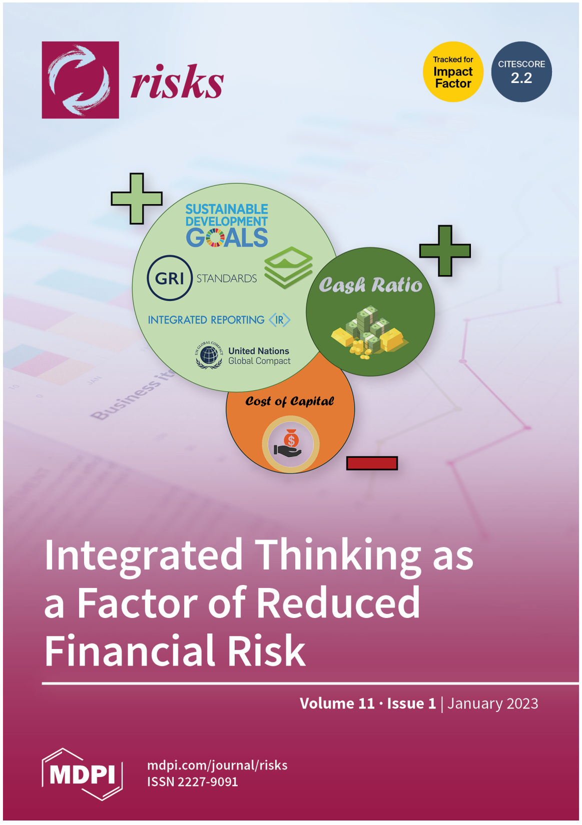
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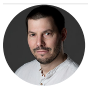

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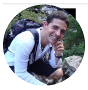

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Rational versus Irrational Behavior of Indonesian Cryptocurrency Owners in Making Investment Decision

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Abstract: The purpose of this study is to investigate the salient factors that influence Indonesian cryptocurrency owners in making their investment decision. This study employs intergroup bias, subjective norms, overborrowing, and spending control to explain cryptocurrency investment behavior. The questionnaire was collected from 309 respondents from the five largest internet user areas: Jakarta, Surabaya, Bandung, Semarang, and Medan. This study executes the research framework using binary logistic regression. The results reveal that intergroup bias and overborrowing are the most impulsive factors contributing to the cryptocurrency investment decisions over the past year. Furthermore, after November 2021, Indonesian crypto owners are more irrational in a bearish period since their investment decisions are driven by their desire to be accepted in the social group. Moreover, when they have overindebtedness, instead of solving their debt problems, they prefer to spend their money on cryptocurrency investments. The subjective norms' influencers suggest that crypto owners not invest when the cryptocurrency price is sharply declining. The findings contribute to the dual-systems perspective and social contagion theories, enriching the empirical study regarding investment behavior.

Keywords: cryptocurrency; intergroup bias; subjective norms; self-control; overborrowing; spending control; survey

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1. Introduction

Cryptocurrency investors frequently act irrationally in making investment decisions. This study explores how intergroup bias, subjective norms, and self-control factors influence the rationality of investment decisions. Empirical evidence has shown that investors do not always act rationally (Ahmad and Wu 2022), including in the cryptocurrency market. Previous research has been conducted on the behavioral bias in the equity market (Kumari et al. 2020; Ahmad and Wu 2022; Ahmad 2022; Ahmed et al. 2022; Lei and Salazar 2022; Liang et al. 2022), commercial real estate market (Kinatta et al. 2022), and cryptocurrency market (Ryu and Ko 2019). Ryu and Ko (2019) have conducted exceptional research on cryptocurrency investment decisions, which shows that strong impulses and weak self-control impact speculative bitcoin investments. The study of behavioral bias can help in understanding individual investors from different environments, resulting in discrete investment decisions. An individual has a common tendency to imitate, refer, and observe other behavior, specifically in a declining or unstable market condition (Yu et al. 2018; Shah et al. 2019).

In this study, there are four types of behavioral bias: intergroup bias, subjective norms, overborrowing, and spending control. First, intergroup bias is a tendency to behave more positively and provide greater rewards for their group members than outside groups (De Dreu and Kret 2016; Fujino et al. 2020). Intergroup bias in this study is focused on bias originating from a secondary group of investors' social environment, which is identical with lower intimacy and a lower frequency and duration of interaction—for example, religion-based groups or sports groups. Although group members have similar interests, the members' purpose is to build social networks, bridging and bonding capital (Lei and Salazar 2022) that can increase the members' income and wealth status (Zhang et al. 2018). This is consistent with the findings of Chan et al. (2022), which suggest that collectivist social values influence individual financial behavior due to a sense of solidarity in homogeneous communities. Furthermore, in a game task experiment, intergroup bias impacts individuals' tendency to invest more in their group than in outside groups (Fujino et al. 2020). Individual behavior that is more positive towards their group members potentially results in irrational investment decisions since the trust bias toward their group influences the investment decision. The social contagion theory supports this argument (Bakker et al. 2010). Second, in the theory of planned behavior (TPB), subjective norms refer to beliefs about the expectations from peers and the most important persons to an individual, which motivates the individual to fulfill these expectations. Subjective norms in this study focus on a primary group of investors' social environment: peers, the most important persons, and the price trend. Subjective norms are a significant determinant influencing investment decisions—for instance, adopting and using technology (Ajzen 1991). Third, overborrowing reflects financial behavior related to high credit interest or excessive loans (Kawamura et al. 2021). Overborrowing is frequently associated with the impulsive behavior of buying or investing without thinking about the future. Investors associated with high overborrowing behaviors have a propensity for investing in cryptocurrency, though in a high uncertainty period, they support an irrational investment decision. Finally, spending control bias is a compulsive buying behavior associated with unstable, self-inconsistent, and negative emotions and perceptions of oneself (Liu and Zhang 2021). Weak spending control behavior can generate irrational investment decisions. However, studies on behavior bias in cryptocurrency investment decisions, particularly intergroup bias, subjective norms, and self-control bias, are still limited, and this motivates this study. To fill this gap, this study aims to expand on Ryu and Ko (2019) by examining whether intergroup bias, subjective norms, and self-control bias influence the investment decisions regarding whether to invest or not in the cryptocurrency market.

From 2021 until the third quarter of 2022, cryptocurrency markets faced enormous challenges, with a very significant decline in market value, even though there have been several small surges in the past few weeks. This study collected a survey from crypto owners regarding their decisions during that period. The first half of 2022 was a terrible period for the cryptocurrency market. Bitcoin and Ethereum, the two largest cryptocurrencies, declined by more than 50 percent from their highs in November 2021 (Gailey and Haar 2022). Based on Figure 1, the Bitcoin market, compared to the Indonesian Rupiah, had decreased by around 67% since its highest position on 8 November 2021 (963 million to 314 million on 20 August 2022, when the data collection was performed). The bearish market has the potential to influence investors' perceptions as market participants as well as the social environment in which investors interact. Then, it has an impact on rational or irrational investors' behavior in cryptocurrency investment decisions. Uncertainty conditions generally lead to various positive or negative attitudes in the social environment that can influence investors' investment decisions. Investors who decided to invest or not invest in cryptocurrencies over the past year show that the dual-system perspective, which is a reflexive and reflective system, runs in harmony in the decision-making process. The reflexive system is fast, impulsive, automatic, and unconscious, whereas the reflective system is slow, controlled, conscious, and analytical (Ryu and Ko 2019). The factors of intergroup bias, subjective norms, overborrowing, and spending control bias can trigger the dual-system perspective, resulting in rational or irrational behaviors in the investment decisions.

Figure 1. Bitcoin to Indonesian Rupiah from November 2021 to November 2022. Source: Google Finance (2022).

Positive or negative attitudes towards cryptocurrency investment originate from the investors' social environment and create a more significant gap when the market is in a declining condition. The cryptocurrency market has unique characteristics that are different from those of conventional markets—for example, stocks and property markets. Cryptocurrencies provide a new alternative investment. Individuals believe that digital money is the money of the future (Bhatt 2022), and the number of users is increasing progressively. However, cryptocurrencies are risky speculative investments despite their inherent digital future potential. Most Southeast Asian countries, including Indonesia, Malaysia, and Vietnam, consider cryptocurrency illegal as a medium of exchange but legal as an investment or commodity. In addition, Thailand has just started to tighten the regulation of cryptocurrencies (Cointelegraph 2022). Therefore, it is critical for investors and potential investors to understand the applicable regulations and make decisions with a complete understanding of the potential risks.

Individual investors from the same geographic area were more likely to adopt biased behavior than cross-country investors (Choi 2016). Indonesia has seen a 280 percent growth in the number of crypto investors since 2020, from 1.5 million to 4.2 million individuals, with a daily trading volume reaching USD 117.4 million (Blockchain Association of Indonesia 2022). A study by Gemini (2022) entitled "Global State of Crypto Report" found that 41 percent of Indonesians between the ages of 18 and 75 with an income of more than USD 14,000 per year own cryptocurrencies. The research also found that 61 percent of Indonesian respondents agree that crypto is the future of money, which is the highest rate in the Asia Pacific (Gemini 2022). This study uses data from the Indonesian cryptocurrency market for three main reasons. First, there has been an acceleration of digital economic growth in Indonesia after the COVID-19 pandemic. As the largest economy in Southeast Asia, Indonesia has shown a significant increase in the value of the digital industry, from USD 41 billion in 2019 to USD 77 billion in 2022. It is driven primarily by e-commerce (Google, Temasek, Bain & Company 2022). The digital financial services increase is dominated by digital investment, which increased to 31% CAGR (Compound Annual Growth Rate) in 2022 and will increase to an estimated 74% CAGR in 2025 (Google, Temasek, Bain & Company 2022). These data show the significant potential of Indonesia's digital investment in Southeast Asia. Second, the number of individual Indonesian investors investing in cryptocurrency is greater than those investing in stocks in 2022. As of June 2022, the number of cryptocurrency investors was 15.1 million versus 9.1 million stock investors, despite the fact crypto investment is still relatively new in Indonesia (CNBC Indonesia 2022). Third, cryptocurrency investors in Asia are dominated by the young generation (Fujiki 2020, 2021; Santoso and Modjo 2022), so they fit the Indonesian demographic profile. Based on data for 2022, 78 percent of Indonesian crypto owners are between the age of 18 and 44 (TripleA 2022). Therefore, the Indonesian market provides a unique setting for researchers to analyze the influence of individual bias behavior on cryptocurrency investment decisions.

The findings of this study provide novel evidence supporting the dual-system perspective and contagion theory by emphasizing the importance of understanding the influence of intergroup bias, subjective norms, and self-control bias on investors' rational or irrational behavior in the decision-making process. Recent studies investigate the effect of subjective norms and self-control (Ryu and Ko 2019), financial literacy and investment experience (Zhao and Zhang 2021; Fujiki 2021), and attitude towards and trust in cryptocurrency investment decisions (Stix 2021). This research is different from these studies in the following ways. First, although the Ryu and Ko (2019) study was conducted during the declining market of cryptocurrencies, the Ryu and Ko (2019) study did not discuss the intergroup bias factor and did not analyze which factors determine investment decisions in cryptocurrencies. Second, although Zhao and Zhang (2021), Fujiki (2021), and Stix (2021) found that several factors were proven to influence crypto owners' investment decisions, their studies did not address intergroup bias, subjective norms, and self-control bias as factors influencing the decisions. Thus, this study is novel, since this study demonstrates that intergroup bias and subjective norms result in different stimuli for crypto owners' investment decisions. Intergroup bias contributes to the decision to invest in the market despite the declining conditions. On the other hand, subjective norms contribute to the decision to not invest in cryptocurrencies when market conditions experience a significant decline. This study also finds that overborrowing can result in the irrational behavior of investors who keep investing in cryptocurrency in declining conditions.

This study contributes to the cryptocurrency literature in the following ways. First, this study contributes to the development of cryptocurrency literature in Asia, which is synonymous with a collectivist culture that is vulnerable to the contagion effect of investment behavior. It provides empirical evidence supporting dual-system and social contagion theories by identifying intergroup bias, subjective norms, and overborrowing bias as the impulsive factors contributing to the cryptocurrency investment decisions. Second, an analysis of individual investors' biased behavior is performed in an extreme declining period which is still limited. During periods of significant market decline, the risk associated with cryptocurrency investments for owners with vulnerable risks, such as contagion risk and financial risk, increases. Therefore, irrational investors are more inclined to invest in cryptocurrency during adverse periods. Finally, this study enhances the behavioral finance literature on the rational and irrational behavior of crypto owners in making investment decisions by providing evidence of the effect of intergroup bias, subjective norms, and overborrowing bias on cryptocurrency investment decisions.

The discussion of this study is divided into several sections. Section 2 discusses the literature review and hypothesis development. Section 3 describes the research methodology, including the sample selection and analysis model. Section 4 shows the results of the statistical tests, the interpretation of the results, and theoretical and practical implications. Finally, Section 5 describes the conclusions, the limitations of the study, and potential future research.

2. Literature Review

2.1. Intergroup Bias and Subjective Norms in Cryptocurrencies Investment Decisions

Behavioral research of individual crypto owners, especially in emerging markets, is an interesting topic and has broad future potential. Kumar et al. (2022), who conducted a bibliometric study in the field of behavioral finance, suggest that additional research is needed to understand the factors that influence investors' behavior in the markets. According to Kumar et al. (2022), individual decision makers differ fundamentally, contributing to differences in financial behavior in investment decision making. The suggestion from Da Gama Silva et al. (2019) is to analyze bias behavior when the cryptocurrency market is in a sharp decline, since it has the potential to provide new findings for the development of the literature.

This study discusses biased behavior with two focuses: intergroup bias and subjective norms. First, intergroup bias is the tendency for members of one group to behave more positively and provide greater rewards than those outside the group (De Dreu and Kret 2016; Fujino et al. 2020). Collectivist culture has a strong positive influence on financial behavior (Chan et al. 2022). The impact of intergroup bias on the investment market is more destructive than the subjective norms because it involves more irrational and illogical thinking and blindly imitates the actions of others because of psychological and emotional factors. The need to be recognized as part of a social group can also lead to biased behavior in investment decisions. Second, subjective norms are beliefs about the expectations or important references of others that motivate investors to meet these expectations (Ajzen 1991)—for example, expectations from peers, the most important persons, and references to market trends. Crypto owners are inclined to follow advice from the closest social environment, including peers, the most important persons in making investment decisions, and price trends. Crypto investors rely on peers to reduce their potential risk due to wrong investment decisions. Bias investors try to match the investment performance of peers by relying on others' investment decisions. The two types of biased behaviors have different motivations and produce different behaviors in investment decisions.

2.2. Hypothesis Development

2.2.1. Intergroup Bias and Contagion Effect in Collectivist Culture

Intergroup bias is a bias behavior of decision making caused by the contagion effect from a secondary social group. The contagion effect arises because investors have a high level of trust (Bakker et al. 2010) towards other members of the social club through regular interaction. The perspective of social contagion theory is relevant to investment decisions since individuals tend to adopt similar behavior when they trust the information provided by members of their social network (Westaby et al. 2014). The three characteristics of the social contagion effect that influence intergroup bias are being aware of the knowledge that others have, appreciating what other persons know, and gaining access to one's thinking patterns (Borgatti and Cross 2003). The convergence of attitudes and beliefs depends on exposure to information obtained when communicating between social networks or groups (Peters et al. 2017). The interaction between members of a social group or social network, as bridging and bonding capital (Lei and Salazar 2022), can increase the members' wealth status. Furthermore, biased investors obtain financial knowledge, resources, and business opportunities from their groups, which in turn increase their income (Zhang et al. 2018).

Areas inhabited by various ethnic groups are one of the causes of massive contagion effect behavior (Chan et al. 2022). Concern over one's immediate ethnic survival leads to solidarity in genetically homogeneous communities, which is conducive to developing collectivist cultures (Chan et al. 2022). Cultures based on certain groups or ethnicities, such as beliefs, norms, and social values, tend to remain or not easily change over a long time (Gorodnichenko and Roland 2017). The existence of various ethnic groups in Indonesia is one of the motivating factors for research on intergroup bias.

Hypothesis 1 (H1). *Intergroup bias has contributed to cryptocurrency investment decisions over the past year.*

2.2.2. Subjective Norms and Cryptocurrency Investment Decisions

The subjective norm in this study focuses on the influence of the closest social environment, which are peers and the most important persons, and market trends in the cryptocurrency market. During an adverse period, influencers of subjective norms tend to suggest not to invest in cryptocurrencies. They prefer to manage their risk exposure since cryptocurrency is a speculative investment (Ryu and Ko 2019). Long-term goals, rational, and analytical, are the drivers of the influencers of subjective norms. The primary social group of investors—for example, peers, the most important persons—contribute to the decision to avoid investing in cryptocurrency during a terrible period. Ouimet and Geoffrey (2020) found that peers from the same employer firm influence individual financial decisions.

In contrast, subjective norms may also result in investors' impaired technical knowledge and reasoning abilities, causing errors in judgment. Consequently, investors make irrational decisions, which can adversely affect their returns (Ahmad and Wu 2022). Based on the arguments that have been explained, the research hypothesis is

Hypothesis 2 (H2). *Subjective norms have contributed to cryptocurrency investment decisions over the past year.*

2.2.3. Self-Control Behavior and Cryptocurrency Investment Decisions

Self-control is the ability to regulate emotions and behavior and inhibit individual impulses to achieve long-term results (Sekścińska et al. 2021). This study focuses on two dimensions of self-control: overborrowing and spending control. Previous studies that discussed financial behavior focused more on linking self-control with financial risk-taking or gambling risks, but issues related to investment choice were mostly ignored (Sekścińska et al. 2021). This study argues that overborrowing and spending controls contribute to the cryptocurrency investment decisions.

Overborrowing reflects financial behavior that is synonymous with high credit interest or excessive loans (Kawamura et al. 2021). Overborrowing is often associated with impulsive behavior, whereas, in decisions to buy or invest, individuals act without thinking about the future. Gathergood (2012) showed that individuals who act impulsively tend to use various types of credit, including consumer credit, which makes them more vulnerable to financial risk. This is in line with the studies by Friehe and Schildberg-Hörisch (2017) and Kocher et al. (2019), who found that low self-control increases risk-taking in investment decisions. Investors with a high level of debt tend to raise their risk exposure irrationally and invest in high-risk and speculative investments based on their emotions.

The other type of self-control is spending control. Low spending control is when individuals engage in impulsive consumer behavior or compulsive buying (Neuner et al. 2005). Liu and Zhang (2021) found that compulsive buying was associated with unstable, self-inconsistent, and negative emotions and perceptions of oneself. Furthermore, compulsive buying is similar to individuals who focus on materialistic values as a strategy to alleviate anxiety in response to insecurity symptoms (Kasser and Ahuvia 2002). Cryptocurrency is a speculative investment with a high volatility and the potential for greater returns, thus providing an impulse for individuals with low spending control. This study contends that low spending control contributed to the investment of cryptocurrencies in a highly uncertain period. In contrast, investors with high spending control will choose to refrain from investing in cryptocurrencies in a declining period.

Hypothesis 3a (H3a). *Overborrowing behavior has contributed to cryptocurrency investment decisions over the past year.*

Hypothesis 3b (H3b). *Spending control has contributed to cryptocurrency investment decisions over the past year.*

3. Methodology

3.1. Sample Selection and Questionnaire Study

The sample of this study is 309 respondents who are active crypto owners in Indonesia and are actively involved in social clubs. The period of distributing the questionnaire link lasted four weeks, from the beginning to the end of August 2022. The links were distributed to 997 respondents who are members of a pooled database of a credible and trusted survey service organization. Individuals who filled out the survey received a GoPay/OVO voucher of IDR 10,000, equivalent to USD 0.65. A total of 532 individuals did not have cryptocurrencies, so they were excluded from the sample. Forty respondents were disqualified for filling out the questionnaire incorrectly, twenty-five respondents did not complete filling out the questionnaire, and ninety-one respondents were not actively involved in any social club. This study uses several demographic criteria in the sample selection to avoid sample selection bias. First, the sample is an equal number of men and women. Second, the sample respondents came from five cities, with a balanced number of 80 respondents per city and a total of 400 respondents. Third, three age categories are the sample of this study, namely, 21–30 years, 31–41 years, and 41–50 years. Respondents who did not fall into these three categories were excluded from the sample. Finally, the respondents were actively involved in social clubs or clubs over the past year. A total of 91 respondents were not actively involved in social clubs or clubs; therefore, they were excluded from the sample.

This study conducted several stages of sample selection. First, this study accurately and precisely specified the population. The population of crypto owners in Indonesia is difficult to determine, and data are unavailable. Alternatively, this study uses the 2022 population of internet users provided by the Association of Indonesian Internet Service Providers (APJII). Previous studies have found that crypto owners are active internet users who use the internet at least once per week (Stix 2021). Second, the sampling frame phase was determined. A sampling frame is all the available elements of a population that has a chance of being selected for the survey (Dobosh 2018). The respondents in this study are verified members of a pooled database provided by a trusted surveyor service organization. The individual targets are crypto owners who have a basic understanding and are actively involved in social clubs. The respondent data based on the level of crypto knowledge indicated that as many as 67.6 percent have a basic knowledge of cryptocurrency and 25.9 percent have thorough knowledge. Third, the sampling technique was determined, and random probability sampling was used. Probability sampling is when all the elements of a sampling frame have an equal chance of being selected for the sample. The use of random sampling can reduce bias and increase the likelihood that the sample is representative (Dobosh 2018). The method of distributing the survey was conducted online for 1100 individuals who are verified members of a database of surveyor services organizations, so all individuals had the same opportunity to be selected as samples.

This study included a validation question in the form of simple mathematical addition to ensure that the respondents filled out the questionnaire consciously. If the respondent answers incorrectly, it is assumed that the respondent was not fully conscious when answering the question, and the respondent is disqualified. There are five sections to the questionnaire questions. The first is demographic information and the screening of currently active crypto owners. If the respondent does not have any cryptocurrencies, the respondent is disqualified. The second is information regarding cryptocurrency acquirement over the past year. The second part also asked about the subjective norms in cryptocurrency purchase decisions. The third section involves the questions of intergroup bias, beginning with the definition of a social club and the decision to participate actively in a social club. Respondents who answered that they had not been actively involved in a social club did not fill in this section and were excluded from the sample. In the questionnaire, our study provides examples of secondary social groups that are religious-based groups or sports clubs. This secondary group's members are the same people for a set period, so interactions occur regularly rather than just once or twice. Regular interaction with the social group is the main key to building trust between members, which can cause a contagion effect on investment behavior. In the fourth section, the respondents were asked about the overborrowing experienced over the past year. Finally, there was the question of overborrowing and spending control.

The period of crypto ownership is the past year. This study uses binary logistic regression and divides the dependent variable into two groups of crypto owners. Respondents who obtained cryptocurrencies over the past year are assigned number one, while those who do not meet the criteria are assigned number two. A year cap was chosen to limit the current motivation that causes respondents to buy cryptocurrencies. Stix (2021) stated that a more extended crypto buying period could introduce research bias, as motivations and influencing factors could potentially differ from those of the study population. In addition, when the survey was conducted, the cryptocurrency market conditions were decreasing. Da Gama Silva et al. (2019) also suggests analyzing biased behavior when the cryptocurrency markets are in a sharp decline because it has the potential to provide new findings for the development of the literature.

This study uses binary logistic regression to analyze Indonesia's factors influencing crypto ownership over the past year, especially in five big cities concentrated in Java and Sumatra, Bandung, Semarang, Surabaya, Medan, and Jakarta. These five cities were chosen because the population of internet investors in these five cities represented 43.61% of the population of internet investors in Indonesia, with an average internet penetration ratio per province of 78.98% (APJII 2022). The internet investors per province and provincial capital are shown in Table 1.

Table 1. The largest internet users in Indonesia by province capital city.

The Largest Internet Users Based on Provinces	Capital of the Province	Contribution to Indonesia's Total Internet Users	Internet Penetration Ratio of Each Province
West Java	Bandung	14.74%	82.4%
East Java	Surabaya	10.93%	72.9%
Central Java	Semarang	10.36%	76.9%
North Sumatra	Medan	4.34%	79.3%
DKI Jakarta	Jakarta	3.24%	83.4%
Total contribution nationally		43.61%	
Average internet penetration per province			78.98%

Source: Association of Indonesian Internet Service Providers (APJII 2022).

The sampling technique uses random sampling, and the sample size is determined based on the number of variables, where ten observations are needed for each variable studied. Peduzzi et al. (1996) and Peng et al. (2002) use a minimum sample ratio of 10 to 1, with a minimum sample size of 100. The formula is n = 10k/p, in which n is the number of minimum samples, k is the number of predictors, and p is the smallest proportion of binary cases in the population. The minimum sample size for a four-predictor model is 167; thus, the sample size of 309 respondents meets the requirement. Data collection was carried out through surveys with an online distribution in five provincial capitals with the most significant internet investors in Indonesia.

There are several stages to preparing the instrument. First, the questionnaires from previous references were translated into Indonesian and modified according to the research objectives. Second, the survey instrument was assessed by two experts: Professors and practitioners in investment and accounting behavior. Third, a pilot project was held for 30 individuals not included in the research sample. Questionnaire questions that do not pass the validity and reliability test will not be used in the survey. Finally, the instrument was translated back into English for publication purposes.

3.2. Definition of Variables and Model Analysis

3.2.1. Dependent Variables

The dependent variable of this study is cryptocurrency investment over the past year (PYI). The dependent variable is operationalized by a dummy variable, given a score of 1 if yes or a score of 2 otherwise. This study modifies the measurement of PYI from Stix's (2021) study by focusing more on exploring the factors contributing to the decision to invest in cryptocurrency over the past year, especially during periods of extreme decline in cryptocurrency markets. The dependent variable and the indicators are presented in Table 2.

Table 2. Definition of variables and indicators.

Construct	Indicators	Code
	Dependent variable	
Past year investment	Invest in cryptocurrencies over the past year.	PYI
	Independent variables	
Intergroup bias	The reason to invest in cryptocurrencies is to be recognized in a social group.	IB
	The reason to invest in cryptocurrencies is to follow the action of other group members.	
	The reason to invest in cryptocurrencies is believing that other members have more knowledge about cryptocurrencies.	
	The reason to invest in cryptocurrencies is the better performance of other group members.	
Subjective norms	Invest in a cryptocurrency whose value is rising in the market.	SN
	Investment decisions are based on the actions of others.	
	The reason to invest in cryptocurrencies is to follow the same pattern of decisions as other investors.	
	The reason to invest in cryptocurrencies is that friends or coworkers believe that investing in cryptocurrencies is popular.	
	The reason to invest in cryptocurrencies is that the most important persons to me also invest in cryptocurrencies.	
	The reason to invest in cryptocurrencies is that people around me are doing so.	
Overborrowing	How frequently have you used consumer credit over the past year?	OB
	How frequently have you run out of money in your bank account over the past year?	
	How frequently have you had difficulty paying debts over the past year?	
	How frequently have you borrowed money at extremely high-interest rates over the past year?	
Spending control	When making spending decisions, I carefully consider my financial situation.	SPC
	When making a cryptocurrency investment decision, I try to spend my money wisely.	
	When making a cryptocurrency investment decision, I try to put in only a little time or effort.	

3.2.2. Predictor Variables

This study employs four predictor variables: intergroup bias, subjective norms, overborrowing, and spending control bias. The predictor variables use five-point Likert scales. Harpe (2015) stated that the response measured by five-point Likert scales is continuous data, so it is relevant to the independent variable in the logistic regression model. The intergroup bias modified the questions from the study by Kumari et al. (2020), and the subjective norm predictor used modified the questionnaire (Taylor and Todd 1995; Kumari et al. 2020; Kinatta et al. 2022). The instrument of overborrowing and spending control variables modified the research questionnaire (Eysenck and Eysenck 1978; Tangney June Price and Boone 2004; Kawamura et al. 2021; Sekita et al. 2022). The predictor variables and the indicators are presented in Table 2.

3.2.3. Demographic Variables

The demographic variables in this study include gender, city of residence, age, occupation, and activeness in social clubs. This study uses demographic variables as sample selection criteria to avoid sample selection bias. First, the respondents were divided into two gender groups (Male and Female) with equal numbers (Table 3). Second, the respondents came from five cities, with a balanced number of eighty respondents for each area (Table 3). Third, three age categories are the sample of this study, namely, 21–30 years, 31–41 years, and 41–50 years. Finally, the respondents were actively involved in social clubs or clubs over the past year. Several studies have found that demographic variables are associated with the ownership of cryptocurrencies. For example, Fujiki (2020) found that crypto owners in Japan are primarily male, are under 30 years old, have a high pretax income, work at private or public companies, are the main source of income from a business, and have a graduate school education level.

Table 3. Demographics of respondents.

Past Year Investment (PYI)	%	Gender	%	Age	%	Occupation	%	Area	%
Sample of 400 crypto owners									
Yes	30.0	Male	47.8	21–30	49.8	College student	4.3	Jabodetabek	20.0
No	70.0	Female	52.2	31–40	37.3	Private employee	76.5	Surabaya	20.0
				41–50	13.0	Business owner	15.3	Semarang	20.0
						Full-time housewife	3.3	Bandung	20.0
						Unemployment	0.8	Medan	20.0
A sample of 309 crypto owners actively involved in social clubs									
Yes	35.9	Male	44.0	21–30	52.4	College student	4.5	Jabodetabek	23.3
No	64.1	Female	56.0	31–40	38.2	Private employee	74.8	Surabaya	16.2
				41–50	9.4	Business owner	17.2	Semarang	24.9
						Full-time housewife	2.9	Bandung	23.9
						Unemployment	0.6	Medan	11.7

Research model:

$$\eta 1 = \eta\beta + \beta 1\xi 1 + \beta 2\xi 2 + \beta 3\xi 3 + \beta 4\xi 4 + \varepsilon \quad (1)$$

Information
$\eta 1$ = Past year investment (PYI)
$\eta\beta$ = Constant coefficient
$\beta 1\xi 1$ = Intergroup bias (IB)
$\beta 2\xi 2$ = Subjective norms (SN)
$\beta 3\xi 3$ = Overborrowing (OB)
$\beta 4\xi 4$ = Spending self-control (SPC)
ε = Error disturbance

4. Empirical Result

4.1. Demographic and Descriptive Statistics

In this study, 309 of the 400 crypto owners were actively involved in social clubs. Table 3 presents the demographics of respondents, including the percentage of past year investments (PYI), gender, age groups, type of occupation, and area. PYI describes respondents who invested in cryptocurrency over the past year as 35.90 percent of the total respondents. The remaining 64.10 percent are crypto owners who did not invest in cryptocurrency. The age group of respondents is between 21 and 50 years, whereas the age category of 21 to 30 years dominates by 52.4%. Most respondents work in the private sector (74.8 percent), followed by business owners at 17.2 percent in the next position. This study conducts the Fisher exact test between gender and the dependent variable. The results show a significant (two-sided) Fisher exact test value of 0.153 (>0.05), confirming that the sample is free from gender bias problems.

Table 4 shows the descriptive statistics of the dependent variable of PYI using categorical data, whereas the answer "yes" is given the number 1, and 2 is given otherwise. Independent variables apply the mean score of the item indicators using a five-point Likert scale.

Table 4. Descriptive Statistics.

	N	Mean	STD	Min	Max	VIF
PYI	309	1.641	0.481	1	2	
IB	309	3.435	0.823	1.00	5.00	1.882
SN	309	3.306	0.754	1.20	4.80	1.859
OB	309	1.965	0.795	1.00	5.00	1.015
SPC	309	4.123	0.656	1.00	5.00	1.035

4.2. Hypothesis Result

The hypothesis testing begins with the determination of the validity and reliability of the indicators. The validity results using Pearson Correlation show coefficient values between 0.614 and 0.889 ($r > 0.60$) for each item indicator, so it can be concluded that item indicators can be used to measure the construct. The examination of reliability with Cronbach's alpha shows that a value greater than 0.60 can be interpreted as being of high reliability and as an acceptable index (Pallant 2001). The Cronbach's alpha values were 0.807, 0.807, 0.728, and 0.612 for IB, SN, OB, and SPC. The corrected item-total correlation ranged from 0.388 to 0.741, indicating good scales (Ferketich 1991). The Pearson correlation results in Table 5 display that the correlation coefficient between variables does not exceed 0.7. Thereby, it can be concluded that there is no strong correlation between variables, or it is at a moderate correlation level (Schober et al. 2018; McLeod 2022).

Table 5. Pearson Correlation matrix.

	PYI	SN	IB	OB	SPC
PYI	1				
SN	0.191 **	1			
IB	−0.028	0.675 **	1		
OB	−0.207 **	−0.008	0.025	1	
SPC	0.051	−0.004	0.104	−0.108	1

** significant at the 0.01 levels.

A binary logistic regression was employed to determine the impact of intergroup bias, subjective norms, and self-control derived from the factor analysis on the crypto investment decision. Table 6 shows the results of the logit model with the Wald test. The empirical result confirms that the intergroup bias (IB), subjective norms (SN), and overborrowing (OB) factors were significant ($\rho < 0.05$) predictors of the odds of PYI. In contrast, the spending control (SPC) factor was unconfirmed to predict the odds of PYI. Furthermore, the influencers in the group of subjective norms (SN) do not suggest that crypto owners invest during the heaviest period. On the contrary, intergroup bias (IB) and overborrowing (OB) have been predictors of cryptocurrency investment over the past year. This study found that overborrowing bias (OB) has a stronger predictive ability regarding investing in cryptocurrency than intergroup bias (IB). The exponential values of intergroup bias (IB) and overborrowing (OB) are 0.423 and 0.576, respectively, indicating that the ability to predict the odds ratio of PYI is greater in overborrowing (OB). The coefficient $\beta 1$ of intergroup bias (IB) reveals that the odds ratio of investing in cryptocurrencies over the past year decreases when the value of IB increases by one. The coefficient $\beta 1$ of the subjective norm (SN) is 1.204, and the exponential coefficient is 3.333, meaning that the odds ratio of investors who did not invest in cryptocurrencies over the past year increases by 3.333 times as the value of SN increases by one when the other predictors are held constant.

Table 6. Coefficient of Predictor Factors.

	Dependent: Past Year Investment (PYI)				
	β	**S.E.**	**Wald**	**Sig.**	**Exp(β)**
IB	−0.859	0.233	13.556	0.000	0.423
SN	1.204	0.251	23.095	0.000	3.333
OB	−0.551	0.162	11.577	0.001	0.576
SPC	0.227	0.198	1.311	0.252	1.254
Constant	−0.230	1.039	0.049	0.825	0.794

The goodness-of-fit statistics assess the fit of the logit model to the actual outcomes (Peng et al. 2002). The omnibus test shows a significant model χ^2 (6) of 14.545 with a ρ-value of 0.000 ($\rho < 0.05$) for the PYI model. The −2 log likelihood (−2LL) estimate measures how well the estimated model fits with categorical data (Suthar et al. 2010). The value of −2LL for the model is 363,157. Hosmer and Lemeshow's (Hosmer et al. 1997) test result demonstrates a non-significant value of 0.069 ($\rho > 0.05$). Thereby, the model fit can be preserved.

A logit model is predicted accurately, including correctly predicting the outcome (Hosmer et al. 1997). Table 7 shows an ability to predict the PYI model of 73.463 percent. The ability to predict the crypto owners' decision not to invest in cryptocurrency (91.919 percent) is better than that predicting investment decisions over the past year (40.541 percent). The predictive ability of the model for cryptocurrency investment decisions (PYI = yes) is below 50 percent or weak. In other words, other factors not analyzed in the model influence investment decisions during the extreme declining period.

Table 7. Predicted Results.

		Predicted		
		Past Year Investment (PYI)		
Observed		Yes	No	Percentage Correct
Past Year Investment (PYI)	Yes	45	66	40.541
	No	16	182	91.919
Overall Percentage				73.463

Several assumptions must be met in logistic regression. First, the linearity assumption uses box-tidwell transformation (Osborne 2017; Field 2018) to check for linearity between predictors and the logit. The results of the linearity test reveal that the box-tidwell transformation for the four independent variables is not significant in relation to the dependent variable, meaning that the linearity assumption is met. Second, the multicollinearity test in Table 4 shows a Variance Inflation Factor (VIF) value between 1.015 and 1.882 for the four independent variables.

4.3. Discussion

The results from this study show that intergroup bias (IB) and overborrowing (OB) behaviors are the most stimulating factors contributing to the cryptocurrency investment decision in an adverse market. Both factors contribute to irrational behavior in making an investment decision, specifically in the high-uncertainty conditions over the past year. Investors with the characteristics of having a high trust bias towards their social group and high overborrowing behavior had a tendency to invest in cryptocurrency over the past year when the price dropped by 67% from the highest point in November 2021 to the end of August 2022, when the data collection was performed. However, this study provides evidence that subjective norms (SN) of the primary social environment caused crypto owners to refrain from investing in cryptocurrency over the past year.

Different types of social environments have distinctive effects on cryptocurrency investment decisions in a high-uncertainty market. The dual-system perspectives can explain these distinctive effects, which discuss reflexive and reflective perspectives (Ryu and Ko 2019). Cryptocurrency investment, as a speculative investment activity, emerges as a natural response to individual high- and low-impulse interactions (Ryu and Ko 2019). When impulsive and reflexive investors react most strongly, investors can make irrational decisions. Nevertheless, a reflective perspective encourages rational behavior. These two impulses go hand in hand. Investors can receive different impulses of investing or not investing in cryptocurrency simultaneously. The dual-system perspective, reflexive and reflective, does not occur in isolation but side-by-side in speculative cryptocurrency investments. Investors who decided to buy or not buy crypto over the past year show that the reflexive and reflective system runs in harmony in the decision-making process, whether influenced by intergroup bias or subjective norms. This is consistent with the findings of Da Gama Silva et al. (2019), who found that negative news in the cryptocurrency markets is related to behavior bias.

Intergroup bias from the secondary group of investors' social environments, such as religion-based groups and sports groups, contributes to irrational behavior when making an investment decision. There are two fundamental explanations related to intergroup bias and irrational behavior. First, investors who are actively involved as members in a social group tend to behave more positively, provide greater rewards, and have higher trust in the group members than outside groups, which is known as trust bias. The trust bias encourages investors to behave identically to their group members and make irrational investment decisions since they want to be recognized in the group. Furthermore, intergroup bias encourages investors to act fast, impulsive, automatically, and unconsciously in making investment decisions to obtain financial knowledge, resources, and business opportunities from their social groups, which can increase their income. Interaction between members of a social group or network, as bridging and bonding capital (Lei and Salazar 2022), can increase the members' income and wealth status (Zhang et al. 2018). Second, cryptocurrency investments provide different options because of their attractive characteristics, their high volatility, their higher average returns, the accessibility of weekend trading, and their low correlation with traditional assets. These characteristics are the advantages of investment diversification (Brière et al. 2015). Then, the social group, which generally prioritizes individual wealth status and exclusive networking, tends to stimulate the irrational behavior of crypto owners in making investment decisions.

Regarding the subjective norms, this study shows that the investors received a stimulus from the primary group of their social environment—for example, peers, the most important persons—and the price trends to not invest in cryptocurrency in the adverse period. Cryptocurrency is a speculative investment instead of a long-term investment (AFM 2022). Indonesian regulations state that crypto is illegal as a medium of exchange. However, it is allowed to be traded as a commodity (Jakarta Globe 2022), thereby expanding its function as a speculative investment. Previous studies also confirmed that Bitcoin is mainly used as a speculative asset rather than an alternative currency (Blau 2017; Baur et al. 2018). Thus, in a high-uncertainty condition, persons in the closest social environment of crypto owners tend to act cautious, slow, controlled, conscious, and analytically, exposing the reflective system. They try to convince crypto owners not to invest in cryptocurrency during the heaviest period.

Besides intergroup bias, the other impetus to invest in cryptocurrency in the declining market arises from overborrowing bias. The reason is that individuals with low self-control often act on a reflexive perspective, leading to high levels of unplanned (Friese and Hofmann 2009) and irrational behavior. This is consistent with the findings of Ryu and Ko (2019), who stated that strong impulses and weak self-control drive speculative investment behavior in the cryptocurrency context. Easy access to fintech credit markets increases the risk of individuals falling into debt traps (Yue et al. 2022). Liu and Zhang (2021) explained that the easy access to online consumer credit became one of the causes of severe financial risk. The digital credit market trap is a challenge faced by crypto owners, who generally always come into contact with digital media.

The theoretical and practical implications of this study are described in several sections. First, there are minimal survey studies on biased behavior and cryptocurrency investment decisions, so this study enriches the literature on the irrational decisions of crypto owners, especially in Asia. Several crypto owners studies that are relevant to this study include those of Fujiki (2021) in Asia, Stix (2021) in Europe, and Zhao and Zhang (2021) in the USA. More specifically, studies with a sample of crypto owners in the Asia region have yet to receive much attention. Second, this study adds to the understanding of the social contagion theory in analyzing the role of intergroup bias in crypto owners' decisions in one of Southeast Asia's largest countries, Indonesia. Indonesia is identical to the collective community and young-age generation that is relevant to intergroup bias behavior and cryptocurrency investment. Third, this study provides a new understanding of the dual-system perspective by exploring two types of social environments: subjective norms and intergroup bias. Subjective norms and intergroup bias provided a strong, different impetus for cryptocurrency investment in adverse market conditions. Subjective norms have caused investors to refrain from investing in cryptocurrency over the past year. On the contrary, intergroup bias contributes to cryptocurrency investment even in declining market conditions. Fourth, the findings of overborrowing bias in cryptocurrency investment decisions open a new perspective in which crypto owners with overborrowing behavior have a tendency to act impulsively and irrationally, mainly when associated with a speculative investment in adverse market conditions. Finally, this study's practical implication is to provide government input to prevent vulnerable individual investors from buying or investing in cryptocurrencies.

5. Conclusions and Limitations

This study investigates whether intergroup bias, subjective norms, and self-control bias are predictors of crypto owners' investment decisions over the past year of the declining cryptocurrency market. Self-control bias in this study explores two types of behaviors: overborrowing and spending control. The results reveal that intergroup bias and overborrowing are the most impulsive factors contributing to the cryptocurrency investment decision over the past year, especially in the heaviest period. The empirical results indicate that intragroup bias due to the contagion effect from secondary groups of investors' social environments—for example, religious-based groups or sports clubs—encouraged investors to invest in the cryptocurrency market even though the market was in adverse conditions. Intergroup bias behavior that is more positive towards one's group members than those outside the group potentially results in irrational behavior, since the trust bias toward one's group influences the investment decision. The other finding is that overborrowing bias causes investors to behave irrationally, since instead of solving their debt problems, they prefer to spend their money on cryptocurrency investment in adverse market conditions.

In contrast, this study reveals that the subjective norm from the primary group of one's social environment—for example, peers, the most important persons—and the market price influence the decision not to invest in the adverse cryptocurrency market. The subjective norm factor indicates the reflective system, which is slow, controlled, and analytical in making investment decisions during significant cryptocurrency price declines. The different results between the influence of subjective norms, intergroup bias, and overborrowing biased behaviors explain that there is a dual-system perspective, reflexive and reflective, which investors experience simultaneously and which influences investment decisions. When the impulsive and reflexive system reacts most strongly, investors can generate irrational behavior and make irrational investment decisions. However, the reflective perspective encourages rational behavior. Finally, spending control bias is unconfirmed as a predictor of cryptocurrency investment decisions.

This research has some limitations. First, the location of the crypto owner population cannot be determined. Alternatively, internet users are used as the population of crypto owners in this study. Since not all internet users are crypto owners, there is the possibility for differences between internet users and crypto owners. Second, with regard to the number of crypto owners that responded to this study, it is still necessary to gather additional samples from all over Indonesia in order for them to accurately represent cryptocurrency investors. Third, this study does not distinguish between investors who make direct or indirect investments through funding. Therefore, there is a potential for investment decisions to be biased due to the influence of fund managers. Finally, the model's ability to anticipate the decision not to invest in cryptocurrency is greater than its ability to predict the decision to invest. In addition, the results of this study must be interpreted with caution due to the possibility of other factors predicting the decision during a gloomy phase. Therefore, it is anticipated that future studies will enhance the predictive model by incorporating more variables that have the ability to affect the choice to invest in cryptocurrencies during a gloomy phase.

For future studies, our research recommends developing a model including other biased behaviors and investors' demographic variables that affect vulnerable decisions by cryptocurrency investors. Future research needs to explore the other dimension of bias behaviors, which are still extensive and should investigate the influence of biased behaviors on cryptocurrency investment decisions in international settings.

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Article

Rational Versus Irrational Behavior of Indonesian Cryptocurrency Owners in Making Investment Decisions

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Abstract: The purpose of this study is to investigate the salient factors that influence Indonesian cryptocurrency owners in making their investment decision. This study employs intergroup bias, subjective norms, overborrowing, and spending control to explain cryptocurrency investment behavior. The questionnaire was collected from 309 respondents from the five largest internet user areas, Jakarta, Surabaya, Bandung, Semarang, and Medan. This study executes the research framework using binary logistic regression. The results reveal that intergroup bias and overborrowing are the most impulsive factors contributing to the cryptocurrency investment decision over the past year. Furthermore, after November 2021, Indonesian crypto owners are more irrational in a bearish period since their investment decisions are driven by their desire to be accepted in the social group. Moreover, when they have overindebtedness, instead of solving their debt problems, they prefer to spend their money on cryptocurrency investments. The subjective norms' influencers suggest that crypto owners not invest when the cryptocurrency price sharp declining. The findings contribute to the dual-systems perspective and social contagion theories enriching the empirical study regarding investment behavior.

Keywords: cryptocurrency, intergroup bias, subjective norms, self-control, overborrowing, spending control, survey.

1. Introduction

Cryptocurrency investors frequently act irrationally in making investment decisions. This study explores how intergroup bias, subjective norms, and self-control factors influence the rationality of investment decisions. Empirical evidence has shown that investors do not always act rationally (Ahmad & Wu, 2022), including in the cryptocurrency market. Previous research on the behavioral bias in the equity market (Kumari et al., 2020; Ahmad & Wu, 2022; Ahmad, 2022; Ahmed et al., 2022; Lei & Salazar, 2022; Liang et al., 2022), commercial real estate (Kinatta et al., 2022), and cryptocurrency market (Ryu & Ko, 2019). Ryu & Ko (2019) has exceptional research on cryptocurrency investment decisions, which show that strong impulse and weak self-control impact speculative bitcoin investments. The study of behavioral bias can help understand individual investors from different environments resulting in discrete investment decisions. An individual has a common tendency to imitate, refer and observe other behavior, specifically in a declining or unstable market condition (Yu et al., 2018; Shah et al., 2019).

In this study, there are four types of behavioral bias: intergroup bias, subjective norms, overborrowing, and spending control. First, intergroup bias is a tendency to behave more positively and provide greater rewards for their group members than outside groups (De Dreu & Kret, 2016; Fujino et al., 2020). Intergroup bias in this study is focused on bias originating from a secondary group of investors' social environment that is identical with lower intimacy, lower frequency, and duration of interaction, for example, religion-based groups or sports groups. Although group members have similar interests, the members' purpose is to build social networks, bridging and bonding capital (Lei & Salazar, 2022) that can increase the members' income and wealth status (Zhang et al., 2018). Consistent with Chan et al. (2022) suggest that collectivist social values influence individual financial behavior, due to a sense of solidarity in homogeneous communities. Furthermore, in a game task experiment, intergroup bias impacts individuals' tendency to invest more in their group than in outside groups (Fujino et al., 2020). Individual behavior that is more positive towards their group members potentially results in irrational investment decisions since the trust bias toward their group influences the investment decision. The social contagion theory supports this argument (Bakker et al., 2010). Second, in the theory of planned behavior (TPB), subjective norm refers to beliefs about the expectations or important references of peers and the most important persons of the investors and motivates them to fulfill these expectations. Subjective norms in this study focus on a primary group of investors' social environment: peers, the most important persons, and the price trend. Subjective norm is a significant determinant influencing investment decisions, for instance, adopting and using technology (Ajzen, 1991). Third, overborrowing reflects financial behavior related to high credit interest or excessive loans (Kawamura et al., 2021). Overborrowing is frequently associated with impulsive behavior to buy or invest without thinking about the future. Investors associated with high overborrowing behavior have a propensity for investing in cryptocurrency, though in a high uncertainty period, support an irrational investment decision. Finally, spending control bias is a compulsive buying behavior associated with unstable, self-inconsistent, negative emotions and perceptions of oneself (Liu & Zhang, 2021). Weak spending control behavior can generate irrational investment decisions. However, studies on behavior bias in a cryptocurrency investment decision, particularly intergroup bias, subjective norms, and self-control bias still limited, so the reason motivates this study. To fill this gap, this study aims to expand on Ryu and Ko (2019) by examining whether intergroup bias, subjective norm, and self-control bias influence the investment decisions whether to invest or not in the cryptocurrency market.

Over the past 2021 until the third quarter of 2022, cryptocurrency markets are facing enormous challenges, with a very significant decline in market value, even though there have been several small surges in the past few weeks. This study collected a survey from crypto owners regarding their decisions during that period. The first half of 2022 was a terrible period for the cryptocurrency market. Bitcoin and Ethereum, the two largest cryptocurrencies, declined more than 50 percent from their highs in November 2021 (Time, 2022). Based on figure 1, the Bitcoin market, compared to the Indonesian Rupiah, had decreased by around 67% since its highest position on November 8, 2021, in the amount of 963 million to 314 million on August 20, 2022, when the data collection was performed. The bearish market has the potential to influence investors' perceptions as market participants as well as the social environment with which investors interact. Then, it has an impact on rational or irrational investors' behavior in cryptocurrency investment decisions. Uncertainty conditions generally lead to various positive or negative attitudes in the social environment that can influence investors' investment decisions. Investors who decided to invest or not invest in cryptocurrencies over the past year show that the dual-system perspective, which is a reflexive and reflective system runs in harmony in the decision-making process. The reflexive system is fast, impulsive, automatic, and unconscious, whereas the reflective system is slow, controlled, conscious, and analytical (Ryu & Ko, 2019). Factors of intergroup bias, subjective norm, overborrowing, and spending control bias can trigger the dual-system perspective, resulting in rational or irrational behaviors in the investment decision.

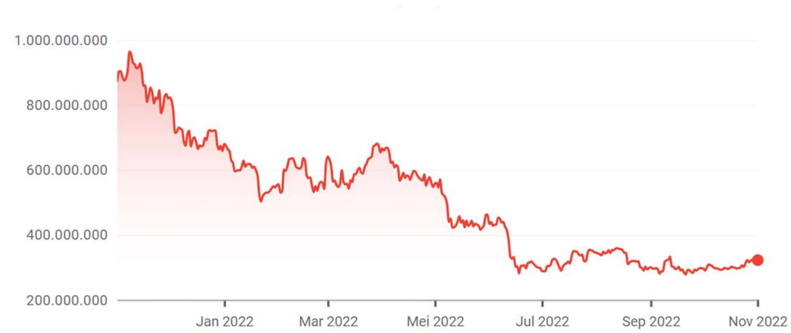

Figure 1. Bitcoin to Indonesian Rupiah from November 2021 to November 2022. Source: Google Finance (2022).

Positive or negative attitudes towards cryptocurrency investment originating from the investors' social environment and create a more significant gap when the market is in a declining condition. The cryptocurrency market has unique characteristics different from conventional markets, for example, stocks and property markets. Cryptocurrencies provide a new alternative investment. Individuals believe that digital money is the money of the future (Bhatt, 2022), and the number of users is increasing progressively. However, cryptocurrencies are risky speculative investments despite their inherent digital future potential. Most Southeast Asia countries, including Indonesia, Malaysia, and Vietnam, consider cryptocurrency illegal as a medium of exchange, though legal as an investment or commodity. In addition, Thailand has just started to tighten the regulation of cryptocurrencies (Cointelegraph, 2022). Therefore, it is critical for investors and potential investors to understand the applicable regulations and make decisions with a complete understanding of the potential risks.

Individual investors from the same geographic area were more likely to adopt biased behavior than cross-country investors (Choi, 2016). Indonesia has seen a 280 percent growth in the number of crypto investors since 2020, from 1.5 million to 4.2 million individuals, with a daily trading volume reaching USD 117.4 million (Blockchain Association of Indonesia, 2022). A study by Gemini (2022) entitled "Global State of Crypto Report" found that 41 percent of Indonesians aged between 18 and 75 with an income of more than $14,000 per year own cryptocurrencies. The research also found that 61 percent of Indonesian respondents agree that crypto is the future of money which is the highest in the Asia Pacific (Gemini, 2022). This study uses data from the Indonesian cryptocurrency market for three main reasons. First, there has been an acceleration of digital economic growth in Indonesia after the COVID-19 pandemic. As the largest economy in Southeast Asia, Indonesia has shown a significant increase in the value of the digital industry from US$41 billion in 2019 to US$ 77 billion in 2022. It is driven primarily by e-commerce (Google, Temasek, Bain & Company, 2022). Digital financial services increase dominated by the digital investment that increase to 31% CAGR (Compound Annual Growth Rate) in 2022 and an estimated 74% CAGR in 2025 (Google, Temasek, Bain & Company, 2022). These data show the significant potential of Indonesia's digital investment in Southeast Asia. Second, the number of individual Indonesia investors investing in cryptocurrency is greater than those investing in stocks in 2022. As of June 2022, the number of cryptocurrency investors was 15.1 million versus 9.1 million stock investors, despite the fact crypto investment is still relatively new in Indonesia (CNBCIndonesia, 2022). Third, cryptocurrency investors in Asia are dominated by the young generation (Fujiki, 2020; Fujiki, 2021; Santoso & Modjo, 2022), so they fit the Indonesian demographic profile. Based on data for 2022, 78 percent of Indonesian crypto owners are aged 18 to 44 years (TripleA, 2022). Therefore, the Indonesian market provides a unique setting for researchers to analyze the influence of individual bias behavior on cryptocurrency investment decisions.

The findings of this study provide novel evidence supporting the dual-system perspective and contagion theory by emphasizing the importance of understanding the influence of intergroup bias, subjective norms, and self-control bias on investors' rational or irrational behavior in the decision-making process. Recent studies investigate the effect of subjective norms and self-control (Ryu & Ko, 2019), financial literacy and investment experience (Zhao & Zhang, 2021; Fujiki, 2021), attitude and trust (Stix, 2021) in cryptocurrency investment decisions. This research is different from the studies in the following ways. First, although the Ryu and Ko (2019) study were conducted during the declining market of cryptocurrencies, the Ryu and Ko (2019) study did not discuss intergroup bias factor and did not analyze which factors determine investment decisions in cryptocurrencies. Second, although Zhao and Zhang (2021), Fujiki (2021), and Stix (2021) found that several factors were proven to influence crypto owners' investment decisions, their studies did not address intergroup bias, subjective norms, and self-control bias as factors influencing the decisions. Thus, this study is novel since this study demonstrates that intergroup bias and subjective norms result in different stimuli on crypto owners' investment decisions. Intergroup bias contributes to the decision to invest in the market despite the declining conditions. On the other hand, subjective norms contribute to the decision not to invest in cryptocurrencies when market conditions experience a significant decline. This study also finds that overborrowing can result in irrational behavior of investors to keep investing in cryptocurrency in declining conditions.

This study contributes to the cryptocurrency literature in the following ways. First, this study contributes to the development of cryptocurrency literature in Asia, which is synonymous with a collectivist culture that is vulnerable to the contagion effect of investment behavior. It provides empirical evidence supporting dual-system and social contagion theories by identifying intergroup bias, subjective norms, and overborrowing bias as the impulsive factors contributing to the cryptocurrency investment decision. Second, analysis of individual investors' biased behavior is performed in extreme declining period which is still limited. During periods of significant market decline, the risk associated with cryptocurrency investments for owners with vulnerable risks, such as contagion risk and financial risk, increases. Therefore, irrational investor more inclined to invest in cryptocurrency during adverse period. Finally, this study enhances the behavioral finance literature on the rational and irrational behavior of crypto owners in making investment decisions by providing evidence of the effect of intergroup bias, subjective norms, and overborrowing bias on cryptocurrency investment decisions.

The discussion of this study is then divided into several sections. Section 2 discusses the literature review and hypothesis development. Section 3 describes the research methodology, including the sample selection and analysis model. Section 4 shows the results of statistical tests, the interpretation of results, theoretical and practical implications. Finally, section 5 describes the conclusions, limitations of the study, and potential future research.

2. Literature Review

2.1. Intergroup bias and Subjective Norms in Cryptocurrencies Investment Decision

Behavioral research of individual crypto owners, especially in emerging markets, is an interesting topic and has broad future potential. Kumar et al. (2022), who conducted a bibliometric study in the field of behavioral finance, suggest additional research is needed to understand the factors that influence investors' behavior in the markets. According to Kumar et al. (2022), individual decision-makers differ fundamentally, contributing to differences in financial behavior in investment decision-making. The suggestion from da Gama Silva et al. (2019) is to analyze bias behavior when the cryptocurrency market is in a sharp decline since it has the potential to provide new findings for the development of the literature.

This study discusses biased behavior with two focuses: intergroup bias and subjective norm. First, intergroup bias is the tendency for members of one group to behave more positively and provide greater rewards than those outside group (De Dreu & Kret, 2016; Fujino et al. 2020). Collectivist culture has a strong positive influence on financial behavior (Chan et al. 2022). The impact of intergroup bias on the investment market is more destructive than the subjective norm because it involves more irrational, illogical thinking and blindly imitates the actions of others because of psychological and emotional factors. The need to be recognized as part of a social group can also lead to biased behavior in investment decisions. Second, subjective norms are beliefs about the expectations or important references of others that motivate investors to meet these expectations (Ajzen, 1991), for example, expectations from peers, the most important persons and references to market trends. Crypto owners are inclined to follow advice from the closest social environment, including peers, the most important persons in making investment decisions, and price trends. Crypto investors rely on peers to reduce their potential risk due to wrong investment decisions. Bias investors try to match the investment performance of peers by relying on others investment decisions. The two types of biased behaviors have different motivations and produce different behaviors in investment decisions.

2.2. Hypothesis Development

2.2.1. Intergroup Bias and Contagion Effect in Collectivist Culture

Intergroup bias is a bias behavior of decision-making caused by the contagion effect from a secondary social group. The contagion effect arises since investors have a high level of trust (Bakker et al., 2010) towards other members of the social club through regular interaction. The perspective of social contagion theory is relevant to investment decision since individuals tend to adopt similar behavior when they trust the information provided by members of their social network (Westaby et al. 2014). The three characteristics of the social contagion effect that influence intergroup bias are being aware of the knowledge that others have, appreciating what other person know, and gaining access to one's thinking patterns (Borgatti, 2003). The convergence of attitudes and beliefs depends on exposure to information obtained when communicating between social networks or groups (Peters et al., 2017). The interaction between members of a social group or social network as bridging and bonding capital (Lei & Salazar, 2022) can increase the members' wealth status. Furthermore, biased investors obtain financial knowledge, resources, and business opportunities from their groups, which in turn increase their income (Zhang et al., 2018).

Areas inhabited by various ethnic groups are one of the causes of massive contagion effect behavior (Chan et al., 2022). Concern over one's immediate ethnic survival leads to solidarity in genetically homogeneous communities, which is conducive to developing collectivist cultures (Chan et al., 2022). Cultures based on certain groups or ethnicities, such as beliefs, norms, and social values, tend to remain or not easily change over a long time (Gorodnichenko & Roland, 2017). The existence of various ethnic groups in Indonesia is one of the motivating factors for research on intergroup bias.

H1: Intergroup bias contributes to the cryptocurrency investment decision over the past year.

2.2.2. Subjective norm and Cryptocurrency Investment Decision

The subjective norm in this study focuses on the influence of the closest social environment, which are peers and the most important persons, market trends on cryptocurrency market. During an adverse period, influencers of subjective norms tend to suggest not to invest in cryptocurrencies. They prefer to manage their risk exposure since cryptocurrency is a speculative investment (Ryu & Ko, 2019). Long-term goal, rational, and analytical are the driver of the influencers of subjective norms. The primary social group of investors, for example: peers, the most important persons contribute to the decision to avoid investing in cryptocurrency during a terrible period. Ouimet & Geoffrey (2020) found that peers from the same employer firm influence an individual financial decisions.

In contrast, subjective norms may also result in investors' impaired technical knowledge and reasoning abilities, causing errors in judgment. Consequently, investors make irrational decisions, which can adversely affect their returns (Ahmad & Wu, 2022). Based on the arguments that have been explained, the research hypothesis is

H2: Subjective norms contributes to the cryptocurrency investment decision over the past year.

2.2.3. Self-control Behavior and Cryptocurrency Investment Decision

Self-control is the ability to regulate emotions and behavior and inhibit individual impulses to achieve long-term results (Sekścińska et al., 2021). This study focuses on two dimensions of self-control, overborrowing and spending control. Previous studies that discussed financial behavior focused more on linking self-control with financial risk-taking or gambling risks, but issues related to investment choice were mostly ignored (Sekścińska et al., 2021). This study argues that overborrowing and spending controls contribute to the cryptocurrency investment decision.

Overborrowing reflects financial behavior synonymous with high credit interest or excessive loans (Kawamura et al., 2021). Overborrowing is often associated with impulsive behavior, whereas in decisions to buy or invest, individuals act without thinking about the future. Gathergood (2012) showed that individuals who act impulsively tend to use various types of credit, including consumer credit which makes them more vulnerable to financial risk. In line with the studies by Friehe & Schildberg-Hörisch (2017) and Kocher et al. (2019), who found that low self-control increases risk-taking in investment decisions. Investors with a high level of debt tend to raise their risk exposure irrationally and invest in high-risk and speculative investments based on their emotions.

The other type of self-control is spending control. Low spending control is when individuals engage in impulsive consumer behavior or compulsive buying (Neuner et al., 2005). Liu & Zhang (2021) found that compulsive buying was associated with unstable, self-inconsistent, negative emotions and perceptions of oneself. Furthermore, compulsive buying is similar to individuals who focus on materialistic values as a strategy to alleviate anxiety in response to insecurity symptoms (Kasser & Ahuvia, 2002). Cryptocurrency is a speculative investment with high volatility and the potential for greater returns, thus providing an impulse for individuals with low spending control. This study contends that low spending control contributed to the investment of cryptocurrencies, in a highly uncertainty period. In contrast, investors with high spending control will choose to refrain from investing in cryptocurrencies in a declining period.

H3a: Overborrowing behavior has contributed to the cryptocurrency investment decision over the past year.

H3b: Spending control has contributed to the cryptocurrency investment decision over the past year.

3. Methodology

3.1. Sample selection and questionnaire study

The sample of this study is 309 respondents who are active crypto owners in Indonesia and are actively involved in social clubs. The period of distributing the questionnaire link is for four weeks, from the beginning to the end of August 2022, to 997 respondents who are members of a pooled database of a credible and trusted survey service organization. Individuals who fill out the survey will receive a GoPay/OVO voucher of IDR 10,000 or equivalent to USD 0.65. A total of 532 individuals did not have cryptocurrencies, so they were excluded from the sample. Forty respondents were disqualified for filling out the questionnaire incorrectly, twenty-five respondents did not complete filling out the questionnaire, and ninety-one respondents were not actively involved in any social club. This study uses several demographic criteria in sample selection to avoid sample selection bias. First, the sample is an equal number of men and women. Second, the sample respondents came from five cities with a balanced number of 80 respondents per city with a total of 400 respondents. Third, three age categories are the sample of this study, namely 21-30 years, 31-41 years, and 41-50 years. Respondents who did not fall into these three categories were excluded from the sample. Finally, respondents were actively involved in social clubs or clubs over the past year. A total of 91 respondents were not actively involved in social clubs or clubs; therefore, they were excluded from the sample.

This study conducted several stages of sample selection. First, this study accurately and precisely specify the population. The population of crypto owners in Indonesia is difficult to determine, and data are unavailable. Alternatively, this study uses the 2022 population of internet users provided by the Association of Indonesian Internet Service Providers (APJII). Previous studies have found that the characteristics of crypto owners are active internet users at least once per week (Stix, 2021). Second, determining the sampling frame phase. A sampling frame is all the available elements of a population that has a chance of being selected for the survey (Dobosh, 2018). Respondents in this study are verified members of a pooled database provided by a trusted surveyor service organization. Individual targets are crypto owners who have a basic understanding and are actively involved in social clubs. Respondent data based on the level of crypto knowledge is as much as 67.6 percent have basic knowledge of cryptocurrency and 25.9 percent on the level of thorough knowledge. Third, determine the sampling technique and use random probability sampling. Probability sampling is when all elements of a sampling frame have an equal chance of being selected for the sample. The use of random sampling can reduce bias and increase the likelihood that the sample is representative (Dobosh, 2018). The method of distributing survey was conducted online to 1,100 individuals who are verified members of a database of surveyor services organizations so that all individuals have the same opportunity to be selected as samples.

This study included a validation question in the form of simple mathematical addition to ensure that respondents filled out the questionnaire consciously. If the respondent answers incorrectly, it is assumed that the respondent was not fully conscious when answering the question, and the respondent is disqualified. There are five sections to the questionnaire questions. First, demographic information and screening of current active crypto owners. If the respondent does not have any cryptocurrencies, the respondent is disqualified. Second, information regarding cryptocurrency acquirement over the past year. The second part also asked about the subjective norm in cryptocurrency purchase decisions. Third, the questions of intergroup bias begin with the definition of a social club and whether the decision to participate actively in a social club. Respondents who answered that they had not been actively involved in a social club did not fill in this section and were excluded from the sample. In the questionnaire, our study provides examples of secondary social groups that are religious-based groups or sports clubs. This secondary group's members are the same people for a set period, so interactions occur regularly rather than just once or twice. Regular interaction with the social group is the main key to building trust between members, which can cause a contagion effect on investment behavior. Fourth, in this section, respondents were asked about the overborrowing experienced over the past year. Finally, the question of overborrowing and spending control.

The period of crypto ownership is the respondent who obtained crypto over the past year. This study uses binary logistic regression and divides the dependent variable into two groups of crypto owners. Respondents who obtained cryptocurrencies over the past year are assigned number one, while those who do not meet the criteria are assigned number two. A year cap was chosen to limit the current motivation that causes respondents to buy cryptocurrencies. Stix (2021) stated that a more extended crypto buying period could introduce research bias as motivations and influencing factors could potentially differ from the study population. In addition, when the survey was conducted, the cryptocurrency market conditions showed decreasing markets. Da Gama Silva et al (2019) also suggests analyzing biased behavior when the cryptocurrency markets are in a sharp decline because it has the potential to provide new findings for the development of the literature.

This study uses binary logistic regression to analyze Indonesia's factors influencing crypto ownership over the past year, especially in five big cities concentrated on Java and Sumatra, Bandung, Semarang, Surabaya, Medan, and Jakarta. These five cities were chosen because the population of internet investors in these five cities represented 43.61% of the population of internet investors in Indonesia, with an average internet penetration ratio per province of 78.98% (APJII, 2022). Internet investors per province and provincial capital are in table 1.

Table 1. The largest Internet users in Indonesia by province capital city.

The largest internet users based on provinces	Capital of the province	Contribution to Indonesia's total internet users	Internet penetration ratio each province
West Java	Bandung	14.74%	82.4%
East Java	Surabaya	10.93%	72.9%
Central Java	Semarang	10.36%	76.9%
North Sumatra	Medan	4.34%	79.3%
DKI Jakarta	Jakarta	3.24%	83.4%
Total contribution nationally		43.61%	
Average internet penetration per province			78.98%

[1]Association of Indonesian Internet Service Providers (APJII), 2022

The sampling technique uses random sampling, and the sample size is determined based on the number of variables, where ten observations are needed for each variable studied. Peduzzi et al. (1996) and Peng (2002) use a minimum sample ratio of 10 to 1, with a minimum sample size of 100. The formula is $n = 10k/p$, in which n is the number of minimum samples, k is the number of predictors, and p is the smallest proportion of binary cases in the population. The minimum sample size for a four-predictor model is 167; thus, the sample size of 309 respondents considers meeting the requirement. Data collection was carried out through surveys with online distribution in five provincial capitals with the most significant internet investors in Indonesia.

There are several stages to preparing the instrument. First, the questionnaires from previous references were translated into Indonesian and modified according to the research objectives. Second, the survey instrument was assessed by two experts: Professors and practitioners in investment and accounting behavior. Third, a pilot project was held first for 30 individuals not included in the research sample. Questionnaire questions that do not pass the validity and reliability test will not be used in the survey. Finally, the instrument was translated back into English for publication purposes.

3.2. Definition of variables and Model Analysis

Dependent variables

The dependent variable of this study is cryptocurrency investment over the past year (PYI). The dependent variable is operationalized by a dummy variable, given a score of 1 if yes or a score of 2 otherwise. This study modifies the measurement of PYI from (Stix, 2021)'s study by focusing more on exploring the factors contributing to the decision to investing cryptocurrency over the past year, especially during periods of extreme decline in cryptocurrency markets.

Predictor variables

This study employs four predictor variables: intergroup bias, subjective norm, overborrowing, and spending control bias. Predictor variables use five-point Likert scales. (Harpe, 2015) stated that the response measured by five-point Likert scales is continuous data, so it is relevant to the independent variable in the logistic regression model. The intergroup bias modified the questions from the study Kumari et al, (2020), and the subjective norm predictor used modified the questionnaire (Taylor & Todd, 1995; Kumari et al, 2020; Kinatta et al, 2022). The instrument of overborrowing and spending control variables modifying research questionnaire by (Eysenck & Eysenck, 1978; Tangney et al, 2004; Kawamura et al, 2021; Sekita et al, 2022).

Demographic variables

Demographic variables in this study include gender, city of residence, age, occupation, and activeness in social clubs. This study uses demographic variables as sample selection criteria to avoid sample selection bias. First, the respondents were divided into two gender groups (Male and Female) with equal numbers (table 3). Second, the respondents came from five cities, with a balanced number of eighty respondents for each area (table 3). Third, three age categories are the sample of this study, namely 21-30 years, 31-41 years, and 41-50 years. Finally, respondents were actively involved in social clubs or clubs over the past year. Several studies have found that demographic variables are associated with the ownership of cryptocurrencies. For example, Fujiki (2020) found that crypto owners in Japan are primarily male, under 30 years old, have a high pretax income, work in private or public companies, are the main source of income from a business and have a graduate school education level.

Table 2. Definition of variables and indicator

Construct	Indicators	Code
	Dependent variable	
Past year investment	Invest in cryptocurrencies over the past year.	PYI
	Independent variables	
Intergroup bias	The reason to invest in cryptocurrencies is to be recognised in a social group. The reason to invest in cryptocurrencies is to follow the action of other group members. The reason to invest in cryptocurrencies is because of believing that other members have more knowledge about cryptocurrencies. The reason to invest in cryptocurrencies is the better performance of other group members.	IB

Subjective norms	Invest in a cryptocurrency whose value is rising in the market.	SN
	Investment decisions are based on the actions of others.	
	The reason to invest in cryptocurrencies is to follow the same pattern of decisions as other investors.	
	The reason to invest in cryptocurrencies is that friends or coworkers believe that investing in cryptocurrencies is popular.	
	The reason to invest in cryptocurrencies is that the most important persons to me also invest in cryptocurrencies.	
	The reason to invest in cryptocurrencies is that people around me are doing so.	
Overborrowing	How frequently using consumer credit over the past year?	OB
	How frequently run out of money in your bank account over the past year?	
	How frequently have you had difficulty paying debts over the past year?	
	How frequently have you borrowed money at extremely high-interest rates over the past year?	
Spending control	When making spending decisions, I carefully consider my financial situation.	SPC
	When making a cryptocurrency investment decision, I try to spend my money wisely.	
	When making a cryptocurrency investment decision, I try to put in only a little time or effort.	

Research model:

$$\eta 1 = \eta\beta + \beta 1\xi 1 + \beta 2\xi 2 + \beta 3\xi 3 + \beta 4\xi 4 + \varepsilon \quad (1)$$

Information
$\eta 1$ = Past year investment (PYI)
$\eta\beta$ = Constant coefficient
$\beta 1\xi 1$ = Intergroup bias (IB)
$\beta 2\xi 2$ = Subjective norms (SN)
$\beta 3\xi 3$ = Overborrowing (OB)
$\beta 4\xi 4$ = Spending self-control (SPC)
ε = Error disturbance

4. Empirical Result

4.1. Demographic and Descriptive Statistics

In this study, 309 of the 400 crypto owners were actively involved in social clubs. Table 3 presents the demographic of respondents, including the percentage of past year investments (PYI), gender, age groups, type of occupation, and area. PYI describes respondents who invested in cryptocurrency over the past year as 35.90 percent of the total respondents. The remaining 64.10 percent are crypto owners who did not invest in cryptocurrency. The age groups of respondents are between 21 to 50 years, whereas the age category of 21 to 30 years dominates by 52.4%. Most respondents work in the private sector (74.8 percent), followed by business owners at 17.2 percent in the next position. This study conducts the Fisher exact test between gender and the dependent variable. The result show an exact significant (2-sided) Fisher exact test value of 0.153 (> 0.05), confirm that the sample is free from gender bias problems.

Table 3. Demographic of respondents.

PastYear-Invest (PYI)	%	Gender	%	Age	%	Occupation	%	Area	%
Sample of 400 crypto owners									
Yes	30.0	Male	47.8	21-30	49.8	College student	4.3	Jabodetabek	20.0
No	70.0	Female	52.2	31-40	37.3	Private employee	76.5	Surabaya	20.0
				41-50	13.0	Business owner	15.3	Semarang	20.0
						Full-time housewife	3.3	Bandung	20.0
						Unemployment	0.8	Medan	20.0
A sample of 309 crypto owners actively involved in social clubs									
Yes	35.9	Male	44.0	21-30	52.4	College student	4.5	Jabodetabek	23.3
No	64.1	Female	56.0	31-40	38.2	Private employee	74.8	Surabaya	16.2
				41-50	9.4	Business owner	17.2	Semarang	24.9
						Full-time housewife	2.9	Bandung	23.9
						Unemployment	0.6	Medan	11.7

Table 4 shows the descriptive statistics of the dependent variable of PYI using categorical data, whereas the answer yes is given the number 1 and 2 otherwise. Independent variables apply the mean score of the item indicators using a five-point Likert scale.

Table 4. Descriptive Statistics.

	N	Mean	STD	Min	Max	VIF
PYI	309	1.641	0.481	1	2	
IB	309	3.435	0.823	1.00	5.00	1.882
SN	309	3.306	0.754	1.20	4.80	1.859
OB	309	1.965	0.795	1.00	5.00	1.015
SPC	309	4.123	0.656	1.00	5.00	1.035

4.2. Hypothesis Result

The hypothesis testing begins with the determination of the validity and reliability of the indicators. The validity results using Pearson Correlation show coefficient values between 0.614 to 0.889 (r> 0.60) for each item indicator so that it can be concluded that item indicators can be used to measure the construct. The examination of reliability with Cronbach's alpha shows that a value greater than 0.60 can be interpreted as high reliability and an acceptable index (Pallant, 2001). Cronbach's alpha values were 0.807, 0.807, 0.728, and 0.612 for IB, SN, OB, and SPC. The corrected item-total correlation ranged from 0.388 to 0.741, indicating good scales (Ferketich, 1991). The Pearson correlation results in table 5 display that the correlation coefficient between variables does not exceed 0.7. Thereby, it can be concluded that there is no strong correlation between variables or is at a moderate correlation level (Schober, 2018; McLeod, 2022).

Table 5. Pearson Correlation matrix.

	PYI	SN	IB	OB	SPC
PYI	1				
SN	0.191**	1			
IB	-0.028	0.675**	1		
OB	-0.207**	-0.008	0.025	1	
SPC	0.051	-0.004	0.104	-0.108	1

** *significant at the 0.01 and 0.05 level

A binary logistic regression was employed to determine the impact of intergroup bias, subjective norms, and self-control derived from factor analysis on the crypto investment decision. Table 6 shows the results of logit model with the Wald test. The empirical result confirms that the intergroup bias (IB), subjective norms (SN), and overborrowing (OB) factors were significant (ϱ<0.05) predictors of the odds of PYI. In contrast, the spending control (SPC) factor was unconfirmed to predict the odds of PYI. Furthermore, the influencers in the group of subjective norms (SN) do not suggest the crypto owners investing during the heaviest period. On the contrary, intergroup bias (IB) and overborrowing (OB) have been predictors of cryptocurrency investment over the past year. This study found that overborrowing bias (OB) has a stronger predictive ability to invest in cryptocurrency than intergroup bias (IB). The exponential values of intergroup bias (IB) and overborrowing (OB) are 0.423 and 0.576, respectively, indicating that the ability to predict the odds ratio of PYI is greater in overborrowing (OB). The coefficient β1 of intergroup bias (IB) reveals that the odds ratio of investing in cryptocurrencies over the past year decreases when the value of IB increases by one. The coefficient β1 of the subjective norm (SN) is 1.204, and the exponential coefficient is 3.333, meaning that the odds ratio of investors who did not invest in cryptocurrencies over the past year increases by 3.333 times as the value of SN increases by one when the other predictors are held constant.

Table 6. Coefficient of Predictor Factors.

	Dependent: PastYearInvestment (PYI)				
	β	**S.E.**	**Wald**	**Sig.**	**Exp(β)**
IB	-0.859	0.233	13.556	0.000	0.423
SN	1.204	0.251	23.095	0.000	3.333
OB	-0.551	0.162	11.577	0.001	0.576
SPC	0.227	0.198	1.311	0.252	1.254
Constant	-0.230	1.039	0.049	0.825	0.794

The goodness-of-fit statistics assess the fit of the logit model to the actual outcomes (Peng et al, 2002). The omnibus test shows a significant model $\chi 2$ (6) of 14.545 with a ϱ-value of 0.000 (ϱ<0.05) for the PYI model. The -2 log likelihood (-2LL) estimate measures how well the estimated model fits with categorical data (Suthar et al, 2010). The value of -2LL for the model is 363,157. Hosmer and Lemeshow's (Hosmer et al, 1997) test result demonstrates a not significant value of 0.069 (ϱ>0.05). Thereby the model fit can be preserved.

Predicting a logit model accurately, including correctly predicting the outcome (Hosmer et al, 1997). Table 7 shows the ability to predict the PYI model of 73.463 percent. The ability to predict the crypto owners' decision not to invest in cryptocurrency (91.919 percent) is better than predicting investment decision over the past year (40.541 percent). The predictive ability of the model for cryptocurrency investment decisions (PYI = yes) is below 50 percent or weak. In other words, other factors not analyzed in the model influence investment decisions during the extreme declining period.

Table 7. Predicted Results.

		Predicted		
		PastYearInvest (PYI)		
Observed		Yes	No	Percentage Correct
PastYearInves (PYI)	Yes	45	66	40.541
	No	16	182	91.919
Overall Percentage				73.463

Several assumptions must be met in logistic regression. First, the linearity assumption uses box-tidwell transformation (Osborne, 2017; Field, 2018) to check for linearity between predictors and the logit. The results of the linearity test reveal that the box-tidwell transformation for the four independent variables is not significant to the dependent variable, meaning that the linearity assumption is met. Second, the multicollinearity test in table 4 shows the Variance Inflation Factor (VIF) value between 1.015 to 1.882 for the four independent variables.

4.3. Discussion

The results from this study show that intergroup bias (IB) and overborrowing (OB) behaviors are the most stimulating factors contributing to the cryptocurrency investment decision in an adverse market. Both factors contribute to irrational behavior in making an investment decision, specifically in the high uncertainty condition over the past year. Investors with the characteristics of having a high trust bias towards their social group and high overborrowing behavior have a tendency to invest in cryptocurrency over the past year when the price dropped by 67% from the highest point in November 2021 to the end of August 2022 when data collection was performed. However, this study provides evidence that subjective norms (SN) of the primary social environment caused crypto owners to refrain from investing in cryptocurrency over the past year.

Different types of the social environment have distinctive effects on cryptocurrency investment decisions in a high-uncertainty market. The dual-system perspectives can explain these distinctive effects, which discuss reflexive and reflective perspectives (Ryu & Ko, 2019). Cryptocurrency investment, as a speculative investment activity, emerges as a natural response to individual high and low-impulse interactions (Ryu & Ko, 2019). When impulsive and reflexive investors react most strongly, investors can make irrational decisions. Nevertheless, a reflective perspective encourages rational behavior. These two impulses go hand in hand. Investors can receive different impulses of investing or not investing in cryptocurrency simultaneously. Dual-system perspective, reflexive and reflective, does not occur in isolation but side by side in speculative cryptocurrency investments. Investors who decided to buy or not buy crypto over the past year show that the reflexive and reflective system runs in harmony in the decision-making process, whether influenced by intergroup bias or subjective norms. Consistent with da Gama Silva et al. (2019) found that negative news in the cryptocurrency markets is related to behavior bias.

Intergroup bias from the secondary group of investors' social environment, such as religion-based groups and sports groups, contributes to irrational behavior when making an investment decision. There are two fundamental explanations related to intergroup bias and irrational behavior. First, investors who are actively involved as members in a social group tend to behave more positively, provide greater rewards, and have higher trust in the group members than outside groups or known as trust bias. The trust bias encourages investors to behave identically to their group members and make irrational investment decisions since they want to be recognized in the group. Furthermore, intergroup bias encourages investors to act fast, impulsive, automatically, and unconsciously in making investment decisions to obtain financial knowledge, resources, and business opportunities from their social groups, which can increase their income. Interaction between members of a social group or network as bridging and bonding capital (Lei & Salazar, 2022) can increase the members' income and wealth status (Zhang et al., 2018). Second, cryptocurrency investments provide different options because of their attractive characteristics, high volatility, higher average returns, accessibility of weekend trading, and low correlation with traditional assets. These characteristics are the advantages of investment diversification (Brière et al., 2015). Then, the social group, which generally prioritizes individual wealth status and exclusive networking, tends to stimulate the irrational behavior of crypto owners in making investment decisions.

Regarding to the subjective norms, this study shows that the investors received a stimulus from their primary group of social environment, for example, peers, the most important persons, and the price trends, not investing in cryptocurrency in the adverse period. Cryptocurrency is a speculative investment instead of a long-term investment (AFM, 2022). Indonesian regulations state that crypto is illegal as a medium of exchange. However, it is allowed to be traded as a commodity (Jakarta Globe, 2022), thereby expanding its function as a speculative investment. Previous studies also confirmed that Bitcoin is mainly used as a speculative asset rather than an alternative currency (Blau, 2017; Baur et al., 2018). Thus, in a high uncertainty condition, persons in the closest social environment of crypto owners tend to act cautious, slow, controlled, conscious, and analytically, exposing the reflective system. They try to convince crypto owners not to invest in cryptocurrency during the heaviest period.

Besides intergroup bias, the other impetus to invest in cryptocurrency in the declining market arises from overborrowing bias. The reason is that individuals with low self-control often act on a reflexive perspective, leading to high levels of unplanned (Friese & Hofmann, 2019) and irrational behavior. Consistent with Ryu & Ko (2019) stated that strong impulses and weak self-control drive speculative investment behavior in the cryptocurrency context. Easy access to fintech credit markets increases the risk of individuals falling into debt traps (Yue et al., 2022). Liu & Zhang (2021) explained that easy access to online consumer credit became one of the causes of severe financial risk. The digital credit market trap is a challenge faced by crypto owners, who generally always come into contact with digital media.

The theoretical and practical implications of this study are described in several sections. First, survey studies on biased behavior and cryptocurrency investment decisions are minimal, so this study enriches the literature on the irrational decisions of crypto owners, especially in Asia. Several crypto owners' studies that are relevant to this study include Fujiki (2021) in Asia, Stix (2021) in Europe, and Zhao & Zhang (2021) in the USA. More specifically, studies with a sample of crypto owners in the Asia region have yet to receive much attention. Second, this study adds to the understanding of the social contagion theory in analysing the role of intergroup bias in crypto owners' decisions in one of Southeast Asia's largest countries, Indonesia. Indonesia is identical to the collective community and young age generation that is relevant to intergroup bias behavior and cryptocurrency investment. Third, this study provides a new understanding of the dual-system perspective by exploring two types of social environments: subjective norms and intergroup bias. Subjective norms and intergroup bias provided a strong different impetus for cryptocurrency investment in adverse market conditions. Subjective norms have caused investors to refrain from investing in cryptocurrency over the past year. Contrary, intergroup bias contributes to cryptocurrency investment even in declining market conditions. Fourth, the findings of overborrowing bias in cryptocurrency investment decisions open a new perspective that crypto owners with overborrowing behavior have a tendency to act impulsively and irrationally, mainly when associated with a speculative investment in adverse market conditions. Finally, this study's practical implication is to provide government input to prevent vulnerable individual investors from buying or investing in cryptocurrencies.

5. Conclusions and Limitations

This study investigates whether intergroup bias, subjective norm, and self-control bias are predictors of crypto owners' investment decisions over the past year of the declining cryptocurrency market. Self-control bias in this study explores two types behaviors, overborrowing and spending control. The results reveal that intergroup bias and overborrowing are the most impulsive factors contributing to the cryptocurrency investment decision over the past year, especially in the heaviest period. The empirical results indicate that intragroup bias due to the contagion effect from secondary group of investors social environment, for example religious-based groups or sports clubs, encouraged investors to invest in the cryptocurrency market even though the market is in adverse conditions. Intergroup bias behavior that is more positive towards their group members than outside group potentially results in irrational behavior since the trust bias toward their group influences the investment decision. The other finding is overborrowing bias causes investors to behave irrationally since instead of solving their debt problems, they prefer to spend their money on cryptocurrency investment in adverse market conditions.

In contrast, this study reveals that subjective norm from primary group of social environment, for example peers, the most important persons, and market price influences the decision not to invest in the adverse cryptocurrency market. The subjective norm factor indicates the reflective system that is slow, controlled, and analytical in making investment decisions during significant cryptocurrency price declines. The different result between influence of subjective norm, intergroup bias and overborrowing biased behaviors explain that there is a dual-system perspective, reflexive and reflective, which investors experience simultaneously and influence investment decisions. When impulsive and reflexive system reacts most strongly, investors can generate irrational behavior and make irrational investment decisions. However, the reflective perspective encourages rational behavior. Finally, spending control bias is unconfirmed as a predictor of cryptocurrency investment decisions.

This research has some limitations. First, the location of the crypto owner population cannot be determined. Alternatively, internet users are used as the population of crypto owners in this study. Since not all internet users are crypto owners, there is the possibility for differences between internet users and crypto owners. Second, with regard to the number of crypto owners that responded to this study, it is still necessary to gather additional samples from all over Indonesia in order for them to accurately represent cryptocurrency investors. Third, this study does not distinguish between investors who make direct or indirect investments through funding. Therefore, there is a potential for investment decisions to be biased due to the influence of fund managers. Finally, the model's ability to anticipate the decision not to invest in cryptocurrency is greater than its ability to predict the decision to invest. In addition, the results of this study must be interpreted with caution due to the possibility of other factors in predicting the decision during a gloomy phase. Therefore, it is anticipated that future studies will enhance the predictive model by incorporating more variables that have the ability to affect the choice to invest in cryptocurrencies during a gloomy phase.

For future study, our research recommends developing a model including other biased behavior and investors' demographic variables that affect vulnerable decisions by cryptocurrency investors. Future research needs to explore the other dimension of bias behaviors which are still extensive and should investigate the influence of biased behaviors on cryptocurrency investment decisions in international settings.

Author Contributions: E.T Prepare original manuscript, research background, literature review, conceptual model, methodology; S.E.H using SPSS software, supervising processing, validation, reliability analysis, and hypothesis analysis; R.W descriptive statistics testing, final article analysis and analysis. J.T Supervision, correcting writing errors. Authorship must be limited to those who have con-tributed substantially to the work reported.

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