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Research paper

Cryptocurrency Purchase Intention: between Trends and Global Economic Dynamics

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Abstract

This research explores the influence of key behavioral factors on cryptocurrency purchase intentions in the context of a volatile digital asset market. Specifically, it investigates how herding behavior and perceived ease of use (PEU) directly affect individual investment decisions to purchase cryptocurrencies, and how global interest rate fluctuations moderate these relationships. Data were collected through an online survey of 210 active cryptocurrency traders in Indonesia and Malaysia, and the analysis employed a cross-sectional quantitative design us-ing structural equation modeling (SEM). The findings reveal that PEU has a significant positive impact on purchase intention by enhancing investor confidence, encouraging proactive information seeking, and alleviating the anxiety typically associated with digital asset investments. Additionally, the results show that global interest rate fluctuations play a moderating role, amplifying the effect of herding behavior on purchase intention. Specifically, higher interest rate volatility increases the influence of social conformity on investor decision-making. This research contributes to the field of behavioral finance and extends prospect theory by demonstrating the complex interplay between technology-related perceptions and macroeconomic risk signals in shaping investment behavior in the cryptocurrency market.

Keywords: *Cryptocurrency; Herding Behaviour; Perceived Ease of Use; Interest Rates; Prospect Theory.*

1. Introduction

Since the emergence of Bitcoin in 2008 by Nakamoto, cryptocurrency has rapidly evolved with the introduction of various digital currencies such as Ethereum, Binance Coin, and others. The primary advantage of these digital assets lies in their ability to eliminate intermediaries in financial transactions, thereby reducing costs and broadening access to the global financial system (Hunhevicz et al., 2024). Although cryptocurrencies offer numerous benefits, the market often experiences significant price fluctuations. This instability is not only attributable to the market's developmental stage but is also influenced by elements of market microstructure and general economic conditions, such as uncertainty in economic policies, volatility, and trading volume (Almeida, Gaio, & Gonçalves, 2024). Moreover, the unique price dynamics of Bitcoin exhibit patterns that differ from traditional assets like gold (Bespalova et al., 2024).

The issue of market efficiency in the context of cryptocurrency has sparked considerable debate (Dincer et al., 2024). Some studies indicate that factors such as herding behavior among individual investors and information asymmetry among traders render the market inefficient, while other research suggests that the cryptocurrency market demonstrates informational efficiency, albeit with varying levels depending on market liquidity (Treiblmaier & Sillaber, 2021). In Indonesia and Malaysia, interest in digital investment—especially cryptocurrencies—has shown significant growth. The increasing number of users on trading platforms such as Binance, Indodax, and Tokocrypto, which has now reached millions, reflects the public's growing enthusiasm to understand and invest in digital assets (Bappebti, 2024; Sakariyahu et al., 2024). This demonstrates that, despite challenges such as immature regulations and high price volatility, the adoption of this technology continues to expand alongside rising public awareness.

Alongside the potential gains, investing in cryptocurrency also carries various risks. Many investors use digital assets as hedging instruments because they offer portfolio diversification through tail risks that differ from those of other global assets (Bajwa, 2025). However, each cryptocurrency exhibits distinct volatility characteristics that evolve, necessitating careful risk management (Barbereau & Bodó, 2023; Ha, 2024).

Numerous studies have examined investor behavior in the cryptocurrency market by focusing on factors such as internal and external motivations, financial literacy, and the application of technology acceptance models (Bespalova et al., 2024; Bouri et al., 2025; Caferra, Morone, & Potì, 2022; Chen & Yang, 2024). For instance, research by Wei et al. (2025) reveals the influence of internal and external motivations on investment intentions, while other studies highlight the role of financial literacy as a moderating factor in markets like Saudi Arabia (Alomari & Abdullah, 2023). Nonetheless, many studies have concentrated on individual variables without integrating other external factors that might also affect investment decisions (Almajali et al., 2022).

In this research, we develop a model that links factors influencing cryptocurrency purchase intention, particularly Bitcoin, on platforms such as Binance, Indodax, and Tokocrypto. Grounded in Prospect Theory, the model explains how investors make decisions based on potential gains and losses relative to a reference point, such as the purchase price of Bitcoin, with loss aversion and emotional factors—particularly fear—playing a crucial role (Aliyu, Abd Wahab, & Kamis, 2025). According to this theory, investment decisions can be seen as a cognitive process where individuals assess risks and rewards, shaping their behavior in response to market dynamics (Colombo & Yarovaya, 2024).

2. Literature review

2.1. Prospect theory

Prospect Theory, introduced by Daniel Kahneman and Amos Tversky in 1979, is a theoretical framework that explains how individuals make decisions under conditions of risk and uncertainty. This theory challenges the fundamental assumption of traditional financial theory that individuals always act rationally by demonstrating that human decision-making is significantly influenced by cognitive biases and psychological factors (Fortin & Hlouskova, 2024).

One of the key concepts within Prospect Theory is loss aversion, which posits that losses are perceived as more painful than the pleasure derived from equivalent gains. In other words, individuals tend to experience greater psychological distress from losses than satisfaction from comparable gains, often leading them to prioritize the avoidance of losses even when opportunities for gains are present (Giannikos, Kakolyris, & Suen, 2023).

In addition to loss aversion, the theory emphasizes the importance of a reference point in the decision-making process. Individuals typically evaluate outcomes by comparing them to an initial state or pre-established expectations, which means that their perception of gains or losses is heavily dependent on how these outcomes are measured against that reference point. This explains why two people in different initial situations might assess the same outcome in very different ways (Krull, Loschelder, & Pelster, 2024).

Within this framework, Prospect Theory illustrates that human behavior in the face of risk is inconsistent. Individuals tend to be risk-averse when dealing with potential gains, yet become risk-seeking when attempting to avoid losses. This behavioral asymmetry in emotional and cognitive responses starkly contrasts with the efficient market theory, which assumes that decisions are always made logically and optimally (Bastianello, Chateauneuf, & Cornet, 2024).

Thus, Prospect Theory not only offers an alternative approach to understanding the decision-making process amidst risk and uncertainty but also provides a more comprehensive framework for predicting investment behavior. This approach allows researchers and financial practitioners to explore the psychological factors that influence decisions more deeply, ultimately enhancing our understanding of the complex and often unpredictable dynamics of financial markets.

2.2. Herding behavior towards cryptocurrency intention

Herding behavior is the tendency of individuals or groups to follow the decisions of others without independent analysis, often driven by social influence or the fear of missing out on opportunities (Gherghina & Constantinescu, 2024). In the investment context, this causes investors to mimic others' decisions, ignore fundamental data, and contribute to high market volatility (Moser & Brauneis, 2023). Such behavior is commonly observed in financial markets, including cryptocurrency, where speculation and asymmetric information lead to extremely fluctuating prices (Yousaf & Yarovaya, 2022).

Prospect Theory and herding behavior are closely intertwined in investment decision-making, especially in unstable markets like cryptocurrency (Kogan et al., 2024). These emotional responses, when combined with herding tendencies, explain why investors can become trapped in decisions driven by fear of missing out or social pressure. Consequently, herding behavior—spurred by the fear of losses or the desire to follow the crowd—can exacerbate market volatility, creating conditions that deviate significantly from the efficient market hypothesis (Rubbaniy et al., 2021).

2.3. Perception of usefulness and ease of use on the intention to use cryptocurrency

The perception of usefulness and ease of use plays a crucial role in enhancing individual investors' intention to purchase Bitcoin, as described in the Technology Acceptance Model (TAM; Enu-Kwesi & Opoku, 2020). According to TAM, individuals are more inclined to adopt a technology when they perceive it as both beneficial and user-friendly (Zaineldeen et al., 2020), which significantly influences their attitudes and decisions regarding innovations like Bitcoin (García et al., 2024).

In addition to TAM, Prospect Theory offers an important perspective on decision-making under risk and uncertainty. This theory explains that individuals are generally more sensitive to potential losses than to equivalent gains—a phenomenon known as loss aversion. In the context of Bitcoin adoption, this implies that investors may hesitate to invest if they fear the possibility of significant losses, even if the technology promises considerable benefits (Wang et al., 2023).

However, when Bitcoin is perceived as a valuable and accessible technology, such positive perceptions can help mitigate uncertainty and alleviate the fear of losses. The combined influence of perceived usefulness and ease of use can reduce investor apprehension, making the potential rewards more compelling despite the associated risks (Yousaf & Yarovaya, 2022).

Ultimately, a favorable view of Bitcoin's utility and simplicity encourages investors to embrace this innovation, effectively overcoming the challenges posed by risk and uncertainty. This synthesis of TAM and Prospect Theory underscores how positive perceptions can drive investment decisions, even in volatile markets.

2.4 The impact of interest rate increases, herding behavior, and perceived ease of use on cryptocurrency purchase intentions

According to Prospect Theory as proposed by Kahneman and Tversky (1979), investors under conditions of risk and uncertainty tend to evaluate gains and losses relative to a reference point they hold. This evaluation is not solely based on absolute values but rather on a comparison between the outcomes and the initial conditions or expectations that have been set (Bastianello et al., 2024).

In the context of rising interest rates, traditional investment instruments such as deposits and bonds become more attractive because they offer a higher degree of certainty and security (Radanliev, 2024). The increase in interest rates boosts the yields from these instruments, thereby attracting investors who prioritize stability in their portfolios (Ullah et al., 2024).

On the other hand, for investors with a higher risk tolerance, cryptocurrencies are often seen as an alternative that promises the potential for much greater returns (Moser & Brauneis, 2023). Although the digital asset market is characterized by high volatility and the possibility of significant losses, the sharp price dynamics can offer opportunities for some investors to achieve exceptional gains (Gupta & Chaudhary, 2022).

Rising interest rates also have an impact on herding behavior in the cryptocurrency market. When several investors begin shifting their funds to digital assets due to the prospect of more attractive returns, others who feel left behind tend to follow this trend. This phenomenon represents a form of cognitive bias where investors seek to reduce uncertainty by mimicking the decisions of the majority (Huang, 2024).

From the perspective of Prospect Theory, herding is explained as a mechanism in which investors rely on collective actions to interpret complex market situations. By following group decisions, they hope to minimize the subjective risks that arise from imperfect information and extreme price fluctuations (Gherghina & Constantinescu, 2024).

Additionally, the perception of ease of use (Perceived Ease of Use or PEU) plays a significant role in influencing investors' intentions to adopt cryptocurrencies. Even though high interest rates make traditional instruments more competitive, the ease of access and use associated with cryptocurrency technology remains attractive to investors seeking convenience in their transactions (Belmonte et al., 2024).

Overall, rising interest rates can reinforce both herding behavior and the perception of ease of use, thereby affecting investors' intentions to purchase cryptocurrencies (Rachana Harish et al., 2025). Investors influenced by cognitive biases and those who tend to follow market trends, while feeling comfortable with accessible technology, are more likely to view cryptocurrencies as an attractive investment opportunity in the face of risk and uncertainty (Bernabei et al., 2023; Wang et al., 2024).

3. Research methodology

3.1. Research designs, approach, target population and sampling designs

This research is quantitative research (Rahmawati, A., & Prastiwi, A., 2021), focusing on the collection and analysis of numerical data to test hypotheses related to herding behavior, perceived ease of use, and the impact of rising interest rates on cryptocurrency purchase intention. Primary data was collected directly from respondents through an online survey questionnaire given to cryptocurrency users in Indonesia and Malaysia registered on the Indodax, Tokocrypto, Binance, Bybit, Uphold, and KuCoin platforms, totaling 21.27 million users. The sample size was determined using Hair's (2014), formula, which requires a minimum of 5–10 times the number of indicators measured; with 21 indicators in the model, the resulting sample comprised 210 users. The questionnaire employed a 5-point Likert scale where 1 indicates strong disagreement and 5 indicates strong agreement chosen for its scalability (Faruqi et al., 2023), allowing the study to overcome geographical and time constraints while ensuring a large number of responses for valid and reliable results with minimized bias.

3.2. Measures and definition of operational variables

This research employs Structural Equation Modeling using the Partial Least Squares (SEM-PLS) approach to examine the relationships among variables through a series of systematic steps (Troiville, Moisescu, & Radomir, 2025). It begins with specifying a theoretical model based on a pre-designed conceptual framework, followed by data collection via online surveys, after which the collected data is cleaned and validated to ensure its accuracy. Next, a measurement model analysis is conducted to assess the validity and reliability of the constructs using indicators such as Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) (Kante & Michel, 2023). The subsequent stage involves structural model analysis, which evaluates the strength and significance of the relationships among variables by examining path coefficients, further tested through bootstrapping procedures to obtain standard error estimates and significance tests. These steps ensure that the results obtained are robust and reliable in confirming the proposed theoretical model (Ringle et al., 2023).

Table 1: Measurement of Variables

Variable	Indicators	References
Cryptocurrency Purchase Intention	- Intention to use Bitcoin - Likelihood of using Bitcoin - Expectation regarding the use of Bitcoin	Al-Amri, R., et al. (2019)
Herding Behavior	- Influence of friends and investment experts on Bitcoin usage - Support from the surrounding environment for Bitcoin usage - Recommendations for using Bitcoin - Positive feelings during Bitcoin trading	Kajol, K., et al. (2025)
Perceived Ease of Use (PEU)	- User-friendly interaction with Bitcoin and ease of use - Confidence in becoming proficient in Bitcoin trading - Willingness to learn Bitcoin trading due to its ease	Obidallah, W. J., et al. (2024)
Interest Rate	- Indicators of increases and decreases in interest rates - Economic uncertainty, on Bitcoin trading decisions	Wang, Y., et al. (2024)

4. Results

4.1. Construct reability and validity

Overall, from table 2 until table 4, the analysis of reliability and construct validity indicates satisfactory results. Reliability indices such as Cronbach's Alpha, rho_A, and Composite Reliability (CR) for Cryptocurrency Purchase Intention, Herding Behaviour, Interest Rate, and Perceived Ease of Use (PEU) are all above the recommended thresholds, with AVE values exceeding 0.5. In particular, Herding Behaviour and Interest Rate exhibit high reliability, while both Moderating Effects report perfect values (1.000), which may indicate either the use of a single item or an extremely high level of measurement consistency. The analysis of inter-construct correlations reveals that Cryptocurrency Purchase Intention is moderately positively correlated with Herding Behaviour (r = 0.294) and Interest Rate (r = 0.331), and negatively correlated with Moderating Effect 1 (r = –0.366) and Moderating Effect 2 (r = –0.300). Furthermore, Herding Behaviour and Interest Rate show a strong positive relationship (r = 0.618), while Moderating Effect 1 and Moderating Effect 2 display very high correlations (r = 0.876), indicating consistent measurement across these variables. Perceived Ease of Use (PEU) also demonstrates moderate positive correlations with Cryptocurrency Purchase Intention (r = 0.321), Herding Behaviour (r = 0.586) and Interest Rate (r = 0.467), but is negatively correlated with both Moderating Effects (r = –0.484 and –0.472). The Variance Inflation Factor (VIF) test for combinations of variables such as Herding Behaviour * Interest Rate and Perceived Ease of Use (PEU) * Interest Rate, as well as for each individual item (with VIF values ranging from 1.305 to 1.985), indicates that there are no significant multicollinearity issues.

Table 2: Pairwise Correlations

Construct	Cryptocurrency Purchase Intention	Herding Behavior	Interest Rate	Moderating Effect 1	Moderating Effect 2	Perceived Ease of Use (PEU)
Cryptocurrency Purchase Intention	0.721					
Herding Behavior	0.294	0.742				
Interest Rate	0.331	0.618	0.726			
Moderating Effect 1	-0.366	-0.638	-0.689	1.000		
Moderating Effect 2	-0.300	-0.636	-0.707	0.876	1.000	
Perceived Ease of Use (PEU)	0.321	0.586	0.467	-0.484	-0.472	0.791

Table 3: Reliability and Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Cryptocurrency Purchase Intention	0.705	0.779	0.810	0.520
Herding Behavior	0.837	0.838	0.880	0.551
Interest Rate	0.824	0.842	0.870	0.528
Moderating Effect 1	1.000	1.000	1.000	1.000
Moderating Effect 2	1.000	1.000	1.000	1.000
Perceived Ease of Use (PEU)	0.703	0.715	0.833	0.625

Table 4: VIF

Construct	VIF
Herding Behavior * Interest Rate	1.000
Perceived Ease of Use (PEU) * Interest Rate	1.000
X1.1	1.985
X1.2	1.731
X1.3	1.408
X1.4	1.787
X1.5	1.762
X1.6	1.622
X2.3	1.357
X2.4	1.376
X2.5	1.378
Y1.1	1.407
Y1.2	1.383
Y1.3	1.305
Y1.4	1.305
Z1.1	1.709
Z1.2	1.813
Z1.3	1.475
Z1.4	1.577
Z1.5	1.392
Z1.6	1.671

4.2. Hypothesis testing

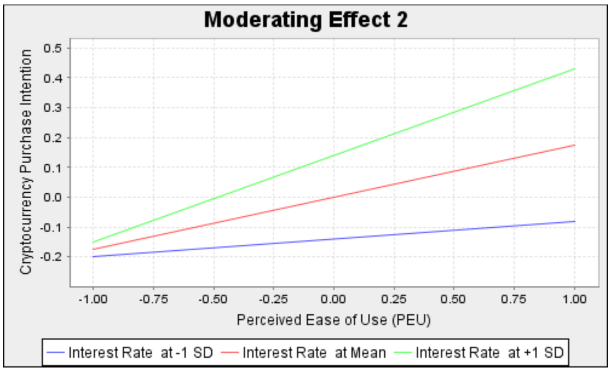
The hypothesis testing demonstrated varied results regarding the influence of each variable on cryptocurrency purchase intention, as shown in Table 4. For H1, which posits that herding behaviour has a positive effect on cryptocurrency purchase intention, the results indicate a very small effect, with an original sample coefficient of 0.002 and a sample mean of 0.014. The T-statistic is a mere 0.018 with an associated p-value of 0.986, suggesting that herding behavior does not significantly contribute to predicting cryptocurrency purchase intention. Therefore, the data do not support H1, indicating that simply following the crowd is not a robust predictor of cryptocurrency purchase decisions.

Next, the analysis of the main effect of interest rate on cryptocurrency purchase intention reveals a positive coefficient of 0.141 (sample mean = 0.168) with a T statistic of 1.357. However, this effect is not statistically significant, as evidenced by the p-value of 0.175. Although there is a hint that rising interest rates might enhance purchase intention, the lack of statistical significance means that this relationship cannot be reliably generalized to the broader population. In contrast, the moderating effect of rising interest rates on the relationship

between herding behaviour and cryptocurrency purchase intention (Moderating Effect 1) is significant. The original sample coefficient is -0.164 (sample mean = -0.150), accompanied by a T statistic of 2.158 and a p-value of 0.031.
The negative coefficient suggests that, contrary to expectations, rising interest rates weaken the effect of herding behaviour on purchase intention. This finding does not support H3, as the data imply that the moderating influence of interest rates reduces rather than strengthens the impact of herding behaviour. Similarly, H4 proposed that rising interest rates would strengthen the effect of perceived ease of use on cryptocurrency purchase intention. The corresponding moderating effect (Moderating Effect 2) yields a positive coefficient of 0.116 (sample mean = 0.123), yet the T statistic of 1.085 and the p-value of 0.278 indicate that this effect is not statistically significant. Consequently, the evidence does not support H4, as there is insufficient proof that rising interest rates enhance the influence of perceived ease of use on purchase intention. On the other hand, H2, which asserts that the perception of usefulness and ease of use has a positive effect on cryptocurrency purchase intention, is supported by the data. Perceived Ease of Use (PEU) exhibits a significant positive effect, with an original sample coefficient of 0.175 (sample mean = 0.182), a T statistic of 2.036, and a p-value of 0.042. This significant relationship underscores that the easier a platform or system is to use, the more likely individuals are to engage in cryptocurrency purchases, aligning well with established technology adoption theories as shown in Graph 1. Overall, the results of the hypothesis testing offer a comprehensive insight into the dynamics of the relationships among variables in the context of cryptocurrency. While herding behaviour and interest rate do not demonstrate significant effects, the roles of Moderating Effect 1 and Perceived Ease of Use (PEU) are influential in shaping purchase intention. These findings underscore the importance of considering both moderating factors and user perceptions of ease of use when developing marketing strategies and technology adoption plans in an increasingly competitive cryptocurrency market.

Table 5: Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Herding Behavior -> Cryptocurrency Purchase Intention	0.002	0.011	0.085	0.019	0.985
Interest Rate -> Cryptocurrency Purchase Intention	0.141	0.161	0.106	1.324	0.186
Moderating Effect 1 -> Cryptocurrency Purchase Intention	-0.164	-0.152	0.076	2.152	0.032
Moderating Effect 2 -> Cryptocurrency Purchase Intention	0.116	0.119	0.100	1.158	0.247
Perceived Ease of Use (PEU) -> Cryptocurrency Purchase Intention	0.175	0.185	0.083	2.116	0.035



Graph. 1: Moderating Effect 2.

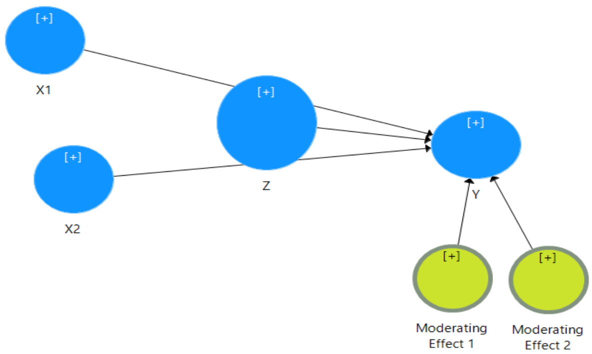


Fig. 1: Research Model in PLS.

5. Discussion

Our research aims to provide a deeper understanding of cryptocurrency purchase intention through the lens of prospect theory, which posits that individuals evaluate potential gains and losses relative to a reference point. In the volatile and uncertain cryptocurrency market, recent research (Sukumaran, Bee, & Wasiuzzaman, 2022) has emphasized that investors are particularly sensitive to risk and loss aversion. By integrating behavioral finance with technology adoption models, our research examines how herding behavior, perceived ease of use (PEU), and interest rates influence cryptocurrency purchase intention.
For Hypothesis H1, which posits that herding behavior has a positive effect on cryptocurrency purchase intention, our analysis reveals an almost negligible effect. With an original sample coefficient of 0.002, a sample mean of 0.014, and a T statistic of 0.018 (p = 0.986), herding behavior does not significantly predict purchase intention. This result aligns with recent findings by Lavan et al. (2024), Mubarack

et al. (2023), and Patel, Gubareva, and Chishti (2024), who reported that in high-risk environments such as cryptocurrency markets, the propensity to follow the crowd is diminished due to heightened loss aversion and skepticism regarding market volatility.

In contrast, Hypothesis H2 asserts that the perception of usefulness and ease of use positively affects cryptocurrency purchase intention. Our findings support this hypothesis: PEU exhibits a significant positive effect, with a beta coefficient of 0.175, a T statistic of 2.036, and a p-value of 0.042. This suggests that user-friendly platforms and intuitive interfaces help mitigate perceived risks and encourage investment. These results are consistent with contemporary studies by Esfahbodi, Pang, and Peng (2022), who found that ease of use is a critical determinant in the adoption of digital financial technologies.

The main effect of interest rate on cryptocurrency purchase intention shows a positive coefficient of 0.141 (sample mean = 0.168) with a T statistic of 1.357, yet this effect is not statistically significant ($p = 0.175$). Although higher interest rates might intuitively signal improved returns, the non-significant results suggest that potential losses and the inherent uncertainty of the crypto market outweigh any direct positive influence. This observation echoes the work of Ul-Abdin et al. (2022), who demonstrated that in high-risk asset classes, market signals such as interest rates have limited predictive power for investor behavior.

Turning to the moderating effects, Moderating Effect 1—which was hypothesized to strengthen the influence of herding behavior with rising interest rates—yields a significant negative effect ($\beta = -0.164$, $p = 0.031$). This finding indicates that as interest rates rise, the impact of herding behavior on purchase intention is weakened. This counterintuitive result is supported by Sukumaran, Bee, and Wasiuzzaman (2022), who suggest that in environments where potential losses are amplified, investors are less inclined to follow crowd behavior, thereby reinforcing the predictions of prospect theory regarding risk aversion.

Conversely, Moderating Effect 2, which proposed that rising interest rates would enhance the effect of PEU on purchase intention, produces a positive coefficient ($\beta = 0.116$) but fails to reach statistical significance ($p = 0.278$). This suggests that while ease of use is an important driver of cryptocurrency purchase intention, its influence is not significantly moderated by fluctuations in interest rates. Such findings are in line with Esfahbodi, Pang, and Peng (2022), indicating that market signals may not interact strongly with user perceptions to boost technology adoption in the context of digital finance. In the cultures of Indonesia and Malaysia, there is a relatively high level of distrust towards digital assets like cryptocurrency, which can be attributed to cultural and social factors. Research by Kshetri (2017) shows that in developing countries, including Southeast Asia, high uncertainty related to the volatility and unclear regulations surrounding cryptocurrency can increase fear and anxiety among investors. On the other hand, trust in digital assets in many developing countries is often low due to a lack of understanding and transparency, which worsens the barriers to the adoption of this technology (Zohar & Sarel, 2019).

Overall, the results of our hypothesis testing provide comprehensive insights into the determinants of cryptocurrency purchase intention. While herding behavior and interest rate as main effects are not significant predictors, the robust positive influence of PEU highlights its critical role in technology adoption. The significant negative moderating effect of rising interest rates on herding behavior further underscores the complex interplay between risk perception and investor behavior in volatile markets. These findings contribute to the literature by integrating prospect theory with contemporary technology adoption models and call for further research to explore additional moderating factors influencing investment decisions in the dynamic cryptocurrency landscape. The volatility of cryptocurrency challenges traditional financial models, as it disregards several basic assumptions in the Efficient Market Hypothesis and Modern Portfolio Theory. Cryptocurrency, with its high volatility and the influence of social behavioral factors (such as PEU and herding behavior), does not fully align with these traditional models. This suggests that the behavior of cryptocurrency markets is more complex and influenced by various psychological, social, and technological factors that cannot always be explained by traditional financial theories.

6. Conclusion

This research offers a unique contribution to the understanding of cryptocurrency purchase intention by integrating prospect theory with contemporary technology adoption models. The findings reveal that while herding behavior and interest rates have a negligible and non-significant effect on purchase intention, perceived ease of use (PEU) plays a critical role in driving adoption. The significant positive effect of PEU underscores the importance of user-friendly platforms and intuitive interfaces in mitigating perceived risks in volatile markets. Furthermore, the moderating effects of interest rates on herding behavior and PEU highlight the complex interplay between risk perception and investment behavior. Our results challenge conventional assumptions regarding the direct impact of market signals, particularly interest rates, and offer new insights into the behavior of cryptocurrency investors, emphasizing the need for further research into moderating factors that influence investment decisions in this rapidly evolving market.

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References

[1] Al-Amri, R., et al. (2019). Cryptocurrency adoption: Current stage, opportunities, and open challenges. *International Journal of Advanced Computing Research, 9*(44), 293-307. https://doi.org/10.19101/IJACR.PID43.

[2] Almeida, J., Gaio, C., & Gonçalves, T. C. (2024). Crypto market relationships with BRIC countries' uncertainty – A wavelet-based approach. *Technological Forecasting and Social Change, 200*, 123078. https://doi.org/10.1016/j.techfore.2023.123078.

[3] Almajali, D. A., et al. (2022). Factors influencing the adoption of cryptocurrency in Jordan: An application of the extended TRA model. *Cogent Social Sciences, 8*(1). https://doi.org/10.1080/23311886.2022.2103901.

[4] Aliyu, S., Abd Wahab, N., & Kamis, N. S. (2025). An analysis of crypto-asset trade, enforcement, and estate planning. *Borsa Istanbul Review [Preprint]*. https://doi.org/10.1016/j.bir.2024.12.008.

[5] Alomari, A. S. A., & Abdullah, N. L. (2023). Factors influencing the behavioral intention to use cryptocurrency among Saudi Arabian public university students: Moderating role of financial literacy. *Cogent Business & Management, 10*(1), 2178092. https://doi.org/10.1080/23311975.2023.2178092.

[6] Bajwa, I. A. (2025). Reinvestment intentions in cryptocurrency: Examining the dynamics of risks and investor risk tolerance. *Digital Business, 5*(1), 100104. https://doi.org/10.1016/j.digbus.2024.100104.

[7] Bastianello, L., Chateauneuf, A., & Cornet, B. (2024). Gain–loss hedging and cumulative prospect theory. *Mathematics and Social Sciences, 131*(September 2023), 40-47. https://doi.org/10.1016/j.mathsocsci.2024.07.003.

[8] Barbereau, T., & Bodó, B. (2023). Beyond financial regulation of crypto-asset wallet software: In search of secondary liability. *Computer Law & Security Review, 49*. https://doi.org/10.1016/j.clsr.2023.105829.

[9] Belmonte, Z. J. A., et al. (2024). Factors influencing the intention to use e-wallet among generation Z and millennials in the Philippines: An extended technology acceptance model (TAM) approach. *Acta Psychologica, 250*(October). https://doi.org/10.1016/j.actpsy.2024.104526.

[10] Bespalova, O., et al. (2024). Crypto assets and CBDCs in Latin America and the Caribbean: Opportunities and risks. *Latin American Journal of Central Banking*, 100157. https://doi.org/10.1016/j.latcb.2024.100157.

[11] Bernabei, M., et al. (2023). Students' use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances. *Computers in Education: Artificial Intelligence, 5*(July), 100172. https://doi.org/10.1016/j.caeai.2023.100172.

[12] Bouri, E., et al. (2025). Tech titans and crypto giants: Mutual returns predictability and trading strategy implications. *Journal of International Financial Markets, Institutions & Money, 99*. https://doi.org/10.1016/j.intfin.2024.102109.

[13] Caferra, R., Morone, A., & Potì, V. (2022). Crypto-environment network connectivity and Bitcoin returns distribution tail behaviour. *Economics Letters, 218*, 110734. https://doi.org/10.1016/j.econlet.2022.110734.

[14] Chen, K. S., & Yang, J. J. (2024). Price dynamics and volatility jumps in bitcoin options. *Financial Innovation, 10*(1). https://doi.org/10.1186/s40854-024-00653-z.

[15] Colombo, J. A., & Yarovaya, L. (2024). Are crypto and non-crypto investors alike? Evidence from a comprehensive survey in Brazil. *Technological Society, 76*(January). https://doi.org/10.1016/j.techsoc.2024.102468.

[16] Cumming, D., et al. (2025). Financing decentralized digital platform growth: The role of crypto funds in blockchain-based startups. *Journal of Business Venturing, 40*(1). https://doi.org/10.1016/j.jbusvent.2024.106450.

[17] Dincer, H., et al. (2024). Understanding the market potential of crypto mining with quantum mechanics and golden cut-based picture fuzzy rough sets. *Blockchain Research and Applications, 100230*. https://doi.org/10.1016/j.bcra.2024.100230.

[18] Esfahbodi, A., Pang, G., & Peng, L. (2022). Determinants of consumers' adoption intention for blockchain technology in E-commerce. *Journal of Digital Economics, 1*(2), 89-101. https://doi.org/10.1016/j.jdec.2022.11.001.

[19] Faruqi, A. F., Yanto, T. R., Izzalqurny, T. R., Rahmawati, A., Ramadhani, N. A., Ratnadewati, N. C., & Ilhamy, M. (2023). Analyzing asset misappropriation through the lens of fraud hexagon theory: Evaluating whistleblowing effectiveness in financial and asset management institutions. *Journal of Information Systems Engineering and Management*, 10(22), 3507. https://doi.org/10.52783/jisem.v10i22s.3507.

[20] Fortin, I., & Hlouskova, J. (2024). Prospect theory and asset allocation. *Quarterly Review of Economics and Finance, 94*(January), 214-240. https://doi.org/10.1016/j.qref.2024.01.010.

[21] Giannikos, C. I., Kakolyris, A., & Suen, T. S. (2023). Prospect theory and a manager's decision to trade a blind principal bid basket. *Global Finance Journal, 55*, 100806. https://doi.org/10.1016/j.gfj.2023.100806.

[22] Gherghina, S. C., & Constantinescu, C. A. (2024). Examining herding behavior in the cryptocurrency market. *Equilibrium. Quarterly Journal of Economics and Economic Policy*. https://doi.org/10.24136/eq.3057.

[23] Giacomini, L., et al. (2025). Factors affecting the decision to adopt cryptocurrency in Indonesia: A cross-sectional study. *Journal of Behavioral and Experimental Economics, 23*, 202-217.

[24] Gupta, H., & Chaudhary, R. (2022). An empirical study of volatility in cryptocurrency market. https://doi.org/10.3390/jrfm15110513.

[25] Ha, L. T. (2024). Gauging the dynamic interlinkage among robotics, artificial intelligence, and green crypto investment: A quantile VAR approach. *Borsa Istanbul Review, 24*(S2), 22-31. https://doi.org/10.1016/j.bir.2024.11.006.

[26] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage.

[27] Huang, S. S. (2024). Liquidity dynamics between virtual and equity markets. *Journal of International Financial Markets, Institutions & Money, 91*(May 2023), 101917. https://doi.org/10.1016/j.intfin.2023.101917.

[28] Kante, M., & Michel, B. (2023). Use of partial least squares structural equation modelling (PLS-SEM) in privacy and disclosure research on social network sites: A systematic review. *Computers in Human Behavior Reports, 10*(April). https://doi.org/10.1016/j.chbr.2023.100291.

[29] Kajol, K., et al. (2025). Drivers influencing the adoption of cryptocurrency: A social network analysis approach. *Financial Innovation [Preprint]*. https://doi.org/10.1186/s40854-025-00757-0.

[30] Krull, S., Loschelder, D. D., & Pelster, M. (2024). The impact of (social) anchors on Prospect Theory's value function. *Quarterly Review of Economics and Finance, 98*(July). https://doi.org/10.1016/j.qref.2024.101916.

[31] Kshetri, N. (2017). *1 Blockchain's roles in meeting key global supply chain management challenges*. *International Journal of Information Management*, 37(6), 33-42.

[32] Lavan, T., et al. (2024). Social isolation and risk-taking behavior: The case of COVID-19 and cryptocurrency. *Journal of Retailing and Consumer Services, 81*(January), 103951. https://doi.org/10.1016/j.jretconser.2024.103951.

[33] Moser, S., & Brauneis, A. (2023). Should you listen to crypto YouTubers? *Finance Research Letters, 54*. https://doi.org/10.1016/j.frl.2023.103782.

[34] Mubarack, K., et al. (2023). International Journal of Social Science Research and Reviews, 6(7), 691-709

[35] Obidallah, W. J., et al. (2024). Beyond the hype: A TAM-based analysis of blockchain adoption drivers in the construction industry. *Heliyon, 10*(19), e38522. https://doi.org/10.1016/j.heliyon.2024.e38522.

[36] Patel, R., Gubareva, M., & Chishti, M. Z. (2024). Assessing the connectedness between cryptocurrency environment attention index and green cryptos, energy cryptos, and green financial assets. *Research in International Business and Finance, 70*. https://doi.org/10.1016/j.ribaf.2024.102339.

[37] Radanliev, P. (2024). The rise and fall of cryptocurrencies: Defining the economic and social values of blockchain technologies, assessing the opportunities, and defining the financial and cybersecurity risks of the Metaverse. *Financial Innovation, 10*(1), 1-34. https://doi.org/10.1186/s40854-023-00537-8.

[38] Rachana Harish, A., et al. (2025). The new supply chain information sharing Renaissance through crypto valuation mechanism of digital assets. *Transportation Research Part E: Logistics and Transportation Review, 195*. https://doi.org/10.1016/j.tre.2025.103962.

[39] Rahmawati, A., & Prastiwi, A. (2021). Effect of good corporate governance and corporate social responsibility on firm value moderated by profitability. *International Journal of Research in Business and Social Science*, 10(4), 59-66. https://doi.org/10.20525/ijrbs.v10i4.1194.

[40] Ringle, C. M., et al. (2023). A perspective on using partial least squares structural equation modelling in data articles. *Data Brief, 48*. https://doi.org/10.1016/j.dib.2023.109074.

[41] Sakariyahu, R., et al. (2024). One crash, too many: Global uncertainty, sentiment factors and cryptocurrency market. *Journal of International Financial Markets, Institutions & Money, 94*, 102028. https://doi.org/10.1016/j.intfin.2024.102028.

[42] Sukumaran, S., Bee, T. S., & Wasiuzzaman, S. (2022). Cryptocurrency as an investment: The Malaysian context. *Risks, 10*(4). https://doi.org/10.3390/risks10040086.

[43] Troiville, J., Moisescu, O. I., & Radomir, L. (2025). Using necessary condition analysis to complement multigroup analysis in partial least squares structural equation modeling. *Journal of Retailing and Consumer Services, 82*(July 2024). https://doi.org/10.1016/j.jretconser.2024.104018.

[44] Ul-Abdin, S. Z., et al. (2022). Overconfidence bias and investment performance: A mediating effect of risk propensity. *Borsa Istanbul Review, 22*(4), 780-793. https://doi.org/10.1016/j.bir.2022.03.001.

[45] Ullah, M., Sohag, K., & Haddad, H. (2024). Comparative investment analysis between crypto and conventional financial assets amid heightened geopolitical risk. *Heliyon, 10*(9), e30558. https://doi.org/10.1016/j.heliyon.2024.e30558.

[46] Wang, C., et al. (2023). An empirical evaluation of technology acceptance model for Artificial Intelligence in E-commerce. *Heliyon, 9*(8), e18349. https://doi.org/10.1016/j.heliyon.2023.e18349.

[47] Wang, Y., et al. (2024). What drives people's cryptocurrency investment behavior. *Journal of Computer Information Systems*. https://doi.org/10.1080/08874417.2024.2329127.

[48] Wei, W., et al. (2025). Applying the technology acceptance model – theory of planned behavior (TAM-TPB) model to study the acceptance of building information modeling (BIM) in green building in China. *Acta Psychologica, 254*(October). https://doi.org/10.1080/08874417.2024.2329127.

[49] Yousaf, I., & Yarovaya, L. (2022). Herding behavior in conventional cryptocurrency market, non-fungible tokens, and DeFi assets. *Finance Research Letters, 50*(September 2021), 103299. https://doi.org/10.1016/j.frl.2022.103299.
[50] Zaineldeen, S., et al. (2020). Technology acceptance model' concepts, contribution, limitation, and adoption in education. *Universal Journal of Educational Research, 8*(11), 5061-5071. https://doi.org/10.13189/ujer.2020.081106.
[51] Zohar, A., & Sarel, D. (2019). *Understanding the Adoption of Cryptocurrency in Emerging Markets*. *Journal of Financial Technology*, 2(1), 1-15.