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The Impact of Behavioral Factors on the Actions of Investors in Cryptocurrency Market

Abstract

The cryptocurrency market is a modern investment platform based on blockchain technology, with a decentralized system, which attracts numerous investors because of potential high returns. Since these markets are relatively new, individual biases are assumed to strongly influence investors' behavior and further investment decisions. Research was conducted using a survey analysis among 109 cryptocurrency investors in Croatia. In order to obtain the results, partial least squares structural equation modeling was used. It was found that herding and overconfidence positively affect investment intention. This implies that investors are more likely to engage in cryptocurrency investments if they follow the crowd and if they tend to overestimate their skills and knowledge. Conversely, prospect theory negatively impacts investment intention, indicating that risk aversion - especially in these emerging markets - reduces investment intentions due to concerns about potential loss. The main limitation is the sample size, which could have been larger if the data collection period had been longer. Additional behavioral factors, as well as personality traits, can be taken into consideration for future research, since investment intention is potentially defined by many other variables. Since there is no similar research for Croatian cryptocurrency investors, this research contributes to the literature by expanding and confirming some of the previous conclusions. The results help to understand the psychology of investors in cryptocurrency markets in order to improve their investment strategies. Additionally, educational programs can be developed, and trading platforms can be improved for the benefit of investors.

Keywords: behavioral finance, cryptocurrency, investment intention, herding, overconfidence, prospect theory

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1. INTRODUCTION

Contrary to the traditional financial theory, the behavioral economic theory is becoming increasingly popular. It assumes that investors are not fully rational when making decisions related to their own investments. Therefore, this paper aims to examine the influence of various behavioral factors on investors' behavior on the volatile cryptocurrency market, which has recently become more and more attractive among the general population. Traditional financial theory states that investor behavior does not significantly affect price fluctuations of cryptocurrencies and other assets in financial markets. The previous statement argues the existence of investor demand, which will certainly be satisfied by arbitration transactions and exchange. Al-Mansour (2020) states that investors typically believe they make investment decisions rationally and logically. However, behavioral finance theory argues that the behavior of investors (emotions, cognitive biases, etc.) significantly affects their performance and the investment intention and, consequently, the asset prices on the market. This implies that behavioral factors are one of the main determinants of financial decisions.

The growing popularity of the behavioral finance theory stems from increasing empirical research demonstrating that behavioral patterns, personality traits, emotions and similar characteristics greatly influence investor behavior. Most of the previous studies have focused on traditional stock markets, but a growing interest in alternative investments, such as cryptocurrency, suggests that these investors are also not entirely rational. Namely, in the context of investments, especially cryptocurrencies, scholars have often focused on exploring the impact of herding behavior and social influence on investor's intention and decisions (Gazali et al., 2018; Al-Mansour, 2020; Bhuvana & Aithal, 2022; Bui, 2022; Kalimasada & Rohim, 2023; Kaur et al., 2024; Sharma et al., 2024). All of the findings imply that crypto investors are greatly influenced by other investors' actions. Market volatility, uncertainty and lack of information are the most common reasons for this kind of behavior. Another investor trait that can influence their behavior is overconfidence, which occurs when investors overestimate their knowledge. It was found that overconfident investors are more prone to investing in general, and that men are more confident compared to women (Al-Mansour, 2020; Sudzina, et al., 2021; Syarkani & Tristanto, 2022; Kaur et al., 2024; Nyhus et al., 2024). Obviously, investors' own optimism, attitude and personality that lead to overconfidence, make them irrational in their investment decisions. Higher subjective knowledge can also lead to speculative investments with negative consequences (Sharma et al., 2024). Individual risk tolerance defines asset preferences and higher risk tolerance has been connected with more risky assets, such as cryptocurrency (Gazali et al., 2018). Moreover, prospect theory's risk aversion and loss aversion have been found to shape investors' decisions and future investment intention (Al-Mansour, 2020; Mattke et al., 2020; Kaur et al., 2024). Previous errors contribute to investors' regret and can make them more risk averse. This risk aversion decreases investment intention in cryptocurrency (Mattke et al., 2020). Risk tolerance has been found to positively affect investment decisions, while experiencing regret had a negative effect (Sa'diyah et al., 2024). Other characteristics, such as financial literacy, fear of missing out, attitude towards investments were also studied. However, despite extensive research on investor behavior, there is a gap in understanding how these behavioral biases specifically influence investment intention in the context of cryptocurrencies, particularly in Europe. Research in a nearby area has only found that Albanian investors are hesitant towards cryptocurrencies and Macedonian crypto-adopters were mostly passive and prone to seeking advice (Nasto & Sulillari, 2021; Levkov et al., 2022). While cryptocurrencies are gaining popularity, they are still relatively underexplored in the Croatian market and broader European context. This research aims to address this gap by examining the behavioral factors that drive investment intention in the cryptocurrency market, with a focus on irrational decision-making patterns such as herding, heuristics, and biases proposed in prospect theory.

2. LITERATURE REVIEW

The cryptocurrency market represents a modern investment platform with a decentralized system. Thanks to decentralization based on cryptographic protocols, it differs significantly from traditional financial markets. Cryptographic protocols provide anonymity, low costs, and faster transactions. Despite high risks, cryptocurrency markets attract investors and the public due to their dynamism, volatility, and high potential returns (Bui, 2022). Market price fluctuations arise not only from the fact that it is a developing market, but also from various variables, such as economic policy uncertainty, market yields, volatility, and asset volume (Youssef, 2022). However, a key factor explaining cryptocurrency market turbulence can be attributed to behavioral financial theory, particularly private investor behavior. In other words, investor demand for a particular currency shapes its price value (Poyser, 2018). The cryptocurrency market is based on blockchain technology, and active participants are often small investors, individuals, and households (Arnerić and Mateljan, 2019). The history of the cryptocurrency market dates back to 2009, when an unknown creator Satoshi Nakamoto introduced Bitcoin, the first cryptocurrency. However, the market experienced its real boom and media attention in 2013, when significant price changes occurred. Investors then recognized the high potential for returns, attracting a broader audience and institutional investors. Bitcoin became the dominant currency, but exhibited long-term volatility and the creation of speculative bubbles. Market interdependence, price fluctuations, and low regulation create challenges for the stability and liquidity of the financial system. Maintaining stability becomes a challenge because cryptocurrency markets operate autonomously, complicating regulatory efforts (Arnerić and Mateljan, 2019). On the other hand, there is interconnectivity with other financial markets, affecting economic activity and capital flows. The cryptocurrency market attracts increasing interest from politicians, institutional, and individual investors worldwide. The new technology provides new investment opportunities that are contrary to traditional ones. Despite the instability of cryptocurrencies that generates speculation and uncertainty, they offer alternative investment possibilities and can serve as a hedge against traditional financial instruments (Youssef, 2022).

The correlation analysis between investor behavior and asset returns is considered in the light of two contrasting financial theories: classical financial theory and behavioral economics theory. Classical financial theory argues that behavioral factors do not influence market prices, while behavioral economics theory acknowledges the impact of behavior on investment decisions, resulting in an influence on market prices and asset value (Al-Mansour, 2020). This theory explores market irregularities, such as cognitive effects and individual perceptions of risk and reward, which classical theories cannot explain, thus contributing to market inefficiency, fragility, and anomalies (Al-Mansour, 2020).

Accordingly, investors are considered irrational participants in the financial market, whose financial decisions are controlled by emotions and sentiment. Views on market (in)efficiency vary according to theoretical positions, with classical financial theory claiming that all markets are efficient, while behavioral financial theory challenges this assertion, highlighting market information inefficiency (Ritter, 2003). American economist Eugene F. Fama introduced the Efficient Market Hypothesis (EMH) in the 1960s, claiming that it is impossible to deceive the market and that individuals act completely rationally, free from emotional influence. Despite being the foundation of modern finance, the EMH theory faces significant controversy and counterarguments from contemporary financial theorists.

This research investigates heuristic factors, herd behavior theory, and prospect theory, which play a crucial role in supporting the behavioral theory of finance. The application of prospect theory, heuristics, and herd behavior theory is necessary to explain the unique nature of the cryptocurrency market. Cryptocurrency prices, which do not reveal all relevant information to investors, are determined by various factors, including investor emotions, instinct, and various speculations, leading to extremely volatile market prices. Prospect theory proves to be a key determinant of individual investment decisions, with investors often basing their choices on their own intuition and instinct (Al-Mansour, 2020).

This theory particularly explains how irrational investors experience gains and losses based on the theory of loss aversion. Investors perceive losses more intensely than gains, resulting in irrational behavior in conditions of increased uncertainty (Ricciardi and Simon, 2000). Investors' loss aversion is based on the assumption that they assign greater importance to losses and gains than the final asset value, with decision weights replacing gains (Sewell, 2007). In other words, irrational investors often focus on changes in wealth rather than wealth levels, which would be typical for rational investors (Ritter, 2003). Prospect theory suggests that individuals deviate from rational behavior when making decisions. This theory is most suitable for describing and predicting individual investment choices in an uncertain and risky environment (Baker and Nofsinger, 2010). Tversky and Kahneman (1974) introduced the concept of prospect theory, opposing the rational behavior of individuals and claiming that investment choices are driven by their cognitive abilities, illusions, and biases (Baker and Nofsinger, 2010).

Heuristics are defined as a set of rules that individuals apply in uncertain conditions to simplify investment decisions (Waweru et al., 2008; Vuković and Pivac, 2024). In other words, the concept of heuristics suggests that individuals do not follow strict laws of probability, but instead they use shortcuts to shape their preferences that prevail over textbook logic (Baker and Nofsinger, 2010). Given the exceptional instability, uncertainty, and speculation propensity in the cryptocurrency market, private investors often succumb to heuristics, i.e., systematic biases in their investment choices that can be one of the key causes of market volatility.

Herd behavior is often used as a decision-making approach (Al-Mansour, 2020), where individuals act collectively without rational consideration, imitating the actions of other investors in the market (Vuković and Pivac, 2024).

The analysis of investor characteristics in the cryptocurrency market focuses on researching and studying the specific traits of each individual investor. Aspects of the relationship with cryptocurrencies and the crypto market are considered by observing characteristics such as risk tolerance, behavioral factors, individual personality traits (e.g., impulsiveness), the ability to react quickly to the market, and the pursuit of novelty and adoption of contemporary trends, along with the choice of information sources. Delfabbro et al. (2021) examine the psychology of the cryptocurrency market, highlighting interesting aspects related to investor characteristics. The authors argue that investors are similar to gamblers, as evidenced by the assumption that those engaged in gambling and high-risk trading are more likely to quickly and successfully adopt cryptocurrencies. Investor decisions are often influenced by internal processes, such as their impulsiveness, excessive self-confidence, and fear of missing opportunities. Investors also show a strong motivation to explore novelties in the market. The illusion of control, according to the theory of behavioral finance, can lead to overestimating one's decision-making abilities and underestimating the risks associated with investing in cryptocurrencies. The fear of missing out is expressed through reluctance to sell, increased feelings of security, and the creation of hope for a better tomorrow (Delfabbro et al., 2021). Increased confidence in investors' own abilities, knowledge, and skills often results in overconfidence, which is closely related to an optimistic mindset. Investors believe they will assess the market better or achieve above-average success. Various influential individuals (influencers) promoting cryptocurrency trading often present their own predictions and speculations, encouraging their followers to take certain trading actions, whether larger or smaller. This sequence of events often causes fluctuations in the market and shapes herd behavior trends among social media users. This behavior also explains the creation of bubbles in investment markets. Experts suggest that individual behavior based on the actions of others has implications such as mimicking others and dismissing one's own information, indicating an optimistic perspective of individual investors and minimizing the likelihood of negative outcomes.

In his examination of behavioral finance within the cryptocurrency market, Poyser (2018) explores herding phenomena by establishing connections with economic theory through empirical research, by exclusively using herding theory as a factor. According to his findings, the analysis suggested a significant role of herding theory in influencing prices within the cryptocurrency market. In other words, behavioral finance factors contribute to determining prices in the cryptocurrency market. This confirms the thesis that investors prioritize public information over their private information in the cryptocurrency market.

Boxer and Thompxson (2020) found that herd behavior exhibits complexity and its impact may vary across different dimensions, depending on the specific context. Their study has shed light on the specific dimension of herding that plays a role in fostering a positive attitude toward cryptocurrency investment. The variable Imitating Others, which can be understood as a factor of herding behavior, has emerged as a significant factor in predicting the attitude toward cryptocurrency investment. It is concluded that those individuals who are more observant of others engaging in cryptocurrency investment tend to replicate this behavior in their own investment decisions. When applied to the surveyed population of online cryptocurrency purchasers, it is conceivable to propose that this dynamic might represent a type of information cascade. In such a scenario, all members participate in herd behavior, even though the whole group may not possess a comprehensive understanding of the market or take new information into consideration (Heshan, 2013).

Bouri et al. (2019a) observed uncertain environments and conducted a particular study on herding behavior in the cryptocurrency market. It was found that herding theory occurred as uncertainty increases. The findings offered valuable perspectives on managing portfolios, handling risks, employing trading strategies, and assessing the effectiveness of the financial market. Bouri et al. (2019b) were inspired by the methods of Chang et al. (2000) and Stavroyiannis and Babalos (2017), and they also tried to demonstrate the fact that herding behavior is present in the cryptocurrency market and that it appears to fluctuate over time. In their separate investigation, they explored the potential for explosiveness in one cryptocurrency to influence similar behavior in others, uncovering evidence of interconnections among those assets.

A study from Din et al. (2021) investigated the impact of behavioral biases on herding for Islamic financial products among 410 respondents through a survey questionnaire. Behavioral biases in question were self-attribution, illusion of control, information availability and herding. The results obtained through PLS-SEM reported that all variables, i.e. information availability, illusion of control and self-attribution showed a positively significant impact on herding. Information availability was found to be the strongest predictor.

According to authors such as Keynes (1937), Bikhchandani and Sharma (2000), Chang et al. (2000), Shiller (2003), Chiang and Zheng (2010), Hassairi (2011), and Bashir et al. (2014) market inefficiencies and external locus of control may lead to herding. According to Din et al. (2021), the Pakistani market is inefficient, so it is not quite a surprise that investors believe that they don't hold full-scale information in their own hands, while they also believe that other investors have utter and better information. That is the exact reason why investors become doubtful and uncertain, which is the main cause that leads to herding behavior among them. In a state of uncertainty, when the lack of information occurs, investors tend to behave in a certain way, believing that others have fuller knowledge and are better informed. As a consequence, there is a certain amount of individuals that are constantly trying to obtain information by imitating decisions of other financial market participants.

Coskun et al. (2020) investigated the existence of herding behavior in the cryptocurrency market, regarding the uncertain market environment. The authors obtained a negative and statistically significant correlation between return dispersion and market returns, showing evidence of herding behavior. This is supported by the study by Economou et al. (2018), who stated that herding could show asymmetric behavior during periods of market growth and decline. In the study by Economou et al. (2015) it is stated that down-markets lead to herd behavior because they lead investors to sell their financial assets in order to avoid potential losses, especially in the event that bad market conditions are prolonged.

Studies have also found that investors' overconfidence positively affects attitude and decision to invest (Syarkani & Tristanto, 2022). Even personality traits, such as extraversion and agreeableness were used to measure one's overconfidence and it was found that cryptocurrency early adopters were more overconfident, especially through extraversion. Males were found to be at least three times more likely to use cryptocurrency (Sudzina, et al., 2021).

Both overconfidence and herding were analyzed as predictors of investment decisions among Millennial generation in Malang City. It was found that only herding had a significant effect, while overconfidence did not significantly affect investment decisions of Millennials (Kalimasada & Rohim, 2023).

A recent study by Kaur et al. (2024) found that herding, overconfidence and loss aversion significantly positively influenced investment decisions in the cryptocurrency market directly, as well as indirectly through FOMO (fear of missing out) as the mediator.

As it can be seen, herding was most extensively explored in the context of cryptocurrency market, most likely since it is still a new and unknown type of market and potential investors do not have enough information and/or knowledge to engage in such activities. However, multiple behavioral factors were found to be predictors of investment decisions and intentions. Therefore, the research states the following hypotheses:

H1. Herding significantly influences investment intention in the cryptocurrency market.

H2. Overconfidence heuristic significantly influences investment intention in the cryptocurrency market.

H3. Prospect theory's risk aversion significantly influences investment intention in the cryptocurrency market.

3. DATA AND METHODOLOGY

The research is focused on identifying behavioral factors that influence future cryptocurrency investment intentions, therefore a survey questionnaire was chosen as an adequate data collection method. The questionnaire, designed according to previous research (Al-Mansour, 2020; Bui, 2022) was distributed online in the period from June to November 2023. In addition to basic socio-demographic questions, the survey measured respondents' level of agreement with specific statements on their behavior on the cryptocurrency market and the investment intention, on a 5-point Likert scale, where 1 indicates strong disagreement, and 5 indicates strong agreement with a statement. The target population comprised cryptocurrency investors in Croatia. Since investor names are not publicly available, the survey was distributed through investment companies (such as Electrocoin.hr), as well as through platforms such as Telegram and Facebook where there are groups of networked cryptocurrency investors. A total of 109 valid responses were collected. The sample includes 77.6% of male and 22.4% of female respondents. Almost half of the sample is younger than 30 years (42.1%). Most of the respondents are highly educated, since only 21.1% have not obtained any college degree. Most frequent degree among the respondents is a graduate degree (36.8%). When it comes to the investment period, a majority has been investing in cryptocurrencies 1-3 years (42.1%), while only 18.4% of investors have been on the crypto market for over 6 years.

Since the research hypotheses regarding the influence of three chosen behavioral factors on investment intention on the cryptocurrency market were tested using partial least squares structural equation modeling (PLS-SEM), the sample size of 109 cases is considered sufficient. Namely, PLS-SEM, as a non-parametric approach to SEM, can effectively handle both larger and smaller samples (Hair et al., 2017; Vuković, 2024). According to the sample size recommendations in PLS-SEM (Hair et al., 2017), for a model with 3 independent constructs, a sample size of 37 cases is sufficient to achieve 80% statistical power for detecting R^2 values of at least 0.25, with a 5% significance level. Additionally,

Table 1. Items

Code	Item	Mean	SD
HERD1	Other investors' decisions of choosing cryptocurrency types have an impact on my investment decisions.	2.83	1.076
HERD2	Other investors' decisions of the cryptocurrency volume have an impact on my investment decisions.	2.08	1.156
HERD3	I usually react quickly to the changes of other investors' decisions and follow their reactions to the cryptocurrency market.	2.42	1.219
H1	I believe that my skills and knowledge of the cryptocurrency market can help me to outperform the market.	3.66	1.002
H2	I completely rely on my previous experiences in the market for my next investment.	3.62	1.078
H3	I am capable of identifying the low point of the market.	3.59	1.002
P1	After a prior gain, I am more risk-seeking than usual.	3.33	1.037
P2	After a prior loss, I become more risk-averse.	3.28	1.224
INV1	I intend to invest in cryptocurrency at some point in the future.	4.18	1.156
INV2	It is likely that I will invest in cryptocurrency in the future.	4.21	1.123
INV3	I expect to invest in cryptocurrency in the future.	4.17	1.185

Source: Author's work according to Al-Mansour (2020) and Bui (2022)

a power analysis for an effect size of 0.15, a 5% error probability, and a model with 3 independent constructs indicates that with 109 cases, the achieved statistical power is 0.93, confirming that the sample size in the study is sufficient. PLS-SEM method was chosen as data analysis approach, since the variables in the model reflect behavioral concepts, i.e. constructs, which can only be measured indirectly. Additionally, the model explores the future investment intention, making it prediction-oriented, not just confirmatory. Moreover, the multivariate normality of the data is violated and the sample size is rather small for covariance-based SEM (CB-SEM), thus creating problems with convergence in model estimation (Hair et al., 2017; Sarstedt et al., 2023; Vuković, 2024). Data were analyzed using SmartPLS 4 (Ringle et al., 2024).

Items and their codes that are used in the model are shown in Table 1. Additionally, mean and standard deviation of each item is displayed. It can be seen that cryptocurrency investors are not very prone to herding behavior. However, they are neutral to moderately prone to overconfidence heuristic. As for the prospect theory elements, the investors are neutral, showing that there is no preference in lower or higher risk aversion. The tendency for future investments in cryptocurrency among the investors is high.

4. RESULTS AND DISCUSSION

The research model includes four constructs. Behavioral factors: herding (HERD), overconfidence heuristic (H) and prospect theory (P) have the role of exogenous factors in the model and their impact on the endogenous factor investment intention (INV) is observed. Firstly, convergent validity and reliability of the constructs were assessed (Table 2). All outer loadings for the indicators are statistically significant and substantially high, except for two items (HERD3 and H3) with loadings below 0.6. However, they were retained in the analysis, since they did not violate the overall construct validity. Convergent validity was tested using average variance extracted (AVE), which is above the threshold of 0.5 for all indicators. This implies that each individual construct explains more than 50% of its indicators' variance (Hair et al., 2017; Vuković, 2024). Thus, AVE values support the retention of items with lower loadings, as items can be accepted at lower loadings as long as they do not compromise AVE (Hair et al., 2019), and they are statistically significant, showing their meaningful contribution to their respective constructs. Furthermore, prior research has used these indicators (Al-Mansour, 2020; Bui, 2022) and their exclusion from the model would compromise the theoretical integrity of the constructs. Composite reliability values are above 0.7, confirming high levels of reliability. Considering all of these results, it can be concluded that all items adequately measure their corresponding constructs.

Table 2. Convergent validity and reliability results

Construct	Item	Outer loading	AVE	Composite reliability
Herding (HERD)	HERD1	0.854***	0.555	0.785
	HERD2	0.784***		
	HERD3	0.568*		
Heuristics (H)	H1	0.869***	0.529	0.757
	H2	0.810***		
	H3	0.418**		
Prospect theory (P)	P1	0.716***	0.629	0.771
	P2	0.863***		
Investment intention (INV)	INV1	0.986***	0.969	0.989
	INV2	0.989***		
	INV3	0.977***		

***p<0.01, **p<0.05, *p<0.10

Source: Author's work

Further analysis shows the results of discriminant validity testing. This test shows if the constructs in the model are truly conceptually different from the rest of the constructs in the model (Henseler et al., 2015, Hair et al., 2019). Firstly, according to the Fornell and Larcker criterion, discriminant validity is supported. Namely, the correlations between the constructs are lower than the square root of AVE for each construct (Table 3).

Table 3. Discriminant validity according to Fornell-Larcker criterion

	H	HERD	INV	P
H	0.727			
HERD	-0.065	0.745		
INV	0.407	0.160	0.984	
P	-0.003	0.147	-0.183	0.793

Source: Author's work

Discriminant validity was also confirmed with testing through heterotrait-monotrait (HTMT) ratio of correlations. HTMT is the ratio of the correlations between the indicators that measure different constructs and the correlations of the indicators that measure the same construct. Logically, the ratio should be as low as possible. As it can be seen from Table 4, all HTMT values are significantly lower than the threshold of 0.85, supporting the discriminant validity of the constructs (Henseler et al., 2015).

Table 4. Discriminant validity according to HTMT ratio

	H	HERD	INV	P
H				
HERD	0.237			
INV	0.459	0.193		
P	0.182	0.321	0.280	

Source: Author's work

Since the outer model's validity measures are satisfactory, in the next step, hypotheses were tested through the structural (inner) model (Table 5). It can be concluded that all behavioral factors significantly influence investment intention in the cryptocurrency market. Firstly, herding has a positive significant effect on investment intention (ß=0.219, p=0.031), making it a positive predictor of investors' future investment intention. This suggests that individuals who rely on other investors' decisions - regarding cryptocurrency types, volume and market actions - are more likely to invest in the future. This is expected, because investors who tend to imitate other people's actions are more likely to imitate the timing of an investment. This is especially true for cryptocurrency market, which is still relatively new and unknown to a high share of population. Thus, these unexperienced investors are probably more prone to herding behavior. The result is in line with previous research (Al-Mansour, 2020; Bui, 2022; Kalimasada & Rohim, 2023; Kaur et al., 2024; Sharma et al., 2024). Herding behavior may be greatly influenced by investor experience, financial literacy and other personality traits. The research sample shows that a majority of the respondents are not very experienced, since they have been investing for less than 3 years. This contributes to the positive herding effect. Although most of the respondents have some level of college degree, their financial literacy remains unknown. As already mentioned, investors with a lack of available information, knowledge or self-esteem tend to imitate the actions of others and invest at the same time, instead of making their own unique decisions. This is inevitably an important factor in the cryptocurrency market, as market volatility and uncertainty can make a confusing environment for investors, especially for those with specific internal traits, which should be studied in the future. In conclusion, the hypothesis H1. Herding significantly influences investment intention in the cryptocurrency market – can be accepted.

Additionally, overconfidence heuristic also positively affects investment intention (ß=0.421, p<0.001), showing that people who exhibit higher overconfidence, i.e. they have higher tendency to overestimate their skills and abilities, also have higher investment intentions. The result is in accordance with most of the previous research that claims overconfidence contributes to investment adoption and decisions (Al-Mansour, 2020; Sudzina, et al., 2021; Syarkani & Tristanto, 2022; Kaur et al., 2024), while it contradicts the findings of Kalimasada & Rohim (2023), who found no significant influence of overconfidence on investment decisions among Millennials. The result seems expected, since people will want to repeat a certain behavior, such as investing in cryptocurrency, if they perceive that they are extremely successful in it. Higher share of male investors, as well as high education levels, may contribute to overall higher overconfidence in the sample. According to this result, the hypothesis H2. Overconfidence heuristic significantly influences investment intention in the cryptocurrency market – can be accepted as true.

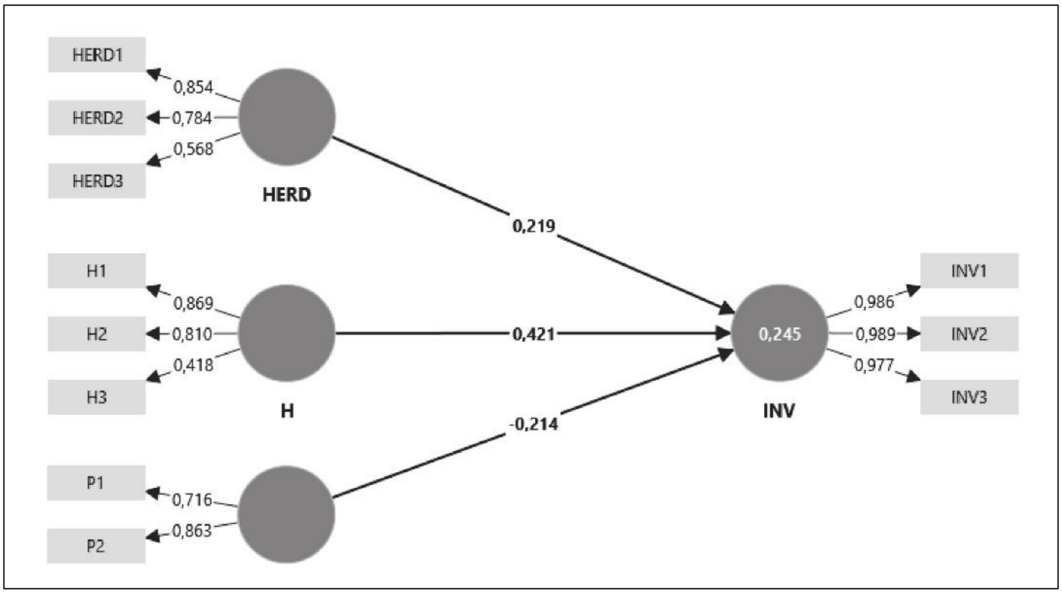
Lastly, prospect theory negatively affects investment intention (ß=-0.214, p=0.004). This shows that investors who make their decisions mostly based on money gains and losses, instead of the state of their money (wealth level), consequently have lower investment intentions. This could be due to differences in risk aversion, so higher levels of risk aversion often come after a prior loss. This loss causes an individual to feel more concern about similar future investments, therefore lowering their investment intentions. The finding contradicts previous research that has shown that prospect theory factors and loss aversion itself positively affect investment decisions (Al-Mansour, 2020; Kaur et al., 2024), but it is consistent with the findings of Gazali et al. (2018) and Sa'diyah et al. (2024). However, there is a lack of research directly connecting risk aversion with investment intention. Instead, other variables, such as different investment decisions, are used. Therefore, this is a unique finding stating that the factors of prospect theory actually decrease future investment intentions, due to increasing emotions of fear, sadness or individual's personality in general. Thus, the hypothesis H3. Prospect theory's risk aversion significantly influences investment intention in the cryptocurrency market – can be accepted as true.

Table 5. Structural model results

	Path coefficient	t-value	p-value
HERD → INV	0.219	2.163	0.031
H → INV	0.421	4.922	<0.001
P → INV	-0.214	2.887	0.004

Source: Author's work

Figure 1. Path diagram with estimates



Source: Author's work according to SmartPLS 4

Figure 1 presents the model with both outer and inner model estimates. The coefficient of determination (R^2=0.245) indicates that the model's in-sample predictive power is moderate (Ringle et al., 2014). More precisely, the combination of behavioral factors, i.e. the exogenous constructs in the model, explains 24.5% of the variance in the construct INV.

PLS-SEM's predictive approach is particularly interesting for social sciences. The model's out-of-sample predictive power was evaluated with the PLSpredict procedure. Key endogenous construct INV is examined for this purpose (Hair et al., 2017; Shmueli et al., 2019; Vuković, 2024) and the results are displayed in Table 6. Since all Q^2 predict values are positive, it means that PLS model has lower prediction errors than the linear regression (LM) model, which represents the naïve benchmark. The predictive power is then assessed by comparing the root mean squared error (RMSE) and mean absolute error (MAE) values of the PLS model with LM model. All RMSE and MAE values are lower in the PLS model compared to the LM model. Thus, the model has high predictive power (Shmueli et al., 2019), making it reliable for generalization and replication.

Table 6. PLS Predict results

Item	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
INV1	0.148	1.074	0.819	1.106	0.831
INV2	0.140	1.048	0.782	1.070	0.802
INV3	0.167	1.088	0.820	1.107	0.839

Source: Author's work

5. CONCLUSION

As the cryptocurrency market evolves and attracts new investors, understanding their behavior becomes increasingly important. These markets are still new and unknown, based on blockchain technology, with a decentralized system, offering high returns. For these reasons, it is attractive to many people, but not a lot of them are sufficiently educated or familiar with how it actually works. Similar to stock investments, especially in this kind of market full of uncertainty, behavioral finance theory is important for understanding investors' behavior and intentions to invest.

This research observed the impact of key behavioral factors on investment intention in the Croatian cryptocurrency market. The observed factors included herding behavior, overconfidence heuristic and risk aversion as a part of the prospect theory. It was found that herding and overconfidence have a positive effect on investment intention, and prospect theory has a negative effect. This implies that one's intention to invest in cryptocurrencies depends on other investors' actions, suggesting lack of experience. However, this is not a surprising result, since herding was found to be present on multiple cryptocurrency markets, which are still not familiar to a large share of population. These findings are entirely consistent with previous research (Al-Mansour, 2020; Bui, 2022; Kalimasada & Rohim, 2023; Kaur et al., 2024; Sharma et al., 2024). Herding is consistently being recognized as a positive predictor of cryptocurrency investment intention. Namely, it can be seen that Croatian cryptocurrency investors are not very experienced and in general, it is known that herding is common in Croatia. Furthermore, a lack of quality information and knowledge about the way these markets work contribute to herding behavior. A better understanding of the underlying causes of herding can provide more insightful results. Along with investor experience, their own personality traits, insecurity and emotions can trigger irrational herding behavior.

On the other hand, the impact of overconfidence suggests that people who are more prone to overestimate their knowledge and skills have higher investment intention, which is a logical result. This shows that some experienced and/or very confident investors are a part of the studied sample and that they mostly rely on their own skills, intuition and knowledge when making the decision whether to invest or not. This result confirms most of the previous research findings (Al-Mansour, 2020; Sudzina, et al., 2021; Syarkani & Tristanto, 2022; Kaur et al., 2024; Nyhus et al., 2024) and contradicts others (Kalimasada & Rohim, 2023). Although the research by Kalimasada & Rohim (2023) found no significant influence of Indonesian Millennials' overconfidence on their investment decisions, the effect itself was positive and their sample size was rather small. Additionally, Croatia is generally considered more developed than Indonesia, which can be another reason for contradicting results. A higher share of men and highly educated individuals in the sample may contribute to higher overconfidence of investors. Overall, overconfidence was confirmed to be one of the crucial factors that increases investment intention in cryptocurrency market.

Lastly, prospect theory's negative effect shows that people who base their decisions on gains and losses are less likely to invest in cryptocurrency. This is closely related to people's perception changes under different conditions. Thus, if an individual experiences a loss, he/she can become more risk averse, due to more concern about future events and avoidance of similar outcomes in their future investments. The finding does not align with some previous research (Al-Mansour, 2020; Kaur et al., 2024), while it confirms the findings of others (Gazali et al., 2018; Mattke et al., 2020; Sa'diyah et al., 2024). It is important to note that the variables in these studies are not entirely comparable, thus the research contributes to the literature by connecting prospect theory, mainly risk aversion, directly with investment intention. Nevertheless, the measures for prospect theory can be expanded with loss aversion and mental accounting to get a wider picture of the behavioral patterns in the cryptocurrency market. The drivers of risk aversion, such as personality traits, can be further explored. Different emotions can also be analyzed as a consequence of individual's risk aversion.

In conclusion, investors are not entirely rational and are significantly influenced by various behavioral factors. This study extends the field of behavioral finance by providing more evidence of psychological factors in the decision making process of investors in the cryptocurrency market, focusing on key factors of behavioral finance theory. Moreover, it is important to understand individual behavior from multiple aspects. Investors themselves should be aware of their behavioral biases and personality traits that can possibly influence their decisions and intentions, in order to improve them and to become better at risk management. Additionally, financial advisors can help investors develop more effective investment strategies according to their behavioral biases. Trading platforms can also integrate educational content for their potential investors in an attempt to improve their investors' decisions.

The research limitation can be recognized in the sample size, which might not be an accurate representation of the population, so increasing the sample size should be considered for future research. Although a significant influence of all studied behavioral factors on the investment intention was found, it is important to consider other potential predictors in this type of analysis. Incorporating personality traits, investor experience, emotions, financial literacy and other behavioral patterns into the model would give an even better insight into the drivers of investment intention in cryptocurrency. Additionally, a cross-country comparative analysis would provide a broader range of useful findings and perspectives.

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Utjecaj bihevioralnih faktora na ponašanje **investitora na tržištu kriptovaluta**

Sažetak

Tržište kriptovaluta je moderna investicijska platforma temeljena na blockchain tehnologiji, s decentraliziranim sustavom, koja privlači brojne investitore zbog potencijalno visokih povrata. Budući da su ova tržišta relativno nova, pretpostavlja se da individualne pristranosti imaju veliki utjecaj na oblikovanje ponašanja investitora i daljnjih namjera ulaganja. Istraživanje je provedeno anketnim upitnikom na uzorku od 109 investitora koji ulažu u kriptovalute u Hrvatskoj. Za dobivanje rezultata korištena je metoda strukturalnog modeliranja metodom parcijalnih najmanjih kvadrata. Utvrđeno je da ponašanje krda i pretjerano samopouzdanje pozitivno utječu na namjeru ulaganja. To implicira da će se investitori vjerojatnije uključiti u ulaganja u kriptovalute ako slijede gomilu i ako su skloni precijeniti svoje vještine i znanje. Suprotno tome, prospektna teorija negativno utječe na namjeru ulaganja, pokazujući da averzija prema riziku, posebno na ovim novo popularnim tržištima, smanjuje te namjere zbog zabrinutosti oko potencijalnog gubitka. Glavno ograničenje rada je veličina uzorka, koja bi se mogla povećati duljim razdobljem prikupljanja podataka. Dodatni čimbenici ponašanja, kao i osobine ličnosti, mogu se uzeti u obzir za buduća istraživanja, budući da je namjera ulaganja potencijalno definirana mnogim drugim varijablama. Budući da ne postoji slično istraživanje za hrvatske ulagače u kriptovalute, ovo istraživanje doprinosi literaturi proširujući i potvrđujući neke od prethodnih zaključaka. Rezultati pomažu u razumijevanju psihologije investitora na tržištima kriptovaluta kako bi poboljšali svoje investicijske strategije. Osim toga, mogu se razviti edukativni programi i poboljšati platforme za trgovanje u korist investitora.

Ključne riječi: bihevioralne financije, kriptovalute, investicijska namjera, ponašanje krda, pretjerano samopouzdanje, prospektna teorija