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Examining the Intention to Invest in Cryptocurrencies:

An Extended Application of the Theory of Planned Behavior on Italian Independent Investors

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ABSTRACT

Among investors of cryptocurrencies there are supporters and detractors; this claims for the identification of the behavioral and socio-demographic factors that push to invest (or not) in cryptocurrencies. A survey has been administered to 275 Italian investors. Together with socio-demographic features (gender, income, age, and education), behavioral factors derived from the theory of planned behavior (attitude, subjective norm, and perceived control behavior) and from the financial behavior literature (illegal attitude, herding behavior, perceived risk, perceived benefit, and financial literacy) have been collected and analyzed. While attitude, illegal attitude, subjective norms, perceived behavioral control, herding behavior, and perceived risk have a positive impact on investors' intentions. Socio-demographic factors and financial literacy have no influence on the intention to invest in cryptocurrencies. This is the first study that comprehensively investigates the influence of behavioral and socio-demographic factors on the intention of investors to invest in cryptocurrencies.

KEYWORDS

Behavioral Finance, Bitcoin, Cryptocurrency, Intention, Investment Decision, Socio-Demographic Features, Theory of Planned Behavior

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1. INTRODUCTION

Recent years have seen the development of many *cryptographic currencies*, also known as "cryptocurrencies"; thus: digital representation of value that can be exchanged online for goods and services as well as for speculation (Lewis, 2018). The first cryptocurrency to be introduced was Bitcoin in 2008 by Satoshi Nakamoto (2019). Since then, approximately 7000 other cryptocurrencies have been introduced, about 3000 of which (e.g., DashRipple, Ethereum, LiteCoin, Monero, Tether, and Zerocash) are actively traded today. Many of them are basically clones of Bitcoin, although with different parameters such as different supplies and transaction validation times; others, instead, emerged from significant innovations of blockchain technology (e.g., electronic supplementary material) (ElBahrawy et al., 2017). However, Bitcoin currently dominates the market with a capitalization of about 600B U.S. dollars as at January 2021 (Coinmarketcap, 2021).

Briefly, cryptocurrencies work using a technology called blockchain: a decentralized system spread across many computers that manages and records transactions; in practice, this system works as a public ledger (DuPont, 2019). Thanks to that, individual users can send and receive native tokens, the 'virtual coins', while collectively validating the transactions via the blockchain (Lewis, 2018).

Stemming from the above innovative technology, there are some important benefits of exchanging cryptocurrencies (DuPont, 2019): *i)* the capacity to transfer and trade considerable amounts of money anonymously and quickly across the Internet; *ii)* the governmental free design, *iii)* the decentralized processing and recording system that can be more secure than traditional payment systems, and *iv)* the presence of very low transaction costs. On the other hand, according to the review of Corbet et al. (2019), there are three controversial features of cryptocurrencies: *i)* they are not domiciled in a specific country, leading to a huge problem of defining a regulatory alignment, *ii)* anonymity of users, lack of intermediary financial institutions, and the contemporary escalation in the use of darknet allowing cybercrime activities such as money-laundering (see Albrecht et al., 2019; Choo, 2015).

Due to these positive and negative facets of cryptocurrencies, Corbet et al. (2019; p. 190) highlighted their "main attraction appearing to be sourced in their role as a speculative asset" (see also Glaser et al., 2014). This is also supported by the fact that 70% of existing Bitcoins are held in dormant accounts (Weber, 2016) and that cryptocurrencies seem to exhibit speculative bubbles (Ammous, 2018; Cheah and Fry, 2015; Madey, 2017).

From the above, cryptocurrencies can be perceived as an opportunity or as a threat, leading to identify two main groups of cryptocurrency audience among investors (Yelowitz & Wilson, 2015): *i)* supporters (e.g., Blythe Masters, former Managing Director at J.P. Morgan Chase & Co.; Investopedia, 2019) who want to invest in them and believe in their speculative power, and *ii)* detractors (e.g., Ray Dalio, Bridgewater Associates founder; Forbes, 2020) who forecast a bubble for cryptocurrencies due to their near-to-zero *real* value. Despite the fact that both groups are formed by recognized investors, the question is to identify what inner factors discriminate them. In this vein, the research question at the basis of this work is: *what are the behavioral and socio-demographic factors that influence the intention to invest in cryptocurrencies?* This question has been already answered in some terms, but scholars have reached contrasting results. For example, Arias-Oliva et al. (2019) found that social influence and perceived risk do not affect the intention to invest in cryptocurrencies, while other scholars found contradictory findings (e.g., Bannier et al., 2019; Lammer et al., 2019; Pelster et al., 2019).

To answer the above-introduced lively research question, the *Theory of Planned Behavior* (TPB) lens (Ajzen, 1991; Montano & Kasprzyk, 2015) was adopted. The TPB postulates that there are three factors that lead to the intention to perform an action: the 'attitude' towards the effect of the action, the 'subjective rule' – thus the perception that a given behavior is or is not expected to be significant to an individual –, and the perceived behavioral control in performing the intended behavior. Moreover, as a result of interviews conducted with four Italian cryptocurrency specialists with experience in cryptocurrency trading at both national and international level, the following financial behavior variables playing a pivotal role in cryptocurrency investment decisions have been added to the study: herding behavior (Merli & Roger, 2013), perceived risk (Weber & Milliman, 1997), illegal attitude (Narayanan et al., 2016), and financial literacy (Fernandes et al., 2014). Finally, some socio-demographic characteristics – i.e., gender, age, education, and income – have also been analyzed to find out whether they influence the intention to invest in cryptocurrencies (in line with prior works, see Maula et al., 2005; Warsame & Ireri, 2016).

A paper-based survey administered to 275 Italian independent investors was carried out collecting data on their behavioral predispositions and their socio-demographic features according to the introduced design. Evidence was then analyzed through factor analysis, t-test, Analysis of Variance (ANOVA), and multiple linear regression analysis. Results showed that while (positive) attitude, subjective norms, and perceived control behavior have a positive impact on investors' intentions to invest in cryptocurrencies, socio-demographic features have no influence.

In brief, this study unveils the influencing role played by behavioral factors and socio-demographic characteristics on the intention to invest in cryptocurrencies; in doing that, this work adds evidence that supports the influence of specific behavioral variables that were not recognized as significant in other prior studies, such as social influence and perceived risk (Arias-Oliva et al., 2019). Moreover, the presented results complete prior investigations on the relationship between behavioral factors and socio-demographic characteristics –regarding the intention to invest in cryptocurrencies – due to the inclusion of a more complete set of playing variables (e.g., Gazali et al., 2019; who did not include the perceived control behavior variable at the basis of TPB). Among them, it is worth noticing the addition of the 'illegal attitude' variable, which is able to investigate if investment in cryptocurrencies is driven by the willingness of investors to store money outside tracked and legal channels or to undertake illegal activities through cryptocurrencies.

The presented results are of high interest for policymakers, cryptocurrency administrators, and bank managers/shareholders who are interested in fostering (because of the fast and publicly shared transaction process) or limiting (because of the possibility of money laundering) the adoption of cryptocurrencies. Moreover, financial behavior scholars (e.g., Chuen et al., 2017; Kengatharan & Kengatharan, 2014; Nagy & Obenberger, 1994) can benefit from the results of this work to expand on prior models describing individual investor behavior according to behavioral factors and socio-demographic features (Senarathne, 2019).

2. THEORETICAL BACKGROUND

2.1 Factors Influencing the Intention to Invest in Cryptocurrencies

As previously introduced, some scholars have already investigated the factors that influence investment in cryptocurrencies. In this regard, Li and Wang (2017) first highlighted, through a theory-driven empirical study of the Bitcoin exchange rate (against USD) determination, that investment in cryptocurrencies is highly sensitive to economic fundamentals (e.g., economic indicators of the foreign country such as interest rate, transaction volume of cryptocurrencies, and price volatility). However, this study was conducted without directly asking investors about the determinants that push them to invest in cryptocurrencies or not, but it was reliant on secondary data on stock exchanges. The same pitfall is shared by a number of other studies, such as Sohaib et al. (2019) who administered a questionnaire to 160 graduate and undergraduate students and staff at the University of Technology Sydney, and Shahzad et al. (2018) who collected responses from 376 randomly chosen people. Apart from the lack of investor sampling among the discussed studies, none adopted a clear and recognized model, such as the *Theory of Planned Behavior*, which clearly links behavioral factors with the intention to invest.

2.2 Theory of Planned Behavior (TPB) and the Intention to Invest in Cryptocurrencies

The *Theory of Planned Behavior* (TPB) was firstly elaborated by Ajzen (1991) as a development of the *Theory of Reasoned Action* (TRA). According to the TPB, the organizational agent's intention to pursue an action can be predicted by looking at: *a) attitude* towards the effect of the action and the belief that the action will lead to a certain effect; *b) subjective norm* (known as *normative belief*) – the perception that a given behavior is or is not expected to be significant to an individual (e.g., family), and *c) perceived behavioral control* – the beliefs of how well the individual can conduct courses of action required to deal with future situations. In this regard, the TPB significantly differs from the TRA because of the inclusion of the perceived behavioral control variable, which has been demonstrated, leading to better predictions in terms of likelihood of transforming an intention in a behavior rather than the former (TRA) (Chang, 1998; Madden et al., 1992).

In general, TPB has been used frequently in a wide range of behavioral research, such as anticipating intentionality of customers to choose banking products, entrepreneurial intentions of young researchers, household financing, consumer intentions to buy green products (Feola et al., 2019). The only study that attempted to examine the intention to invest in cryptocurrencies, according to a recognized behavioral model to predict intentions, is the one by Gazali et al. (2019), who adopted the TRA despite its recognized limits and further developments. In particular, Gazali et al. (2019) analyzed the relationship between attitudes, subjective norms, financial risk tolerance and perceived benefits from (the last two have been conveniently added to the model) the intention to invest in Bitcoin, finding a positive influence from all of them in the intention to invest. However, as introduced, their results were not satisfactory, mainly due to the small sample of respondents (i.e., 45) and from not having sampled investors.

The reported positive influence of attitude of individual investors on cryptocurrencies can be explained by the aspired level of financial stability that investors seek through investments, substantiating, *de facto*, a risk tolerant predisposition. In their recent work, Mendoza-Tello et al. (2018) administered a questionnaire to 125 participants (consisting of university and post graduate students (52%), professors (8%), business managers (10%), company employees (25%), and government workers (5%)) and empirically demonstrated that seeing some benefits in using cryptocurrencies elicits their intention to invest in them.

From that:

H1: Attitude positively influences an investor's intention to invest in cryptocurrencies

Behavioral finance scholars have investigated the influence of subjective norms through the application of the TPB lens for the investigation of how investment decisions are made. In this regard, Arias-Oliva et al. (2019) did not find any significant influence of this variable concerning the intention to invest in cryptocurrencies. Other scholars, instead, found that investors' choices are often made according to the recommendations provided by colleagues, friends, and relatives; in fact, sometimes, these suggestions are intentionally sought by peers for investment decisions (Sondari & Sudarsono, 2015). However, the subjective norm can be also elicited by the culture in which investors are embedded, as demonstrated by Warsame and Ireri (2016) when investigating the behavior (using the TPB) of investors towards "sharia compliant" bonds (i.e., Sukuk). In sum, subjective norms seem to have the ability to increasingly put pressure on investors in order to act (i.e., positive influence) and to do it in a certain way; this influence is not conveyed only through verbal or written communication, but it can happen also by watching or interacting with the behaviors of others (Ali, 2011). Therefore, hypothesis 2 could be stated as follows:

H2: Subjective norm positively influences an investor's intention to invest in cryptocurrencies

In his study on the intention to invest in companies' stocks, Ali (2011) operationalized perceived control behavior as the easiness of carrying out a particular behavior; in particular regarding the availability of time and skills to evaluate the company and money to invest. In particular, he found a positive influence of perceived control behavior on the intention to invest. The same positive influence, using similar operationalizations, has been found by Arias-Oliva (2019) when investigating cryptocurrency adoption in Spain – however, without sampling investors – as was the case for Shahzad et al. (2018) in China. Therefore, hypothesis 3 could be stated as follows:

H3: Perceived control behavior positively influences an investor's intention to invest in cryptocurrencies

Finally, a series of studies implementing the TPB in investment decisions – besides the investigation of the proper variables of the theory – looked at the influence of socio-demographic characteristics on the intention to invest in financial products. In this vein, it must be registered that there is no scientific uniformity about the above-defined influences. On the one hand, a few studies found that gender, age, education, and income do not significantly influence the intention to invest in cryptocurrencies. This clearly emerged from the study of Maula et al. (2005) on micro-angel investments, and from Warsame and Ireri's (2016) study about the behavioral intention to use Sukuk; the latter generally found that there were no significant moderating effects on investment intention based on gender, age, and level of education. On the other hand, a larger series of recent studies, more focused on cryptocurrencies, discovered that a significant difference in the socio-demographic characteristics among investors may lie in gender. Indeed, according to Lammer et al. (2019) and Hasso et al. (2019), it is men and not women who invest more in cryptocurrencies; both studies justify these results with the supposed higher grade of financial literacy of men (here meant as "the degree to which one understands key financial concepts and possesses the ability and confidence to manage personal finances"; Remund, 2010; p. 284). In support of this last statement, Bannier et al. (2019) have claimed that women possess weaker knowledge regarding the characteristics of Bitcoin compared to men, which is in line with the finding of Lusardi and Mitchell (2008) who discovered that, on average, US women have low/very low levels of financial literacy. Hence, it can be hypothesized that:

H4a: Men are significantly more likely than women to invest in cryptocurrencies
H4b: There are no significant differences in the means to invest in cryptocurrencies across age segments
H4c: There are no significant differences in the means to invest in cryptocurrencies across education segments
H4d: There are no significant differences in the means to invest in cryptocurrencies across income segments

2.3 Factors Influencing Cryptocurrency Investment Intentions

As pointed out within the introduction, and thanks to the interviews with four Italian cryptocurrency specialists, this study includes other behavioral factors, apart from those present in the TPB; this enhances, *de facto*, the explanatory power of the TPB and the adopted procedure is in line with similar studies trying to identify the behavioral drivers of cryptocurrency investors (see Arias-Oliva et al., 2019). In this vein, Narayanan and colleagues (2016) conceptually advanced that investors in cryptocurrencies may be attracted by their ability to finance illegal activities and practices without being traced, due to the anonymity provided; due to the latter, tax evasion is another emerging big concern for regulators. This has been recently supported also by Dyntu and Dykyi (2018) through an analysis of historical stages of cryptocurrency creation and cases of money laundering, where criminals who used cryptocurrency have been identified and charges have been pressed; it resulted in anonymity and decentralization, i.e., the two main innovative features of cryptocurrencies, which are the characteristics that push people to use them for illegal activities (Joy, 2018). From that:

H5: Illegal attitude positively influences an investor's intention to invest in cryptocurrencies

Herding behavior can be defined as the attitude of one individual (e.g., an investor) in imitating the actions carried out by other people (Merli & Roger, 2013); in our case, other cryptocurrency investors. For the sake of clarity of this study, following Sun (2013) (see also Phan & Zhou, 2014), it is worth acknowledging the distinctions occurring between herding behavior and subjective norms' constructs. In particular, these two differ on: *i)* information sources (subjective norm comes from one's reference group while herding behavior has a much broader information source); *ii)* the motivations behind action (for those who care about social norms, there is an expectation that the adoption decision may later be judged by the reference group, while people implementing a herding behavior do not care about judgment by others); and *iii)* the manner in which information has been obtained (for those who care about social norms, information sources depend primarily on messages received from others, while people implementing a herding behavior depends on observations of other people's behavior).

Stemming from the premises above, the following has been produced with regard to herding behavior and cryptocurrencies. Kengatharan and Kengatharan (2014) and da Gama Silva et al. (2019) undertook an indirect analysis (based on cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD) tests) of the 50 most liquid and capitalized cryptocurrencies, and found that cryptocurrency investors tend to follow and copy what other investors are doing within the cryptocurrency market – leading to the excess of volatility and short term trends that feature in this market, or better, that characterize this market (Liu & Tsyvinski, 2018). Results of this study have been later supported by Coskun et al. (2020) and Gurdgiev and O'Loughlin (2020) – despite the fact they did not directly test this behavioral variable in the same way as da Gama Silva et al. (2019).

H6: Herding behavior positively influences an investor's intention to invest in cryptocurrencies

Despite Arias-Oliva et al. (2019) not finding any significant influence of perception of risk on the intention to invest in cryptocurrencies, in an empirical research comparing characteristics and behavior of cryptocurrency and non-cryptocurrency investors, Lammer et al. (2019) found that the former are more active traders (9.0 versus 2.0 trades per month). In addition, they take more risks in the composition of their portfolios by holding single stocks, equity derivatives, and warrants. This is maybe due to the fact that cryptocurrency investors' behavior, as demonstrated by Lammer et al. (2019) and Aloosh and Ouzan (2020), appears to be influenced just in a small part by a price bias. Yet, Pelster et al. (2019) found, by recurring to the analysis of individual brokerage data, that the overall behavior of cryptocurrency investors is driven by excitement-seeking; in particular, when engaging in cryptocurrency trading, investors simultaneously increase their risk-seeking behavior in stock trading as they increase their trading intensity and use of leverage. Accordingly:

H7: Perception of risk positively influences an investor's intention to invest in cryptocurrencies

In order to explain the gender gap in the knowledge of cryptocurrency characteristics, Bannier and colleagues (2019) found that measures for actual financial literacy accounts for approximately 40% of the gender gap in Bitcoin literacy. This proposes financial literacy as an explanatory variable of the behavior of investors towards cryptocurrencies – in line with other works assigning value to the financial literacy variable to explain the willingness to invest in financial assets (Stolper & Walter, 2017). However, the same was not found by Arias-Oliva et al. (2019), whose empirical analysis of financial behavior variables influencing investors' behavior showed that financial literacy did not have a significant influence on the intention to invest in cryptocurrencies. This last result is in contrast with the important discovery by Lusardi and Mitchell (2014), who found a positive result for this relationship through their review of empirical papers and their resultant findings on the influence of financial literacy on economic decision making. Accordingly:

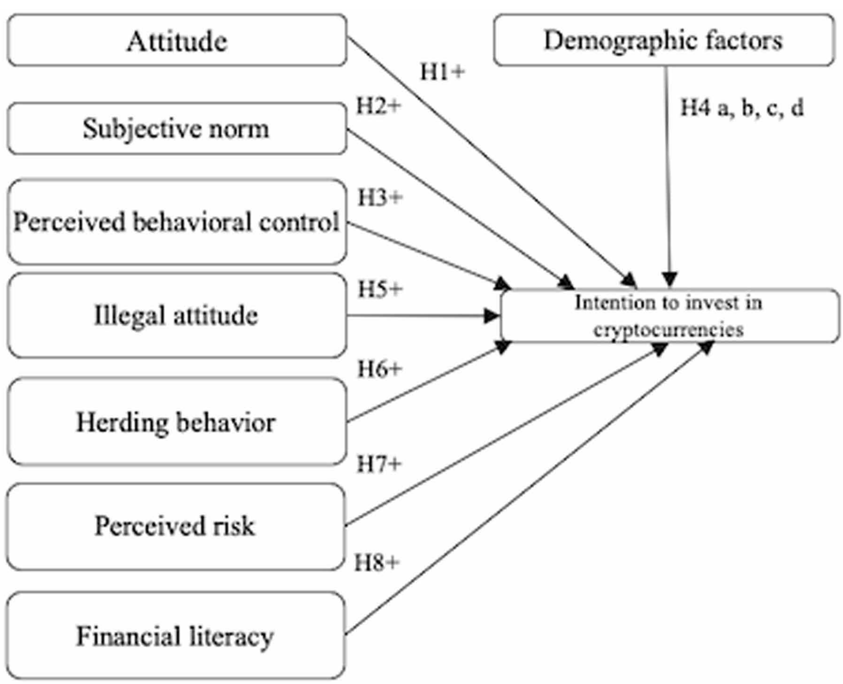
H8: Financial literacy positively influences an investor's intention to invest in cryptocurrencies

The research model to be tested is summarized in the Figure 1.

3. METHODOLOGY

In line with previous studies (e.g., Arias-Oliva et al., 2019; Shahzad et al., 2018), to answer the research question at the base of this study, a paper-based survey was developed. In order to build the questionnaire, first, four Italian cryptocurrency specialists – i.e., a CEO of a trading platform, a blockchain engineer, an expert journalist on cryptocurrencies, and a cryptocurrency philosopher – with more than 5 years' experience in cryptocurrency trading at both national and international level, were the subjects of an interview. In particular, the semi-structured interview started with general questions, at the individual level, and with the research question of this work "*what are the behavioral and socio-demographic factors that influence the intention to invest in cryptocurrencies?*". Transcripts of the answers to this unique question were thematically analyzed in an inductive way (Braun & Clark, 2006). In general terms, thematic analysis is a widely used qualitative research technique consisting of analyzing written, verbal, or visual communication messages. In particular, the inductive thematic analysis, by which new themes are free to emerge without the use of an initial codebook, has been implemented (Boyatzis, 1998). Inter-rater reliability among researchers has been high (Cronbach's alpha = 0.92) and, similarly to other studies (Cristofaro et al., 2020), when disagreeing, together they deepened the analysis in order to emerge with a shared vision of the sentence meaning and related theme.

Figure 1. The research model



From the above inductive thematic analysis, it emerged that herding behavior, perceived risk, and financial literacy were important variables to consider when assessing the intention to invest in cryptocurrencies. A suggestion was also made of inserting an open-ended question on how many hours per week the investors usually spend on trading to verify if they do so on a regular basis. To establish reliability and validity of the questionnaire, the latter was initially administered to an initial sample of 25 financial investors and verified before it was utilized for the survey. Cronbach's alpha was used to measure reliability of random errors resulting in 0.822, which indicated a high level of accuracy. Subsequently, the questionnaire was printed and administered, in person and one-to-one, to the participants of the biggest Italian event dedicated to blockchain and cryptocurrency: Blockchain Week Rome 2020. Recruiting participants from specialized conferences/workshops/events is a data collection method that has already been proved to be solid for finding informed respondents (e.g., Guest et al., 2013). In total, 361 responses have been collected and 275 qualified for the analysis; those eliminated were due to incomplete answers to any of the questions. The demographic variables of independent investors are reported in Table 1.

According to Table 1, the respondents were 57% (n=157) men and 43% (118) women. Regarding age, the majority of participants were 28-38 (44%) years old, followed by 38-48 (27%) years old, 18-28 (20%) years old, and above 48 (9%) years old. The largest share of the respondents (60%) had a high education diploma (Bachelor's degree), while, with regard to income, the majority of the participants (54%) have asserted to earn between 10.000€ to 30.000€ per year. All of the respondents have affirmed to investing and trading regularly: on average, 30 hours per week were spent on trading.

As previously stated, the survey was constructed on the main behavioral variables of the TPB and other important research reported in the financial behavioral literature. In particular, the following variables have been inserted in the questionnaire: i.e., attitude (5 items) from Bryne (2005) and Ganzach et al. (2008), subjective norms (3 items) from Gazali et al. (2019), perceived behavioral control (4 items) from Shahzad et al. (2018) and Arias-Oliva et al. (2019), herding behavior (3 items) from

Table 1. Description of sample data

Characteristics		Count	Percentage
Gender	Men	157	57%
	Women	118	43%
Age	18-28	55	20%
	28-38	121	44%
	38-48	74	27%
	Above 48	25	9%
Education	High school	14	5%
	College	28	10%
	Bachelor's degree	164	60%
	Master's degree	66	24%
	Ph.D.	3	1%
Income	Less than 10,000€	28	10%
	From 10,000€ to 30,000€	148	54%
	From 30,000€ to 50,000€	71	26%
	From 50,000€ to 70,000€	14	5%
	Above 70,000€	14	5%

Kengatharan and Kengatharan (2014), perceived risk (3 items) from Faqih (2016), financial literacy (2 items) from Hastings et al. (2013), illegal attitude (3 items) adopted from Wang and McClung (2011), and intention to invest (5 items) from Ali (2011) and Chen et al. (2016). It is also worth noticing that, following the methodological instructions of McNeeley (2012) for designing questionnaires dealing with sensitive topics, items pertaining to illegal attitude have been posed in the third person. The final version of the survey was composed of 28 closed-ended questions, all based on a five-point Likert scale, an open-ended question on the number of trading hours per week, and a section aimed at collecting the following socio-demographic characteristics of investors: gender, age, education, and income. Items of the survey were administered in English to avoid translation problems; in this regard, participants in the survey were pre-warned when approached and were formally asked if they felt confident in taking the questionnaire in English.

Finally, after collection, the data were cleaned and entered into SPSS IBM version 20 for data analysis; this is a widely-used program for data analysis in scientific research (Field, 2013), and also for the investigation of behavioral and socio-demographic variables (e.g., Abatecola & Cristofaro, 2016). In particular, following the indications by Hair et al. (2014), the data analysis consisted of factor analysis, t-test, Analysis of Variance, and multiple linear regression analysis.

4. RESULTS

4.1 Factor Analysis and Reliability Analysis

Firstly, a Principal Component Analysis (PCA) (with Varimax rotation) was implemented to verify the dimensions in the scales. PCA is a variable reduction technique: a large sample of observable variables (that can be measured directly) is empirically reduced – through a so-called linear transformation – in fewer latent variables, which are a linear combination of weighted observed variables (Field, 2013). Results of the PCA are shown as follows:

To conduct a reliability analysis, Cronbach's alpha analysis was used for each factor. Table 2 shows that all values of Cronbach's alpha were >0.6 and all values of correlated item-total correlation for each item were >0.3, suggesting that all factors are reliable and could be used for subsequent analysis.

The results of KMO and Bartlett's Test showed that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.844 (which is higher than the usually required 0.5). Similarly, Bartlett's test of sphericity also showed significant results ($p<0.05$). All the standardized loadings of the variables were greater than 0.7 and significant (Table 3).

Table 2. Cronbach's alpha analysis result

Factor	Item	Item-total Correlation	Cronbach's alpha
Attitude	AT1, AT2, AT3, AT4, AT5	0.561 – 0.611	0.811
Subjective norm	SN1, SN2, SN3	0.533 – 0.607	0.732
Perceived behavioral control	PBC1, PBC2, PBC3, PBC4	0.600 – 0.712	0.855
Illegal attitude	IA1, IA2, IA3	0.712 – 0.706	0.722
Herding behavior	HB1, HB2, HB3	0.611 – 0.709	0.788
Perceived risk	PR1, PR2, PR3	0.672 – 0.744	0.822
Financial literacy	FL1, FL2	0.679 – 0.711	0.804
Intention to invest	INV1, INV2, INV3, INV4, INV5	0.724 – 0.883	0.928

Table 3. PCA analysis result

Rotated Component Matrix[a]									
Questions substantiating variables	Items	Component							
		1	2	3	4	5	6	7	8
Using cryptocurrencies will increase my opportunities to achieve important goals for me	AT1	0.687							
Using cryptocurrencies will help me achieve my goals more quickly	AT3	0.622							
Using cryptocurrencies will increase my standard of living	AT5	0.601							
The people who are important to me will think that I should invest in cryptocurrencies	SN2		0.712						
The people who influence me will think that I should invest in cryptocurrencies	SN1		0.701						
People whose opinions I value would like me to invest in cryptocurrencies	SN3		0.699						
I have the necessary resources to invest in cryptocurrencies	PBC5			0.812					
I have the necessary knowledge to invest in cryptocurrencies	PBC3			0.722					
Cryptocurrencies are compatible with other technologies that I use	PBC1			0.701					
I can get help if I have difficulty investing in cryptocurrencies	PBC4			0.676					
I can use cryptocurrencies for non-legal activities	IA1				0.655				
Using cryptocurrencies will help me in masking my identity in transactions	IA2				0.623				
Using cryptocurrencies will help me in hiding money rather than using other traditional channels	IA3				0.592				
Other investors' decisions of investing in cryptocurrencies have an impact on my investment decisions	HB1					0.732			
Other investors' decisions of the cryptocurrency volume have an impact on your investment decisions	HB3					0.656			
Other investors' decisions of buying and selling cryptocurrencies have an impact on my investment decisions	HB2					0.633			
Investing in cryptocurrencies is risky	PR3						0.912		
There is too much uncertainty associated with the investment in cryptocurrencies	PR1						0.901		
Compared with other currencies/investments, cryptocurrencies are riskier due to their high volatility	PR2						0.876		
I have a good level of financial knowledge	FL1							0.763	
I have a high capacity to deal with financial matters	FL2							0.665	
I intend to invest in cryptocurrencies	INV1								0.903
I predict that I will invest in cryptocurrencies	INV2								0.922
I will invest in cryptocurrencies on a regular basis	INV3								0.894
I believe using cryptocurrencies to timely fulfil my obligations	INV4								0.842
I intend to use cryptocurrencies as an alternative means of investment	INV5								0.812
Extraction method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Explained variation % = 71.3%. a. Rotation converged in 6 iterations.									

Kaiser's criterion based on eigenvalues suggested that all factors have to be retained. This solution explained 71.3% of the total variation of the intention to invest, which confirms the correct statistical functioning (similar to Arias-Oliva et al., 2019).

4.2 Correlation Analysis and Multiple Linear Regression

A correlation analysis was initially performed to ascertain how the dependent variable correlates with other independent factors included in the study. The dependent variable is the investor intention to invest in cryptocurrencies (INV), while the independent predictors are attitude (AT), subjective norms (SN), perceived behavioral control (PBC), illegal attitude (IA), herding behavior (HB), perceived risk (PR), and financial literacy (FL).

Results of pairwise correlation among the dependent variable (INV) with independent variables (AT, SN, PBC, IA, HB, PR, and FL) highlight that INV is significantly correlated to all independent variables except for FL. Therefore, these independent factors could be used for multiple linear regression analysis. Multiple linear regression analysis is a method used to identify the strength of the effect that independent variables have on a dependent variable (Field, 2013) to understand how much the latter will change when independent variables are modified. In this study, multiple linear regression is used to find the significant independent factors that influence the intention to invest in cryptocurrencies. The three independent variables and the dependent one were entered into the regression model.

Table 4 highlights the summary statistics of the fitted model. The analysis depicts that the model R-square is 71%, which means the model estimation has a high and good fit. The values of R-square showed that all the independent variables explained 71.3% of the dependent variable's variation (INV). The results of the ANOVA presented are to test the model's overall significance. The p-value for the F-statistic ANOVA is 0.000, less than 0.01, therefore, it was concluded that the overall model is significant. It can also be concluded that all coefficients significantly differ from zero, simultaneously (Table 5).

Table 4. The regression analysis result – model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.802[a]	.663	.660	.57436755	1.932
a. Predictors: (Constant), AT, IA, SN, PBC, HB, PR, FL					

Table 5. The regression analysis result – model estimation

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.422	0.412		1.011	0.201
	AT	0.776	0.031	0.622	8.722	0.000
	PBC	0.122	0.034	0.122	1.943	0.011
	SN	0.121	0.066	0.121	2.222	0.030
	IA	0.435	0.032	0.234	3.221	0.001
	HB	0.412	0.033	0.233	1.001	0.007
	PR	0.755	0.077	0.545	8.987	0.000
	FL	0.333	0.022	0.131	2.331	0.321

The independent variables (AT, SN, PBC, IA, HB, PR, and FL) have p-values of 0.000, 0.011, 0.030, 0.001, 0.007, 0.000, and 0.321, respectively, i.e., they – except for FL – significantly influence INV in a positive way (beta= 0.622, beta= 0.122, beta= 0.121, beta= 0.234, beta= 0.233, beta= 0.545, and beta= 0.131). From that, the following hypotheses are supported: H1, H2, H3, H5, H6, H7, while H8 is rejected (Table 6).

4.3 Impact of Demographic Factors

As gender is dichotomous, a t-test for two independent samples was applied to investigate whether there was a significant difference between gender groups in their intention to invest in cryptocurrencies. A t-test for independent samples is the fitting inferential statistical test to implement in this case because it is used to determine if there is a statistically significant difference between the means of two groups, distinguished by a categorical variable and that are assumed to be unrelated (Field, 2013).

First, equality of variance between groups was checked to ascertain whether the data supported the assumption of the test. Results show that the p-value associated with the F-test for equality of variances was 0.423, greater than 0.1, which means homogeneity of variances. Therefore, equal variance (pooled t-test) was used to test hypothesis 4a. The p-value of the t-test was 0.711, greater than 0.1, and therefore concluded that there was no significant difference between gender groups in their intention to invest in cryptocurrencies. Hypothesis 4a is not supported (Table 7).

A one-way ANOVA was also applied and specifically used to determine whether there are any statistically significant differences between the means of three or more independent (unrelated) groups (Field, 2013). In this study, it has been implemented to verify whether any significant differences exist regarding the intention to invest in cryptocurrencies across the various levels (groups) of investors according to their age, education, and income. The equality of variance between groups (levels) was checked to see whether the data supported the assumption of the test. Results of the one-way ANOVA

Table 6. The summary of the hypothesis test

H	Hypothesis statement	Result
H1	Attitude positively influences the intention to invest in cryptocurrencies	Supported
H2	Subjective norms positively influence the intention to invest in cryptocurrencies	Supported
H3	Perceived behavioral control positively influences the intention to invest in cryptocurrencies	Supported
H5	Illegal attitude positively influences an investor’s intention to invest in cryptocurrencies	Supported
H6	Herding behavior positively influences an investor’s intention to invest in cryptocurrencies	Supported
H7	Perception of risk positively influences an investor’s intention to invest in cryptocurrencies	Supported
H8	Financial literacy positively influences an investor’s intention to invest in cryptocurrencies	Not supported

Table 7. The summary of ANOVA and t-test

H	Hypothesis statement	Result
H4a	Men are significant more likely than women to invest in cryptocurrencies	Not supported
H4b	There are no significant differences in means of intention to invest in cryptocurrencies across education segments	Supported
H4c	There are no significant differences in means of intention to invest in cryptocurrencies across income segments	Supported
H4d	There are no significant differences in means of intention to invest in cryptocurrencies across age segments	Supported

test of equal variances for variable age, education, and income showed that the data satisfied the assumption of ANOVA. All the p-values associated with F-statistic ANOVA were >0.1; therefore there were no significant differences in the intention to invest in cryptocurrencies across age, education, and income. Hypotheses 4b, 4c, and 4d are supported, while H4a is rejected.

5. DISCUSSION

All behavioral factors included within the tested model, except for FL, have been found to have a positive influence on the intention to invest in cryptocurrencies. Despite that the lack of effect of FL can be considered exceptional (other studies, indeed, found positive influences; see Guiso & Viviano, 2015), it is worth noticing that some other prior studies did not find any significant effect of FL with regard to investment decisions (e.g., Arianti, 2018). Yet, the meta-analysis (on more than 200 studies) conducted by Fernandes et al. (2014), on the influence of FL and financial education on downstream financial behavior, has shown that interventions to improve financial literacy explain only 0.1% of the variance in financial behaviors studied.

With regard to the other behavioral factors, findings are in line with other works substantiating a positive influence of attitude, subjective norms, and perceived control behavior on the intention to invest (Ali, 2011; Kisaka, 2014; Sondari & Sudarsono, 2015; Warsame & Ireri, 2016), despite not specifically considering the case of cryptocurrencies, which, for inner technological features and the huge uncertainty in its future development for global economics, requires specific investigation.

In particular, the positive influence of attitude explains that investors are prone to invest in cryptocurrencies due to the fact that they expect some benefits, such as increasing the opportunities to achieve important goals, raise the standard of living – all in a quick manner (Gautam, 2015; Mendoza-Tello et al., 2018). However, who invests or has the intention to invest in cryptocurrencies does not always do so for legal activities; indeed, sometimes these means are used to mask their identity for transactions as well as to store money outside legal channels (Dyntu & Dykyi, 2018; Joy, 2018; Narayanan et al., 2016;). In general, the investment is facilitated by the perception of having the control of necessary resources, knowledge, and technology to invest in cryptocurrencies (Arias-Oliva et al., 2019; Shahzad et al., 2018). The intention to invest in them is also fostered by the social circle surrounding the investor; indeed, in line with Ali (2011) and Gazali et al. (2019), results showed the people who are important to the investors or the influence of him/her that push them to invest in cryptocurrencies. This inter-relation among people around the investor, and the bond that he/she has with them, brings the investor to rely on suggestions provided and they follow their investment actions – thus, leading to herding behavior that has a positive influence on investment in cryptocurrencies (Coskun et al., 2020; da Gama Silva et al., 2019; Gurdgiev & O'Loughlin, 2020). This is a common phenomenon in financial markets and the financial literacy of the investor does not have an effect in reducing it or on the intention to invest or not in cryptocurrencies – in line with Arias-Oliva et al. (2019) and in contrast to Lusardi and Mitchell (2014), Stolper and Walter (2017), and Bannier and colleagues (2019). The consequence of this unrestrained herding behavior can be seen in the high volatility and short trends that feature in the market of cryptocurrencies – as demonstrated by Liu and Tsyvinski (2018). However, this high dynamicity of the cryptocurrency market does not discourage investors; on the contrary, they are characterized by an excitement-seeking feeling when engaging in cryptocurrency trading, leading to an increase of their risk-seeking behavior (Aloosh & Ouzan, 2020; Lammer et al., 2019; Pelster et al., 2019), which has the only consequence of raising the intention to invest in cryptocurrencies.

In sum, these results provide specific insights about the intention to invest in cryptocurrencies; in particular, in this work, some novel variables were taken into consideration and compared with prior works, such as the illegal attitude variable, allowing us to provide a complete explanation of the behavior of cryptocurrency investors. According to a methodological point of view, instead, the way this study has been conducted overcomes the limits of prior works in terms of: *i)* the theoretical background adopted and variables tested, and *ii)* the sample size, and appropriateness of the collected sample. With regard to the theoretical background adopted and variables tested, the TPB has been implemented instead of the TRA – overcoming the limits of Gazali et al. (2019) – leading to the inclusion of the perceived control variable, which has been widely considered as the main explanatory factor in the intention to invest in predicting behavior (Ajzen, 1991; Chang, 1998; Madden et al., 1992). This also overcomes the limit of Shahzad et al. (2018) in not having considered the influence of subjective norms. Yet, the inclusion and test of the significance of socio-demographic characteristics offers a greater understanding of what influences the intention to invest in cryptocurrencies with regard to studies that have not considered them (Arias-Oliva *et al*., 2019).

Regarding the socio-demographic characteristics, the young age of investors in this study is a bit in contrast with the higher age of the average Italian financial investor; usually around 45-50 years old, as was found by the recent studies by Feola et al. (2019) and Linciano et al. (2018). However, this result is more aligned with other studies that suggest a younger age of cryptocurrency investors than 'traditional' ones (Hasso et al., 2019). Another contradiction can be seen also in the educational variable; in fact, despite this study having shown that respondents are, on average, people with a Bachelor's degree, the study of Narman et al. (2018), devoted to identifying the profiles of cryptocurrency users through the analysis of the Reddit platform, reported that the education levels of cryptocurrency users are approximately 60% in middle school and 30% in high school. From this heterogeneity of results and the lack of significance of socio-demographics in this work (in contrast with other scholars, Bannier et al., 2019; Hasso et al., 2019; Lammer et al., 2019), it emerges that behavioral factors mainly drive the intention to invest in cryptocurrencies and that cryptocurrency investors form a segment that crosses the borders of different layers of the population.

Finally, the sample size and appropriateness of the collected sample offered results that can be considered as more significant and robust with the respect to that of Gazali et al. (2019), who declared their research suffered due to reaching only a very small sample of subjects for interview (i.e., 45; the presented work considers 275 independent investors).

6. CONCLUSION AND IMPLICATIONS

The study offers a comprehensive investigation of the TPB with regard to the intention to invest in cryptocurrencies, thus considering the influences of attitude, subjective norms, perceived behavioral control, socio-demographic characteristics (gender, age, education, and income), illegal attitude, herding behavior, perceived risk, and financial literacy. The prepared questionnaire was administered to 275 Italian independent investors; the collected data were then validated and evaluated against assumptions and criteria before being analyzed in a regression test.

The results of the study confirm that the attitude to investing in cryptocurrencies – thus the aspiration to achieve important goals and increase the standard of living – and perceived control – thus thinking of having to have the necessary resources, knowledge and help to use cryptocurrencies –positively influence the intention to invest in cryptocurrencies (Arias-Oliva et al., 2019; Gazali et al., 2019; Shahzad et al., 2018; Sondari & Sudarsono, 2015; Warsame and Ireri, 2016). Moreover, one of the main values added to this work has been the discovery that cryptocurrency investors do not always have a legal aim when investing in cryptocurrencies; sometimes they may use cryptocurrencies to explicitly mask their identity for transactions as well as to store money outside legal channels. Equally important, the intention to invest in cryptocurrencies is positively influenced by the so-called subjective norms – thus the influence of family and friends, trustworthy people and the media – which leads to herding behavior of investors (Coskun et al., 2020; da Gama Silva et al., 2019; Gurdgiev & O'Loughlin, 2020) and, as a consequence, to the high instability of the cryptocurrency market (Liu & Tsyvinski, 2018). Investors in cryptocurrencies, however, are not discouraged by this high dynamicity due to the fact that they have a risk-seeking behavior (Aloosh & Ouzan, 2020; Lammer et al., 2019; Pelster et al., 2019). What has not been found significant towards the intention to invest in cryptocurrencies is financial literacy; thus, there is no difference in the intention to invest or not in cryptocurrencies among people with different grades of financial knowledge. This result, in line with other scholars (Arias-Oliva et al., 2019), leads to the conclusion that some financial behavior phenomena, such as herding behavior, cannot be reduced – with reference to the cryptocurrency market – with greater education in financial subjects (see also Fernandes et al., 2014). Yet, this work proves that the herding behavior of cryptocurrency investors is related to their propensity to risky investments, increasing the intention to invest in cryptocurrencies; this relation was only assumed from Senarathne (2019) by using secondary data.

From what has been unveiled, this study offers solid empirical results that, *finally*, establish that the TPB, and related financial behavior variables emerging from the literature, is a useful framework for predicting the behavior of investors in committing resources to cryptocurrencies through a test of all its variables on real independent investors, and also considering their socio-demographic characteristics. Moreover, in terms of geographical scope, this study adds further evidence that the outlined relationships, about the TPB variables and the intention to invest in cryptocurrencies, are valid in different contexts. Indeed, significant results in this Italian study are aligned with the one in Spain (Arias-Oliva et al., 2019), Malaysia (Gazali et al., 2019), and China (Shahzad et al., 2018).

Future studies should consider the results reached by this investigation. Departing from the positive influence of subjective norms, other researchers can enhance the study by focusing on relatives, friends, and the media, which are the main influences affecting the intention to invest in cryptocurrencies. Another avenue for future research is to identify whether perceived control is influenced by other contextual variables, such as the lack of established regulations about cryptocurrencies, which allows investors the freedom to act in the crypto market. Finally, another variable that can be of interest for scholars interested in investigating cryptocurrency investors' behavior – and that substantiates a limit of this work – is the so-called digital literacy. Indeed, it would be interesting to unveil whether more digitally skilled people are more prone to investing in cryptocurrencies rather than those with poor digital literacy. However, it could be hypothesized that digital currency would have not had an effect, if it had been included, stemming from the fact that the sample was composed of young respondents (64% under 40 years old) who had a relevant education level (84% with a Bachelor's degree or higher) to understand the significance of digital currency in today's world. In this vein, a more heterogenous sample, in terms of socio-demographic variables, could be more useful for the investigation of the influence of this variable on the intention to invest in cryptocurrencies. In this regard, future studies may collect answers from investors from different events to increase the chances of depicting more sub-groups of the same cryptocurrency investor population.

Based on the results of this study, some practical implications could be suggested. First, due to the positive influence that subjective norms have on the intention to invest in cryptocurrencies, communications of stakeholders' investors, such as social media and academic conferences, are necessary to increase the awareness of the perils and benefits of investing in cryptocurrencies. Second, administrators of cryptocurrencies, owing to the provided results, can target those interested in investing in cryptocurrencies; from this, they should be cautious in segmenting them according to socio-demographic features. Indeed, from the lack of significance of socio-demographic features and financial literacy, it emerges that cryptocurrency investors are part of a segment that crosses the boundaries throughout the population. In this vein, administrators of cryptocurrencies must be more concerned with the behavioral factors that can discriminate between active investors and those who will not invest. However, what policy makers should really tackle in the near future is the anonymity and regulatory issues, which can allow illegal behaviors (e.g., money laundering). In this regard, it is strongly thought that the solution is not banning cryptocurrencies worldwide. The cryptocurrency system already exists and it is very difficult, due to its digital pillars, for it to be dismantled; thus, avoiding governance will only push cryptocurrency investors and users to continue their activities without being traced. Not allowing the practice or allowing it without establishing rules only has the effect of creating dysfunctions and irregularities at the exchanges, such as fraud, promotion of crime and terrorism, money laundering, and other inefficient phenomena. In this regard, centralizing exchanges, through central banks, is not a viable solution due to the fact that decentralization is the main positive feature of cryptocurrency exchange; however, central bodies can establish an e-cash regime based on a platform able to directly exchange cryptocurrencies with national currencies, and all institutions operating in the value chain should be checked, which is what happens with banks and other financial players.

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