined and literature on the field was reviewed, a theoretical model was developed, adopting the theoretical framework of behavioral finance. This approach assumes that financial and investment decision-making are largely affected by psychological characteristics and cognitive bias. In the next sub-sections, sampling procedures and measures adopted will be discussed. To identify the characteristics of cryptocurrency owners, a person-centered approach was adopted. Specifically, a Latent Profile Analysis was performed to identify sub-groups within the sample. Subsequently, we tested which profiles were more likely to own (or have owned) cryptocurrencies. Details of the analytic plan are further discussed in the next section, then results will be reported and commented.

Data acquisition strategy and description

Data were obtained through an online survey, administered in March 2022 to a pool of 1153 Italian consumers. Data were collected through CAWI methodology, as the questionnaire was hosted and distributed using the Qualtrics online survey platform. Respondents, recruited via e-mail invitations, received a monetary compensation as an incentive for study participation. A quota sampling method was used to check sample representativeness for gender, age, educational level, and geographical area. Written informed consent was obtained from participants before they started the questionnaire. Survey completion required approximately 15 min.

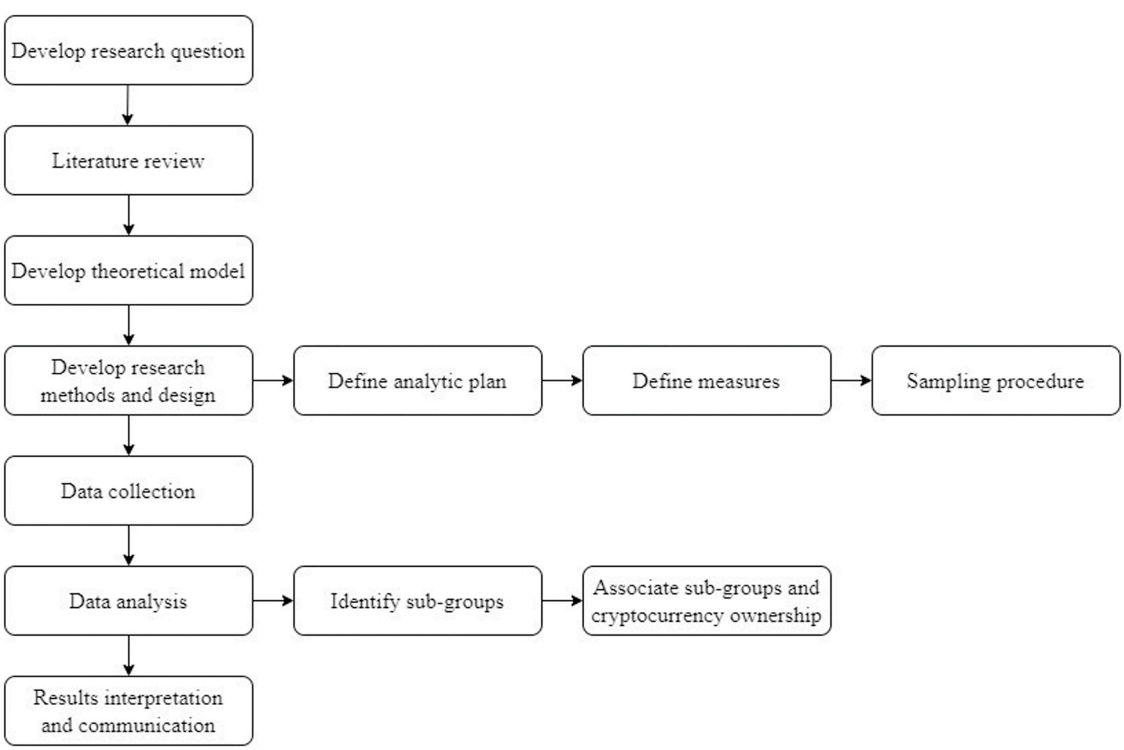

Fig. 1. Research diagram workflow.

The total sample was equally distributed for gender (50% female) and respondents' age ranged from 18 to 50 years old, with a mean of 35.23 years ($SD = 10.09$). Most of the sample (51.9%) had a high-school degree. 30.3% of participants attended university and 17.8% graduated from high school. The majority of respondents (65%) was employed, while 19% were students and the remaining 16% were unemployed.

Considering the geographical area, 41.1% of the participants lived in northern parts of Italy: specifically, 24.3% in the north-west and 16.8% in the north-east. The 23.3% of them lived in central Italy and the rest of the sample (35.6%) was from the south. Finally, as for marital status, 35.7% of respondents was in a stable relationship, the 32.6% of them were single and the remaining 31.7% were married.

Participants were also asked whether or not they were currently holding cryptocurrencies. Cryptocurrency owners represented 7% ($n = 81$) of the whole sample, which is representative of the Italian population. This data is in line with previous studies (Laboure and Reid, 2020; Steinmetz et al., 2021). Instead, 9.6% ($n = 111$) of the sample reported to have owned cryptocurrencies in the past but not anymore.

Measures

Financial literacy

To assess financial literacy, participants were asked to answer four questions regarding investment domains. Three out of four questions are the alleged "Big 3″ developed by Lusardi and Mitchell (2011). These questions measure knowledge about inflation, interest rates, and risk diversification. An additional item was developed to test the understanding of the risk-return trade-off: "There is a direct link between risk and the return on a financial asset, so an investment with a high expected return is probably very risky." Respondents had to choose the correct answer among various alternatives. The total index of financial literacy was then obtained by adding the number of correct answers. The final score ranged between 0 (no correct answers) and 4 (all answers correct).

Investment self-efficacy

Since self-efficacy is a domain-specific construct (Bandura, 1997), a statement has been created ad hoc to measure individuals' perceived investment competencies: "Overall, to what extent do you feel confident in your investment management skills?". The item was developed on a Likert scale, ranging from 1 (Not sure at all) to 7 (Very sure), and considered an autonomous index of confidence in one's own investment capabilities and knowledge.

Financial risk attitude

Attitudes toward financial risk were measured on a six-item scale originally developed for the Dutch National Bank Household Survey (DHS) and subsequently validated by Kapteyn and Teppa (2011). This measure assesses risk attitudes specifically in financial and investment domains. Respondents are asked to express their agreement on a Likert scale ranging from 1 (completely disagree) to 7 (completely agree).

The scale is composed of two factors. The former measures financial risk aversion (e.g., "I would never consider investments in shares because I find this too risky"), whilst the second one represents financial risk tolerance (e.g., "I get more and more convinced that I should take greater financial risks to improve my financial position"). Each factor consists of three items. Higher scores correspond to higher levels of risk tolerance/aversion.

A Confirmatory Factor Analysis was performed to verify the theoretical model of the scale [$\chi^2 = 19.378$, df $= 8$, $p = .013$; RMSEA $= 0.036$ (0.015, 0.056); CFI $= 0.987$; SRMR $= 0.021$] and to save factor scores. Finally, internal consistency was measured for both Risk Aversion ($\omega = 0.665$) and Risk Tolerance ($\omega = 0.753$).

Impulsivity

Individual impulsivity was assessed using BIS-15, a 15-item psychometric instrument developed by Spinella (2007), which is a shorter form of the Barratt Impulsivity Scale (Patton et al., 1995). As well as the original version, the scale is comprised of three factors, representing different facets of impulsivity. The first one is Motor Impulsivity, which indicates the propensity to act without thinking (e.g., "I act on the spur of the moment"); the second factor is Attentional impulsivity, which represents difficulties in focusing attention (e.g., "I get easily bored solving thought problems"); finally, the Non-planning subscale, once items are reversed, measures lack of concerns about the future (e.g., "I plan for the future").

Each sub-scale includes five items. Answers must be indicated on a four-point scale ranging from 1 (rarely/never) to 4 (almost always/always). Higher scores suggest higher levels of impulsivity. Since item 13 had a weak factor loading, it was not considered in the model. For this reason, the Attentional impulsivity subscale was measured by four items.

The triple-factor theoretical model of the BIS-15 scale showed an adequate goodness of fit [$\chi^2 = 487.616$, df $= 74$, $p < .001$; RMSEA $=$ 0.071 (0.065, 0.077); CFI $= 0.946$; SRMR $= 0.048$]. Subsequently, factor scores were saved. Internal consistency scores (ω) of the three sub-scales were respectively 0.801, 0.699, and 0.713.

Cryptocurrency ownership

To identify (current and past) cryptocurrency owners, participants were asked whether they were holding any cryptocurrencies. Specifically, respondents had to report if they were currently holding cryptocurrencies, have owned them in the past, or have never possessed any. This enabled us to distinguish between current cryptocurrency owners, past owners, and those individuals who have never held any cryptocurrencies.

Data analysis

In order to understand how psychological profiles are associated with the decision to adopt cryptocurrency, we had to 1) identify which psychological profiles were present in our sample and, then, 2) assess the association between these profiles and cryptocurrency ownership.

Latent profile analysis: identifying psychological profiles

To identify the groups (i.e., profiles) that best describe the heterogeneity within the current sample for the different psychological factors (financial literacy, investment self-efficacy, financial risk attitude, impulsivity) taken into consideration, we performed a Latent Profile Analysis (LPA) using Mplus software (version 8.7). Based on the Confirmatory Factor Analyses described in the measure section, we saved the factor scores for each sub-dimension of the adopted measurement scales for a total of seven observed indicators: financial literacy, investment self-efficacy, financial risk aversion, financial risk tolerance, motor impulsivity, attentional impulsivity, and non-planning impulsivity. The LPA thus aimed to identify the different ways (i.e., profiles) in which these seven variables interplay in our sample.

We examined fit indices of measurement models, beginning with one profile and adding profiles incrementally. As suggested by Sorgente et al. (2019), the selection of the optimal fitting model(s) was based on statistical tests and descriptive measures of relative model fit. In particular, we adopted the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) as well as the adjusted Lo-Mendell-Rubin likelihood ratio test (adjusted LMR-LRT; Lo, 2001) that compare two consecutive models; if they are not significant, the k-profile model is as good as the (k-1) profile model, so the (k-1) profile model is preferred according to parsimony criterion.

As descriptive measures of relative model fit, we first adopted five information criteria: Akaike Information Criterion (AIC), Consistent AIC (CAIC), Approximate Weight of Evidence Criterion (AWE), Bayesian Information Criterion (BIC), and the sample-size adjusted BIC (ssBIC).

For all criteria, lower values indicate a better fit. Finally, we also adopted two other descriptive measures of relative model fit: the approximate Bayes Factor (BF) and the approximate correct model Probability (cmP), both made popular by Nagin (1999). The BF compares two models at a time (k and $k+1$ model) and the best model is the most parsimonious k-class model with BF > 3. In contrast, the cmP compares all models under consideration. In this case, any model with cmP > 0.10 could be considered a candidate model; however, the best model is the one with the highest value of cmP.

Once selecting the best model(s), the quality of their classification (i.e., assignment of people to profiles) has to be evaluated (Masyn, 2013). The most common diagnostic classification is Entropy (E_k), where values closer to 1 indicate a better classification of cases. Furthermore, the quality of the classification needs to be evaluated by checking the Class Proportion (CP or π_k), the modal class assignment Proportion ($mcaP_k$), the Average Posterior Probability ($AvePP_k$), and the Odds of Correct Classification (OCC_k). In particular, classification can be considered good when the $mcaP_k$ for each profile is included in the 95% CI of the π_k, $avePP_k$ values are equal to 0.70 or higher and OCC_k values are above 5 (Masyn, 2013; Sorgente et al., 2019).

Association between profiles and cryptocurrency ownership

Once the best model of LPA was identified, we saved the factor scores of the categorical latent variable to have an observed variable representing each participant's membership to a specific psychological profile. This observed variable was investigated in relation to cryptocurrency ownership status (i.e., current owners, past owners, and never owned cryptocurrencies), through a chi-square test in SPSS (version 27). As suggested by Sharpe (2015), we adopted standardized residuals to interpret chi-square test results, considering that the larger the residual, the greater the contribution of the cell to the magnitude of the resulting chi-square obtained value.

Results

First of all, descriptive statistics and correlations between the indicators considered to perform the analysis were estimated. Results are summarized in Table 1.

Latent profile analysis: identifying psychological profiles

Ten different measurement models were performed, from the one with only one group (i.e., one psychological profile for the entire sample) to the one with ten groups (i.e., ten different profiles). Fit indices (see Table 2), suggest that the model with six psychological profiles was the one best describing the heterogeneity in our sample. In particular, the two statistical tests (i.e., the VLMR-LRT and the adjusted LMR-LRT) suggest that both the 2- and the 6-profile solutions are acceptable. Among the five information criteria, the AWE indicates the 2-profile solution as the best one, whereas the BIC suggests that the 6-profile solution is the best. The other three criteria (AIC, CAIC, ssBIC) are not fully informative as they continue to decrease with the increase in the number of profiles. The BF indicates that the 6-, the 7-, and the 8-profile solutions are adequate, while the cmP only supports the 6- and 7-profile solutions. As the 6-profile solution met most of the fit indices, we retained this one.

As suggested by Masyn (2013) we evaluated the classification quality of this 6-profile solution; in other words, we assessed the accuracy of participants' classification. First, we found that Entropy was sufficiently high ($E_k = 0.799$) to suggest a high-quality classification. Furthermore, as reported in Table 3, the other classification diagnostics (i.e., Class Proportion; modal class assignment Proportion; Average Posterior Probability; Odds of Correct Classification) too indicated that the 6-profile solution produces well-separated and highly differentiated groups, whose members have a high degree of homogeneity in their responses on the profile indicators.

The six different profiles are represented in Fig. 2. Sociodemographic characteristics of the six latent profiles is reported in Appendices (see Table A.1). The first sub-group represents individuals ($n = 120$; 10.4% of the sample) who have both low financial literacy (objective knowledge) and investment self-efficacy (perception to be competent). Furthermore, they are not favorable to risk (high risk aversion, low risk tolerance) while they have average (i.e., close to 0) levels of impulsivity. We labeled this group "the Knowingly cautious ones" as they are aware of their lack of financial literacy and this awareness, likely, may result in risk aversion in financial domains.

The second psychological profile represents individuals ($n = 325$; 28.2%) who score low on financial literacy and report investment self-efficacy scores higher than the sample mean (i.e., zero). We named this group "the Needlessly confident impulsive risk-seekers" as they show the lowest levels of financial literacy and this unrealistic confidence in their capabilities (i.e., investment self-efficacy above the average score) is matched with low risk aversion and high levels of risk appetite and impulsivity.

An opposite trend was found for the third psychological profile presented in our sample. It includes over one-third of the sample ($n = 433$; 37.6%) and characterizes those with a high level of financial literacy and awareness of their investment capabilities. Furthermore, this cluster reports a higher propensity to take financial risks and impulsivity scores below the average. Thus, it was named "the Self-aware risk-seekers".

The fourth psychological profile consists of individuals ($n = 190$; 16.5%) with both high levels of financial literacy and low investment self-efficacy. As a consequence, this cluster was named "the Underconfident risk-averse ones" as they underestimate their capabilities and prefer to avoid risk (high risk aversion and low risk tolerance) and impulsive decisions (impulsivity dimensions under the mean scores).

As for the fifth psychological profile, we labeled it as "the Overconfident impulsive risk-seekers" since it is represented by individuals ($n = 67$; 5.8%) lacking financial literacy but with the greatest confidence in their investment competencies. This cluster reports the highest levels of risk tolerance and shows higher scores of motor and attentional impulsivity, whilst the non-planning subscale is below the average (i.e., zero).

Finally, the last psychological profile is named "the Fuzzy ones". Indeed, the 18 individuals (1.5%) belonging to this profile gave answers which generate a non-coherent profile. They seem to score very low on all psychological variables considered, except for the non-planning sub-

Table 1
Descriptive statistics and correlations between variables included in the LPA.

Variable	M	SD	1	2	3	4	5	6	7
1. Financial literacy	2.33	1.27	–						
2. Investment self-efficacy	3.91	1.62	.043	–					
3. Risk aversion	4.72	1.20	.104*	−0.083	–				
4. Risk tolerance	3.41	1.39	−0.063	.396*	−0.450*	–			
5. Motor impulsivity	1.94	.62	−0.197*	.020	−0.072	.200*	–		
6. Attentional impulsivity	1.97	.63	−0.206*	−0.035	−0.025	.175*	.809*	–	
7. Non-planning impulsivity	2.16	.57	−0.198*	−0.228*	−0.109*	−0.064	.254*	.188*	–

Note. * $p < .001$.

Table 2
Absolute and relative fit indices for LPA measurement models.

Model	VLMR-LRT	LMR-LRT	AIC	CAIC	AWE	BIC	ssBIC	BF	cmP
1-profile	/	/	19,235.07	19,446.83	19,763.58	19,411.83	19,300.66	<0.001	<0.001
2-profile	$p < 0.001$	$p < 0.001$	19,040.27	19,300.43	19,689.58	19,257.43	19,120.84	<0.001	<0.001
3-profile	$p = .125$	$p = .128$	18,973.77	19,282.32	19,743.88	19,231.32	19,069.33	<0.001	<0.001
4-profile	$p = .125$	$p = 0.129$	18,868.79	19,225.73	19,759.69	19,166.73	18,979.33	<0.001	<0.001
5-profile	$p = .003$	$p = .003$	18,802.30	19,207.66	19,814.02	19,140.66	18,927.84	<0.001	<0.001
6-profile	$p = .007$	$p = .008$	18,717.86	19,171.62	19,850.38	19,096.62	18,858.40	7.78	0.89
7-profile	$p = .495$	$p = .500$	18,681.56	18,598.56	19,934.88	19,100.72	18,837.09	6301.17	0.11
8-profile	$p = .367$	$p = .374$	18,658.66	18,567.66	20,032.78	19,118.22	18,829.18	795.12	<0.001
9-profile	$p = .609$	$p = .610$	18,631.62	18,532.62	20,126.54	19,131.58	18,817.12	0	<0.001
10-profile	$p = .662$	$p = .668$	18,602.63	18,495.63	20,218.36	19,142.99	18,803.13	0	<0.001

Note. VLMR-LRT = Vuong-Lo-Mendell-Rubin likelihood ratio test; LMR-LRT = adjusted Lo-Mendell-Rubin likelihood ratio test; AIC = Akaike Information Criterion; CAIC = Consistent AIC; AWE = Approximate Weight of Evidence Criterion; BIC = Bayesian Information Criterion; ssBIC = sample-size adjusted BIC; BF = Bayes Factor; cmP = approximate correct model Probability.

Table 3
Classification diagnostics for the 6-profile model.

Profile	CP	95% CI	mcaP	AvePP	OCC
Profile 1 (n = 120; 10.4%)	.106	(0.060 0.145)	.104	.791	31.92
Profile 2 (n = 325; 28.2%)	.273	(0.224 0.326)	.282	.840	13.98
Profile 3 (n = 433; 37.6%)	.378	(0.333 0.431)	.376	.881	12.18
Profile 4 (n = 190; 16.5%)	.169	(0.127 0.219)	.165	.849	27.65
Profile 5 (n = 67; 5.8%)	.058	(0.024 0.090)	.058	.809	68.79
Profile 6 (n = 18; 1.5%)	.015	(0.006 0.027)	.016	.869	435.61

Note. CP= Class Proportion; CI = Confidence Interval; mcaP= modal class assignment Proportion; AvePP = Average Posterior Probability; OCC= Odds of Correct Classification.

scale (i.e., the only reversed score sub-scale). This may suggest that they have provided random answers to the survey, making their psychological profiles not fully intelligible. Similar profiles have been found in previous studies as well (e.g., Manzi et al., 2021).

Chi-square test

Having the LPA solution sufficient levels of Entropy, factor scores of the obtained latent variable were saved to have an observed variable describing participant's membership to the six psychological profiles. This variable was associated with the adoption of cryptocurrencies. We found that psychological profiles are significantly associated with cryptocurrency ownership [$\chi^2(10) = 33.264$; $p < .001$; Cramer's $V = 0.120$]. In particular, as reported in Table 4, individuals belonging to the "Self-aware risk-seekers" profile (Profile 3) were more likely to own cryptocurrencies than would be expected by chance. Indeed, 10.2% of individuals included in this groups were currently owning cryptocurrencies. The frequency of crypto owners is thus significantly higher than the whole sample, which reported a frequency of 7%. This profile contains more than half of the total number of cryptocurrency owners. Instead, individuals belonging to the "Needlessly confident impulsive risk-seekers" profile (Profile 2) were more likely to have owned

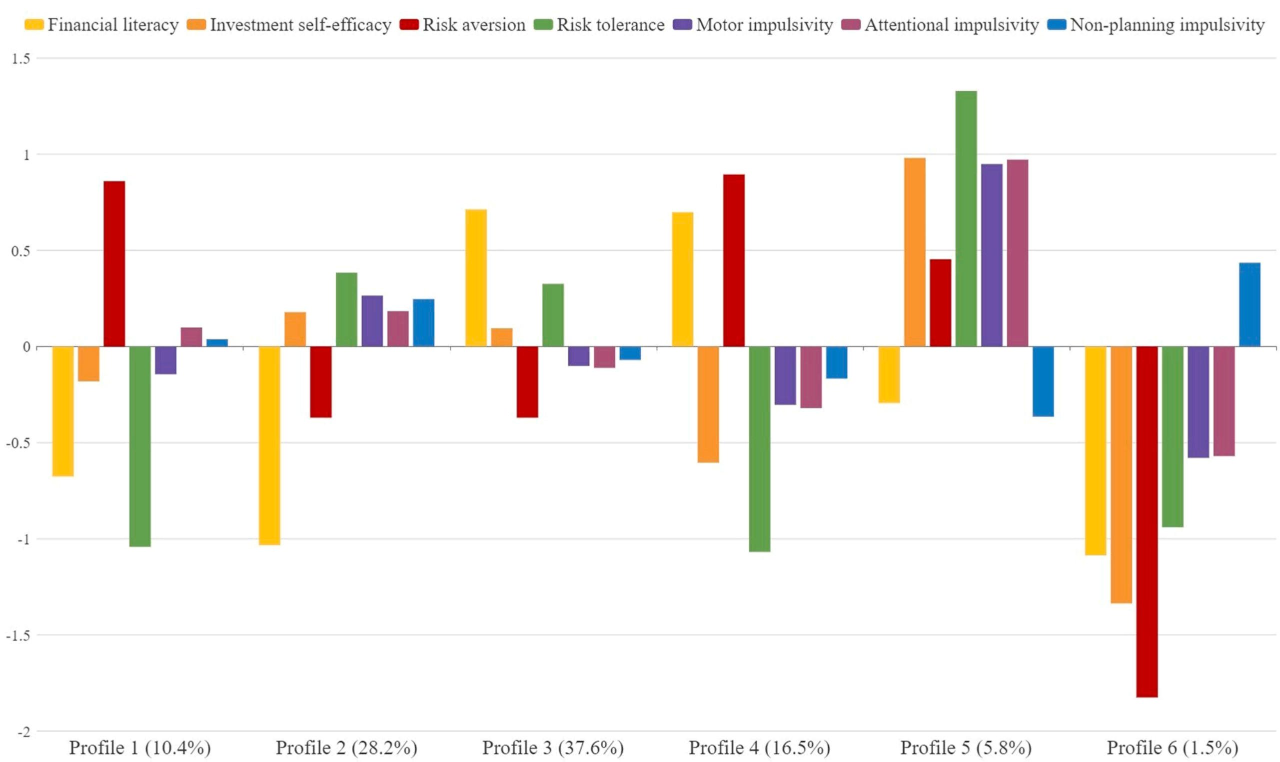

Fig. 2. Representation of the six psychological profiles detected in a sample of 1153 Italian consumers. Values on the ordinate axis correspond to the factor scores mean level for the seven psychological (sub)dimensions taken in consideration to identify profiles (financial literacy, investment self-efficacy, financial risk attitude, motor impulsivity, attentional impulsivity and non-planning impulsivity).

Table 4
Cross-tabulation of personality profiles and cryptocurrency ownership.

	Observed values (adjusted residuals)			
	Crypto owners	Past crypto owners	Never owned crypto	Total
Profile 1 (the Knowingly cautious ones)	8 (−0.2)	2 (**−3.1**)	110 (**2.6**)	120
Profile 2 (the Needlessly confident impulsive risk-seekers)	13 (**−2.5**)	42 (**2.4**)	270 (−0.2)	325
Profile 3 (the Self-aware risk-seekers)	44 (**3.2**)	45 (0.7)	344 (**−2.8**)	433
Profile 4 (the Underconfident risk-averse ones)	8 (−1.7)	13 (−1.4)	169 (**2.3**)	190
Profile 5 (the Overconfident impulsive risk-seekers)	8 (1.6)	8 (0.7)	51 (−1.6)	67
Profile 6 (the Fuzzy ones)	0 (−1.2)	1 (−0.6)	17 (1.3)	18
Total	81	111	961	1153

Note. Adjusted residuals in bold are those that exceed +/- 2 as suggested by Sharpe (2015).

cryptocurrencies in the past but not anymore, as 13% of individuals included in this sub-group reported to be past cryptocurrency owners. The "Knowingly cautious ones" (Profile 1), as well as the "Underconfident risk-averse ones" (Profile 4) were more likely to have never held any cryptocurrencies.

Discussion

The present study aimed to identify the psychological characteristics of cryptocurrency owners. Data collected through an online survey filled by 1153 individuals were used to perform a Latent Profile Analysis and, subsequently, a Chi-square test. Specifically, the LPA allowed us to consider all the psychological variables together in order to profile our sample. Then, the Chi-square test was conducted to investigate which group was more likely to hold (or have held in the past) cryptocurrencies. In other words, this study enabled us to understand which psychological profile is mostly associated with cryptocurrency current and past ownership.

The LPA resulted in six different clusters, which are differently associated with the probability of being (current or past) cryptocurrency owners. However, only the "Self-aware risk-seekers" profile (Profile 3) shows a significant likelihood of currently holding digital tokens, whilst the "Needlessly confident impulsive risk-seekers" group (Profile 2) is more likely to have adopted cryptocurrencies in the past. Finally, the "Knowingly cautious" (Profile 1) ones and the "Underconfident risk-averse" profile (Profile 4) turned out to be less likely to have ever adopted cryptocurrencies. These findings show that financial literacy, financial risk tolerance, investment self-efficacy, and self-control (i.e., low impulsivity) jointly shape the likelihood to own cryptocurrencies. Indeed, profile 3 - the "Self-aware risk-seekers" - is the only one to report scores for the first three variables above the average and lower impulsivity levels. This profile is similar to profile 2 - the "Needlessly confident impulsive risk-seekers" - in terms of self-efficacy and risk attitudes, although it strongly differs for financial literacy and impulsivity scores. This might explain why profile 2 includes a significantly higher share of past cryptocurrency owners. Indeed, we speculate that a lack of adequate financial literacy and their impulsive tendencies might explain why they do not hold cryptocurrencies anymore. Their financial illiteracy and scant regard for future consequences may have led them to misbehaviors. For instance, even though we do not have information on when they sold their digital tokens, it could be possible that some past owners might have sold them during a downturn of cryptocurrency markets due to their inability of properly handling this financial asset.

This trend also suggests that higher risk tolerance and self-efficacy alone are not enough. Financial literacy is also needed within cryptocurrency ownership, together with lower impulsivity. This assumption might explain why profile 5 - the "Overconfident impulsive risk-seekers" - is not associated with the possession of cryptocurrencies. Though this profile reported investment self-efficacy and risk tolerance strongly above the mean score, it lacks adequate financial literacy and self-control (i.e., low impulsivity). However, financial literacy and self-control alone are unable to explain cryptocurrency adoption as well. Indeed, profile 4 - the "Underconfident risk-averse ones" - reported a higher knowledge in financial domains and lower impulsivity levels, although it also manifests a lack of confidence in investment skills and a strong aversion to take financial risks. Something similar happens for profile 1 (the "Knowingly cautious ones"), as it is characterized by low financial literacy, investment self-efficacy and higher risk aversion.

Results of the present study show the advantages of profile-centered analyses, as they enable to evaluate the joint effect of more variables when they assume a specific configuration. Indeed, considering one or two psychological variables at a time may not be enough to explain cryptocurrency ownership, and considering which configurations of these variables is associated with the outcome could improve knowledge on the topic by providing a different perspective. By investigating the effect size of a variable on an outcome, variable-centered approaches neglect to consider that human behavior might be the result of a specific configuration of individual differences or other psychological characteristics. Indeed, while we considered variables already investigated in previous studies, we believe that the adoption of a person-centered approach is the main novelty of the present study, as other studies on the topic were rooted in variable-centered approaches.

The psychological profile that best describes those who currently hold cryptocurrencies is characterized by a combination of high levels of financial literacy, financial risk tolerance, and self-efficacy in investment domains and lower impulsivity scores. These findings are consistent with previous studies (Fujiki, 2020; Gupta et al., 2021; Hacketal et al., 2022; Steinmetz et al., 2021; Stix, 2021).

Concerning financial literacy, cryptocurrency owners report higher levels of knowledge in investment domains. This result is in contrast with some studies (e.g., Zhao and Zhang, 2021), but in agreement with others (e.g., Fujiki, 2020). However, it should be noted that most of the studies that investigated the relationship between objective financial literacy and cryptocurrency ownership relied on old panel data (e.g., Fujiki, 2020; Panos et al., 2020; Zhao and Zhang, 2021). Thus, it is still difficult to conclude whether cryptocurrency holders are actually more financially literate or not. Nevertheless, considering that cryptocurrencies have recently become a mass phenomenon, it could be plausible that they attracted even those with greater financial expertise, who might use digital tokens to diversify their portfolios. Financial literacy could also be called in cause to explain past cryptocurrency ownership as well. Indeed, the profile that mostly includes past cryptocurrency owners (Profile 2) reports a notable lack of financial knowledge. Besides ours, only a few studies have examined the role of financial literacy through objective knowledge rather than a self-assessment. Thus, we auspicate that future studies might deeply analyze the role of financial literacy in cryptocurrency ownership.

As for self-efficacy in investment domains, to our knowledge, no study has previously explored the role that it plays in cryptocurrency adoption. However, our findings coincide with studies that investigated the association between confidence in one's own financial competences and investment decisions (e.g., Allgood and Walstad, 2016). In the present study, it seems that individuals with higher self-efficacy are more likely to hold, or have owned, cryptocurrencies. The result goes along with Zhao and Zhang (2021), which found that perceived financial literacy was a strong driver for cryptocurrency investment behaviors.

Similar to previous works (e.g., Hacketal et al., 2022), the psychological profile which is most likely to own cryptocurrencies (Profile 3) has also shown a greater propensity to take financial risks. A similar trend was also found for the profile associated with past cryptocurrency ownership (Profile 2). This result is also consistent with the intrinsic risky nature of cryptocurrencies. Indeed, cryptocurrencies are an extremely volatile asset, that requires higher levels of risk tolerance. People who are unable to handle the strong downturns that characterize cryptocurrency markets may be subject to misbehaviors and non-optimal decisions, such as panic selling.

The "Self-aware risk-seekers" group (Profile 3) reported impulsivity scores below the average. This finding seems in contrast with previous studies (e.g., Sudzina et al., 2021). Anyway, it should also be considered that past cryptocurrency owners (Profile 2) showed instead a lack of self-control. While impulsive tendencies could also explain why some individuals decided to adopt cryptocurrencies, in line with previous literature, we argue that a combination of impulsivity and low financial literacy might elucidate why they do not hold cryptocurrencies anymore. However, due to the limited literature about the role of self-control and the exploratory nature of our study, no conclusion should be drawn on that point. Concerning the role of impulsivity in cryptocurrency ownership, we auspicate that future studies will consider both those who trade digital tokens and those who invest in cryptocurrencies with a long-term perspective, as they might show differences in impulsivity levels. Indeed, literature reports that trading behaviors could be associated with a lack of self-control. Thus, it may be plausible to find differences depending on the strategy adopted by cryptocurrency owners. In other words, active traders could show higher impulsivity in comparison to the ones that hold tokens with longer-term perspectives.

The present study has some limitations that warrant further consideration. First, the adoption of solely cross-sectional data limits the claims and inferences that could be taken. Considering the dynamic nature of cryptocurrencies, it would be interesting to understand whether different psychological profiles react differently to market volatility and whether they adopt different strategies and behaviors, following market adjustments. Future studies could investigate this topic. Furthermore, since the study focuses only on an Italian sample, generalizations outside the Italian territory should be made cautiously. The present study also did not consider the profile(s) of potential cryptocurrency adopters, as it lacks information on individuals who intended to adopt digital tokens. Future studies should also investigate the psychological characteristics of potential cryptocurrency owners and compare them to those who would never adopt cryptocurrencies. Finally, even though we were able to identify cryptocurrency owners' profiles, no information about their motivations and aims was available in the present study. The reasons why consumers hold, or are intentioned to hold, cryptocurrencies should be deeply investigated. Future studies should also explore whether and how cryptocurrency investors differ from individuals investing in conventional financial assets (e.g., stocks). Indeed, the research design adopted in the present study was not suited for such comparison.

Conclusion

Although cryptocurrencies became widespread in 2017, literature is still scarce, especially regarding the psychological characteristics of cryptocurrency owners. The present study aimed to contribute to fill this gap. Our findings would suggest that psychological characteristics play a key role in cryptocurrency ownership.

In conclusion, are cryptocurrencies new and innovative financial assets, or are they a new frontier of gambling? The results obtained in the present study may suggest that they could be something in the between, as their use might depend on cryptocurrency owners' psychological characteristics. For instance, we found interesting differences between current and past cryptocurrency owners, specifically in impulsivity scores and financial literacy. We speculate that past cryptocurrency owners might have adopted cryptocurrencies without proper knowledge and little thought about consequences, and possibly they sold them given their inability of handling this financial asset. Conversely, we speculate that current owners, thanks to their adequate financial literacy and self-control might conceive cryptocurrencies as financial assets, rather than a new way of gambling. Hence, they could have defined clear investment strategies, instead of trading digital tokens without proper knowledge.

However, it is necessary to explore the matter further. The persistent presence of cryptocurrencies on social media could attract younger individuals, caught up in the hype for digital tokens and attracted by large potential gains. Thus, young people might engage in trading cryptocurrencies without any financial knowledge and capabilities, risking losing money. For instance, literature reports that social media sentiment has a great impact on stock markets (Piñeiro-Chousa et al., 2017). Cryptocurrency markets are strongly influenced by consumers' sentiment as well (Gurdgiev and O'Loughlin, 2020). The internet is plenty of websites, forums, and social media pages talking about cryptocurrencies and inexperienced owners might be more susceptible to the news about the world of digital tokens. Finally, it must be considered that cryptocurrency markets are not regulated by governments and financial institutions (Arli et al., 2020). As a consequence, consumers involved with cryptocurrencies might be at risk of threats, and this could be especially true for those with little experience in financial domains.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Paola Iannello reports financial support was provided by Flowe S.p. A. The present research was conducted within the project "Flowe Observatory", accomplished from January to May 2022 and financed by the Italian fintech Flowe S.p.A. This project was aimed to investigate the levels of financial literacy among Italian population and how it shapes financial behaviors and decision-making. Flowe funded data collection of the sample considered in the study and shared the dataset with the authors. However, the design of the research as well as the methodology, implementation of the study and analysis of data reported in the present study were independently defined and performed by the authors, without any external involvement. The authors also declare that the discussion of results presented in this manuscript represent their personal opinion which are freely reported in the study and were not influenced by the partnership with Flowe S.p.A. The authors declare they had no conflict of interest that could influence the work reported in the present study.

Data availability

Due to legal and commercial agreement with the company funding data collection, supporting data is not available for share.

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This research was conducted in partnership with Flowe S.p.A, which funded data collection. The authors declare they had no conflict of interest that could influence the work reported in the present study.

Code availability statement

The Mplus code used to perform the Latent Profile Analysis (LPA) is available upon request to the authors.

Appendix

Measures

Barratt Impulsiveness Scale-15 (BIS-15; Spinella, 2007):

Fifteen items developed on a 4-point Likert-type scale (1 = rarely/never, 4 = almost always) and divided in three sub-scales: *A* = Attentional impulsivity; *M* = Motor impulsivity; NP = Non-planning impulsivity.

1. I act on impulse. [reversed] (M)
2. I act on the spur of the moment. (M)
3. I do things without thinking. (M)
4. I say things without thinking. (M)
5. I buy things on impulse (M)
6. I plan for job security. [reversed] (NP)
7. I plan for the future. [reversed] (NP)
8. I save regularly. [reversed] (NP)
9. I plan tasks carefully. [reversed] (NP)
10. I am a careful thinker. [reversed] (NP)
11. I am restless at lectures or talks. (A)
12. I squirm at plays or lectures. (A)
13. I concentrate easily. [reversed] (A)
14. I don't pay attention. (A)
15. I get easily bored solving thought problems. (A)

DHS Risk Attitude scale (Kapteyn and Teppa, 2011)

Six items developed on a 7-point Likert-type scale (1 = completely disagree, 7 = completely agree) and divided in two factors: RA = Risk aversion; RT = Risk tolerance.

1. I think it is more important to have safe investments and guaranteed returns, than to take a risk to have a chance to get the highest possible returns. (RA)
2. I would never consider investments in shares because I find this too risky. (RA)
3. If I think an investment will be profitable, I am prepared to borrow money to make this investment. (RT)
4. I want to be certain that my investments are safe. (RA)
5. I get more and more convinced that I should take greater financial risks to improve my financial position. (RT)
6. I am prepared to take the risk to lose money, when there is also a chance to gain money. (RT)

Investment self-efficacy

One item developed on a 7-point Likert-type scale (1 = not sure at all, 7 = very sure).

1. Overall, to what extent do you feel confident in your investment management skills?

Financial literacy

Three items retrieved from the Big Three (Lusardi and Mitchell, 2011).

1. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?
   - More than $102
   - Exactly $102
   - Less than $102
   - Do not know
2. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?
   - More than today
   - Exactly the same
   - Less than today
   - Do not know
3. Please tell me whether this statement is true or false. "Buying a single company's stock usually provides a safer return than a stock mutual fund."
   - True
   - False
   - Do not know

One item developed ad hoc.

1. "There is a direct link between risk and the return on a financial asset, so an investment with a high expected return is probably very risky." This statement is:
   - True
   - False

- Do not know

Table A1

Table A1
Socio-demographic characteristics of the six profiles identified with the LPA.

	Profile 1(10.4%)	Profile 2(28.2%)	Profile 3(37.6%)	Profile 4(16.5%)	Profile 5(5.8%)	Profile 6(1.5%)	Total
Gender							
Female	38.9%	70.8%	62.1%	38.8%	53.5%	38.3%	50%
Male	61.1%	29.2%	37.9%	61.2%	46.5%	61.7%	50%
Age							
18–24	16.7%	18.3%	15.3%	16.4%	28%	23.8%	22.5%
25–34	27.8%	25%	17.9%	29.9%	28.6%	23.6%	24.6%
35–42	33.3%	21.7%	20.5%	29.9%	22.5%	24.9%	23.6%
43–50	22.2%	35%	46.3%	23.9%	20.9%	27.7%	29.3%
Education level							
Middle school	44.4%	23.3%	9.5%	13.4%	26.8%	12.9%	17.9%
High school	44.4%	56.7%	58.4%	35.8%	48%	53.3%	51.9%
University	11.1%	20%	32.1%	50.7%	25.2%	33.7%	30.3%

References

Allgood, S., Walstad, W.B., 2016. The effects of perceived and actual financial literacy on financial behaviors. Econ. Inq. 54 (1), 675–697. https://doi.org/10.1111/ecin.12255.

Almeida, J., Gonçalves, T., 2023. A systematic literature review of investor behavior in the cryptocurrency markets. J. Behav. Exp. Finance 37, 100785. https://doi.org/10.1016/j.jbef.2022.100785.

Ante, L., 2023. How Elon Musk's Twitter activity moves cryptocurrency markets. Technol. Forecast. Soc. Change 186, 122112. https://doi.org/10.1016/j.techfore.2022.122112.

Arias-Oliva, M., Borondo, J.P., Matías-Clavero, G., 2019. Variables influencing cryptocurrency use: a technology acceptance model in Spain. Front. Psychol. 10 https://doi.org/10.3389/fpsyg.2019.00475.

Arli, D., Van Esch, P., Bakpayev, M., Laurence, A., 2020. Do consumers really trust cryptocurrencies? Market. Intell. Plan. 39 (1), 74–90. https://doi.org/10.1108/mip-01-2020-0036.

Auer, R., Tercero-Lucas, D., 2022. Distrust or speculation? The socioeconomic drivers of U.S. cryptocurrency investments. J. Financ. Stabil. 62, 101066 https://doi.org/10.1016/j.jfs.2022.101066.

Bandura, A., 1997. Self-Efficacy: The Exercise of Control. WH Freeman.

Bannier, C.E., Neubert, M., 2016. Gender differences in financial risk taking: the role of financial literacy and risk tolerance. Econ. Lett. 145, 130–135. https://doi.org/10.1016/j.econlet.2016.05.033.

Baur, D.G., Hong, K., Lee, A.V., 2018. Bitcoin: medium of exchange or speculative assets? J. Int. Financ. Markets, Inst. Money 54, 177–189. https://doi.org/10.1016/j.intfin.2017.12.004.

Blau, B.M., 2017. Price dynamics and speculative trading in bitcoin. Res. Int. Bus. Finance 41, 493–499. https://doi.org/10.1016/j.ribaf.2017.05.010.

Bouri, E., Gupta, R., Roubaud, D., 2019. Herding behaviour in cryptocurrencies. Financ. Res. Lett. 29, 216–221. https://doi.org/10.1016/j.frl.2018.07.008.

Chen, C., Liu, L., Zhao, N., 2020. Fear sentiment, uncertainty, and Bitcoin price dynamics: the case of COVID-19. Emerg. Markets Finance Trade 56 (10), 2298–2309. https://doi.org/10.1080/1540496x.2020.1787150.

CoinMarketCap. (2022). Global cryptocurrency charts. https://coinmarketcap.com/charts.

Corbet, S., Lucey, B.M., Urquhart, A., Yarovaya, L., 2019. Cryptocurrencies as a financial asset: a systematic analysis. Int. Rev. Financ. Anal. 62, 182–199. https://doi.org/10.1016/j.irfa.2018.09.003.

Cupak, A., Fessler, P., Schneebaum, A., 2021. Gender differences in risky asset behavior: the importance of self-confidence and financial literacy. Financ. Res. Lett. 42, 101880 https://doi.org/10.1016/j.frl.2020.101880.

Delfabbro, P., King, D.L., Williams, J.S., Georgiou, N., 2021. Cryptocurrency trading, gambling and problem gambling. Addict. Behav. 122, 107021 https://doi.org/10.1016/j.addbeh.2021.107021.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: measurement, determinants, and behavioral consequences. J. Eur. Econ. Assoc. 9 (3), 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x.

Forbes, J.N., Kara, S.M., 2010. Confidence mediates how investment knowledge influences investing self-efficacy. J. Econ. Psychol. 31 (3), 435–443. https://doi.org/10.1016/j.joep.2010.01.012.

Fry, J.C., Cheah, E., 2016. Negative bubbles and shocks in cryptocurrency markets. Int. Rev. Financ. Anal. 47, 343–352. https://doi.org/10.1016/j.irfa.2016.02.008.

Fujiki, H., 2020. Who adopts crypto assets in Japan? Evidence from the 2019 financial literacy survey. J. Jpn. Int. Econ. 58, 101107 https://doi.org/10.1016/j.jjie.2020.101107.

Goetzmann, W.N., Kumar, A., 2008. Equity Portfolio Diversification. Rev. Financ. 12, 433–463. https://doi.org/10.1093/rof/rfn005.

Guiso, L., Jappelli, T., 2008. Financial Literacy and Portfolio Diversification. European University Institute (Working Papers No. 31).

Gupta, S., Gupta, S., Mathew, M.J., Sama, H.R., 2021. Prioritizing intentions behind investment in cryptocurrency: a fuzzy analytical framework. J. Econ. Stud. 48 (8), 1442–1459. https://doi.org/10.1108/jes-06-2020-0285.

Gurdgiev, C., O'Loughlin, D, 2020. Herding and anchoring in cryptocurrency markets: investor reaction to fear and uncertainty. J. Behav. Exp. Finance 25, 100271. https://doi.org/10.1016/j.jbef.2020.100271.

Hackethal, A., Hanspal, T., Lammer, D.M., Rink, K., 2022. The Characteristics and Portfolio Behavior of Bitcoin Investors: evidence from Indirect Cryptocurrency Investments. Rev. Financ. 26 (4), 855–898. https://doi.org/10.1093/rof/rfab034.

Hasso, T., Pelster, M., Breitmayer, B., 2019. Who trades cryptocurrencies, how do they trade it, and how do they perform? Evidence from brokerage accounts. J. Behav. Exp. Finance 23, 64–74. https://doi.org/10.1016/j.jbef.2019.04.009.

Henager, R., Cude, B.J., 2016. Financial literacy and long- and short-term financial behavior in different age groups. J. Financ. Counsel. Plan. 27 (1), 3–19. https://doi.org/10.1891/1052-3073.27.1.3.

Hsiao, Y., Tsai, W., 2018. Financial literacy and participation in the derivatives markets. J. Bank. Finance 88, 15–29. https://doi.org/10.1016/j.jbankfin.2017.11.006.

Johnson, B., Co, S.J., Sun, T., Lim, C.C., Stjepanović, D., Leung, J., Saunders, J.B., Chan, G.C., 2023. Cryptocurrency trading and its associations with gambling and mental health: a scoping review. Addict. Behav. 136, 107504 https://doi.org/10.1016/j.addbeh.2022.107504.

Kapteyn, A., Teppa, F., 2011. Subjective measures of risk aversion, fixed costs, and portfolio choice. J. Econ. Psychol. 32 (4), 564–580. https://doi.org/10.1016/j.joep.2011.04.002.

Keller, C., Siegrist, M., 2006. Investing in stocks: the influence of financial risk attitude and values-related money and stock market attitudes. J. Econ. Psychol. 27 (2), 285–303. https://doi.org/10.1016/j.joep.2005.07.002.

Kim, K., Hanna, S.D., Lee, S.T., 2023. Investment literacy, overconfidence and cryptocurrency investment. Financ. Serv. Rev. 31 (2/3), 121–132. https://doi.org/10.61190/fsr.v31i2/3.3530.

Kim, H.J., Hong, J., Hwang, H.S., Kim, S.Y., Han, D.H., 2020. Comparison of Psychological Status and Investment Style Between Bitcoin Investors and Share Investors. Front. Psychol. 11 https://doi.org/10.3389/fpsyg.2020.502295.

Laboure, M., Reid, J., 2020. The Future of Payments – Part III. Digital Currencies: the Ultimate Hard Power Tool. Deutsche Bank Research.

Lau, Y., 2021. Cryptocurrencies hit market cap of $3 trillion for the first time as Bitcoin and Ether reach record highs. Fortune. https://fortune.com/2021/11/09/cryptocurrency-market-cap-3-trillion-bitcion-ether-shiba-inu/.

Lo, Y., 2001. Testing the number of components in a normal mixture. Biometrika 88 (3), 767–778. https://doi.org/10.1093/biomet/88.3.767.

Lusardi, A., Mitchell, O.S., 2011. Financial literacy around the world: an overview. J. Pension. Econ. Financ. 10 (4), 497–508. https://doi.org/10.1017/s1474747211000448.

Manzi, F., Sorgente, A., Massaro, D., Villani, D., Di Lernia, D., Malighetti, C., Gaggioli, A., Rossignoli, D., Sandini, G., Sciutti, A., Rea, F., Maggioni, M.A., Marchetti, A., Riva, G., 2021. Emerging adults' expectations about the next generation of robots: exploring robotic needs through a latent profile analysis. Cyberpsychol., Behav. Soc. Network. 24 (5), 315–323. https://doi.org/10.1089/cyber.2020.0161.

Mark, J., De Vynck, G., 2022. Crypto winter' has come. And it's looking more like an ice age. Washington. Post. https://www.washingtonpost.com/business/2022/12/18/crypto-winter-ftx-collapse-bitcoin-prices/.

Masyn, K.E., 2013. Latent class analysis and finite mixture modeling. In: Little, T.D. (Ed.), The Oxford Handbook of Quantitative Methods: Vol. 2. Statistical Analysis. Oxford University Press, pp. 551–611.

Mills, D.J., Nower, L., 2019. Preliminary findings on cryptocurrency trading among regular gamblers: a new risk for problem gambling? Addict. Behav. 92, 136–140. https://doi.org/10.1016/j.addbeh.2019.01.005.

Mishra, A.K., Bansal, R., Maurya, K., Kar, S.K., Bakshi, P.K., 2023. Predicting the antecedents of consumers' intention toward purchase of mutual funds: a hybrid PLS-SEM-neural network approach. Int. J. Consum. Stud. 47 (2), 563–587. https://doi.org/10.1111/ijcs.12850.

Morin, A.J.S., Bujacz, A., Gagné, M., 2018. Person-centered methodologies in the organizational sciences. Organ. Res. Methods 21 (4), 803–813. https://doi.org/10.1177/1094428118773856.

Nagin, D.S., 1999. Analyzing developmental trajectories: a semiparametric, group-based approach. Psychol. Methods 4 (2), 139–157. https://doi.org/10.1037/1082-989x.4.2.139.

Nyhus, E.K., Frank, D., Krol, M., Otterbring, T., 2023. Crypto cravings: gender differences in crypto investment intentions and the mediating roles of financial overconfidence and personality. Psychol. Mark. https://doi.org/10.1002/mar.21921.

OECD, 2013. Financial Literacy and Inclusion: Results of OECD/INFE Survey Across Countries and by Gender. OECD Publishing.

Oksanen, A., Mantere, E., Vuorinen, I., Savolainen, I., 2022. Gambling and online trading: emerging risks of real-time stock and cryptocurrency trading platforms. Public Health 205, 72–78. https://doi.org/10.1016/j.puhe.2022.01.027.

Panos, G.D., Karkkainen, T., Atkinson, A., 2020. Financial literacy and attitudes to cryptocurrencies. Soc. Sci. Res. Netw. https://doi.org/10.2139/ssrn.3482083.

Patton, J.H., Stanford, M.S., Barratt, E.S., 1995. Factor structure of the barratt impulsiveness scale. J. Clin. Psychol. 51 (6), 768–774. https://doi.org/10.1002/1097-4679(199511)516.

Piñeiro-Chousa, J., Vizcaíno-González, M., Pérez-Pico, A.M., 2017. Influence of social media over the stock market. Psychol. Mark. 34 (1), 101–108. https://doi.org/10.1002/mar.20976.

Rey-Ares, L., Fernández-López, S., Castro-González, S., Rodeiro-Pazos, D., 2021. Does self-control constitute a driver of millennials' financial behaviors and attitudes? J. Behav. Exp. Econ. 93, 101702 https://doi.org/10.1016/j.socec.2021.101702.

Sekścińska, K., Rudzinska-Wojciechowska, J., Jaworska, D., 2021. Self-control and investment choices. J. Behav. Decis. Mak. 34 (5), 691–705. https://doi.org/10.1002/bdm.2236.

Sharpe, D., 2015. Your Chi-Square test is statistically significant: now what? Pract. Assess., Res. Eval. 20 (8), 1–10. https://doi.org/10.7275/tbfa-x148.

Sonkurt, H.O., Altınöz, A.E., 2021. Cryptocurrency investment: a safe venture or a new type of gambling? J. Gambl. Issues. 47, 199–216. https://doi.org/10.4309/jgi.2021.47.8.

Sorgente, A., Lanz, M., Serido, J., Tagliabue, S., Shim, S., 2019. Latent transition analysis: guidelines and an application to emerging adults' social development. TPM – Test., Psychometr., Methodol. Appl. Psychol. 26 (1), 39–72. https://doi.org/10.4473/tpm26.1.3.

Sousa, A.E., Calçada, E., Morales, P., Borges, A.L.V., 2022. Cryptocurrency adoption: a systematic literature review and bibliometric analysis. Euromed. J. Bus. 17 (3), 374–390. https://doi.org/10.1108/emjb-01-2022-0003.

Spinella, M., 2007. Measuring the executive regulation of emotion with self-rating scales in a nonclinical population. J. Gen. Psychol. 134 (1), 101–111. https://doi.org/10.3200/genp.134.1.101-111.

Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. Rev. Financ. Stud. 19 (4), 1531–1565. https://doi.org/10.1093/rfs/hhj032.

Steinmetz, F., Von Meduna, M., Ante, L., Fiedler, I., 2021. Ownership, uses and perceptions of cryptocurrency: results from a population survey. Technol. Forecast. Soc. Change 173, 121073. https://doi.org/10.1016/j.techfore.2021.121073.

Stix, H., 2021. Ownership and purchase intention of crypto-assets: survey results. Empirica (Dordr) 48, 65–99. https://doi.org/10.1007/s10663-020-09499-x.

Sudzina, F., Dobeš, M., Pavlicek, A., 2021. Towards the psychological profile of cryptocurrency early adopters: overconfidence and self-control as predictors of cryptocurrency use. Curr. Psychol. https://doi.org/10.1007/s12144-021-02225-1.

Uhr, C., Meyer, S., Hackethal, A., 2021. Smoking hot portfolios? Trading behavior, investment biases, and self-control failure. J. Empir. Finance 63, 73–95. https://doi.org/10.1016/j.jempfin.2021.05.006.

Van Rooij, M., Lusardi, A., Alessie, R., 2011. Financial literacy and stock market participation. J. Financ. Econ. 101 (2), 449–472. https://doi.org/10.1016/j.jfineco.2011.03.006.

Yeh, T., Ling, Y., 2022. Confidence in financial literacy, stock market participation, and retirement planning. J. Fam. Econ. Issues. 43 (1), 169–186. https://doi.org/10.1007/s10834-021-09769-1.

Zhao, H., Zhang, L., 2021. Financial literacy or investment experience: which is more influential in cryptocurrency investment? Int. J. Bank Market. 39 (7), 1208–1226. https://doi.org/10.1108/ijbm-11-2020-0552.

Zhu, T., Xiao, J., 2022. Consumer financial education and risky financial asset holding in China. Int. J. Consum. Stud. 46 (1), 56–74. https://doi.org/10.1111/ijcs.12643.