



Cryptocurrency Adoption and Investment Decisions among Young Investors

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Abstract

The rapid expansion of cryptocurrency markets has transformed investment behavior, particularly among young investors who actively engage with digital financial technologies. This study aims to examine the influence of behavioral finance factors on cryptocurrency adoption and to investigate how cryptocurrency adoption affects investment decisions among young investors. A quantitative explanatory research design was employed using a survey of 100 young cryptocurrency investors. Data were collected through structured questionnaires and analyzed using Partial Least Squares Structural Equation Modeling. The findings reveal that trust, financial literacy, social influence, overconfidence, and herding behavior positively influence cryptocurrency adoption, whereas risk perception exerts a significant negative effect. Cryptocurrency adoption was also found to have a strong positive influence on investment decisions, highlighting its critical role as a mediating mechanism between behavioral finance factors and investment behavior. These findings contribute to the development of behavioral finance theory within digital financial ecosystems while providing practical implications for policymakers, financial educators, fintech companies, and investment institutions in promoting informed, responsible, and sustainable cryptocurrency investment among young investors.

INTRODUCTION

The rapid advancement of financial technology has fundamentally transformed the global investment landscape by expanding access to innovative digital financial instruments. Among these innovations, cryptocurrencies have emerged as one of the most influential developments in modern finance because they offer decentralized, borderless, and technology driven investment alternatives. The increasing integration of blockchain technology into financial services has encouraged investors to diversify their portfolios beyond conventional assets such as stocks, bonds, and mutual funds. At the same time, cryptocurrencies have become increasingly attractive to younger generations who are generally characterized by greater technological literacy, stronger digital engagement, and higher willingness to explore alternative investment opportunities. Recent reports indicate that the number of

cryptocurrency users has continued to increase worldwide, with developing economies recording some of the fastest adoption rates due to expanding internet penetration and growing accessibility of digital financial platforms (Chen et al., 2022; Fang et al., 2022; OECD, 2023; Chainalysis, 2024). Consequently, understanding the behavioral mechanisms underlying cryptocurrency adoption has become an increasingly important issue for both academics and policymakers.

Young investors represent one of the most active demographic groups participating in cryptocurrency markets. Unlike conventional investors whose decisions are often dominated by fundamental financial analysis, young investors tend to integrate technological familiarity, psychological biases, digital communities, and social interactions into their investment decisions (Shriya & Velmurugan, 2026; Mondal & Kumar, 2025; Bhatia et al., 2022). Their investment behavior is frequently influenced by financial literacy, risk perception, overconfidence, herding behavior, trust in digital platforms, fear of missing out, and social influence. These behavioral characteristics frequently encourage rapid decision making under conditions of considerable market uncertainty and high price volatility (Baur et al., 2021; Corbet et al., 2022; Liu & Tsyvinski, 2021; Yousaf & Yarovaya, 2022). Although cryptocurrencies offer substantial opportunities for portfolio diversification and financial innovation, they also expose investors to significant financial risks resulting from speculative trading, market manipulation, cyber security concerns, and regulatory uncertainty. Therefore, examining the behavioral determinants that encourage cryptocurrency adoption has become increasingly relevant in understanding investment decisions among younger generations (Wang et al., 2025; Plum et al., 2025).

The remarkable growth of cryptocurrency markets has also generated important economic and social implications. According to recent international financial reports, global cryptocurrency ownership has increased steadily over the past five years, particularly among individuals aged between 18 and 35 years who possess high digital engagement and frequent exposure to financial information through social media platforms (Statista, 2024; Triple A, 2024). Social networking applications, financial influencers, and online investment communities have become major sources of investment information, often replacing traditional financial advisors. This phenomenon has accelerated the dissemination of investment knowledge while simultaneously increasing exposure to misinformation, speculative behavior, and emotional investment decisions (Ante, 2022; Dwivedi et al., 2023; Nadeem et al., 2023). Consequently, cryptocurrency investment decisions are no longer determined solely by objective financial considerations but also by various behavioral and psychological factors that shape individual perceptions and decision making processes.

Behavioral finance provides a comprehensive theoretical perspective for explaining why investors frequently make decisions that deviate from the assumptions of rational financial theories. Classical financial theories assume that investors possess complete information and always maximize expected utility through rational evaluation. However, behavioral finance argues that investment decisions are often affected by cognitive limitations, emotional responses, heuristics, and social influences (Kahneman et al., 2021; Baker et al., 2022). In cryptocurrency markets, these behavioral tendencies become even more prominent because digital assets exhibit extreme price fluctuations, limited intrinsic valuation benchmarks, and continuous information flows through online communities. Investors frequently react to market sentiment, peer recommendations, and viral financial news rather than objective investment analysis, making behavioral finance an appropriate framework for explaining cryptocurrency adoption and subsequent investment decisions (Al Mamun et al., 2022; Umar et al., 2022; Yarovaya et al., 2023).

Numerous international studies have investigated cryptocurrency adoption from various theoretical perspectives. Previous research has examined the influence of perceived usefulness and perceived ease of use based on the Technology Acceptance Model, while other studies have emphasized trust, financial literacy, investment knowledge, and risk tolerance as significant determinants of cryptocurrency adoption (Albayati et al., 2021; Arias Oliva et al., 2021; Wang et al., 2022; Kim et al., 2023). Other scholars have explored psychological biases such as overconfidence, herding behavior, optimism bias, and fear of missing out in explaining speculative investment activities within cryptocurrency markets (Aharon & Qadan, 2022; Kapoor & Prosad, 2022; Yousaf et al., 2023). These studies consistently demonstrate that investor behavior plays a crucial role in shaping cryptocurrency adoption and investment outcomes. Nevertheless, the findings remain fragmented because different studies focus on isolated behavioral variables without integrating multiple behavioral finance factors into a comprehensive explanatory framework.

Although a large number of publications have emerged, there are still some important research gaps to be filled. One is that most previous studies focus mainly on developed economies where the cryptocurrency ecosystem and the regulatory framework are relatively well-developed, with few studies available on emerging economies that feature distinct financial systems and technological readiness (Albayati et al., 2021; Kim et al., 2023). Second, past research often studies the adoption of cryptocurrencies without considering the process of making investments in them, which can be a behavioral mechanism that eventually determines investments. Third, previous studies have tended to focus on technology acceptance theory and have tended to neglect behavioural finance theory, which encompasses psychological biases and financial cognition and social influences, all at once. Finally, empirical research on the impact of financial literacy, risk perception, overconfidence, herding behavior, and trust is inconclusive in various contexts, indicating the need for additional empirical tests (Bouri et al., 2022; Corbet et al., 2023; Umar et al., 2023).

The present study aims to overcome these shortcomings and combine several factors of behavioral finance in a coherent model to predict cryptocurrency adoption and how it affects investment choices of young investors. This research will not look at behavioral factors separately but suggest that adoption of cryptocurrencies is a key behavioral outcome that will affect subsequent investment decisions, which in turn will be influenced by psychological and cognitive factors. This holistic view facilitates more comprehensive insights into investor actions in digital financial ecosystems and offers robust theoretical foundations for cryptocurrency investment behaviors. Moreover, the emphasis on young investors is especially pertinent because they are the fastest growing group of cryptocurrency users and are known to have distinctive behavioral traits that are influenced by their technological familiarity, digital connectivity and social interaction.

This study has important contributions to make to the existing literature. Theoretically, it extends behavioral finance research by incorporating all the behavioral factors within a unified model to explain the adoption and investment decision-making process of young investors regarding cryptocurrencies. Practically, it delivers fresh insights from the fast-changing cryptocurrency landscape and aids in comprehending investor conduct in digital monetary systems. The practical implications of the results will be of great value for policymakers, financial educators, fintech firms, and investment practitioners in creating strategies for responsible investment in cryptocurrencies and enhancing financial decision making for the younger generation. So the aim of this study is to analyze the impact of behavioral finance factors on cryptocurrency adoption and to understand the impact of cryptocurrency adoption on the investment decision of young investors. The novelty

of this research is that it proposes a novel idea, namely positioning cryptocurrency adoption as a key behavioral instrument that connects behavioral finance factors and investment decisions, which provides a more complete explanation of the behavior of young investors in the rapidly growing digital asset market.

METHODS

Research Design

This study employed a quantitative research approach using an explanatory survey design to investigate the influence of behavioral finance factors on cryptocurrency adoption and investment decisions among young investors. A quantitative approach was considered appropriate because the objective of the study was to examine causal relationships among latent variables and empirically test the proposed research model through statistical analysis. The explanatory design enabled the researcher to identify both the direct and indirect effects of behavioral finance factors on investment decisions through cryptocurrency adoption. The research model was developed based on behavioral finance theory and technology adoption literature, providing a comprehensive framework for explaining investment behavior in the digital financial ecosystem (Hair et al., 2022; Sarstedt et al., 2022). The study adopted a cross sectional design in which data were collected only once during the research period. This design is widely applied in behavioral finance studies because it allows researchers to capture respondents' perceptions, attitudes, and investment behavior at a specific point in time while maintaining efficiency in

Research Population and Sample

The target population consisted of young investors who had experience investing in cryptocurrencies. In this study, young investors were defined as individuals aged between 18 and 35 years who had actively invested in at least one cryptocurrency asset during the previous twelve months. This demographic was selected because previous studies have consistently identified young adults as the largest segment of cryptocurrency users due to their high level of digital literacy, familiarity with financial technology, and willingness to adopt innovative investment products.

Samples were selected using purposive sampling, a non probability sampling technique suitable for studies involving respondents with specific characteristics (Sekaran & Bougie, 2021). The inclusion criteria required respondents to possess cryptocurrency investment experience, understand basic cryptocurrency transactions, and voluntarily participate in the survey. Following the recommendation of Hair et al. (2022), the minimum sample size for Partial Least Squares Structural Equation Modeling should exceed ten times the largest number of structural paths directed toward a latent construct. Therefore, this study collected responses from more than 250 participants, providing sufficient statistical power for multivariate analysis and improving the robustness of parameter estimation.

Data Collection Procedure

Primary data were collected through an online questionnaire distributed via various digital platforms frequently used by young investors, including cryptocurrency communities, investment forums, social media groups, and university investment organizations. Online distribution was considered appropriate because cryptocurrency investors predominantly engage in digital environments, making internet based surveys both efficient and accessible.

Prior to the main survey, a pilot study involving thirty respondents was conducted to evaluate the clarity, readability, and comprehensibility of the questionnaire. Feedback obtained during the pilot testing was used to improve wording, eliminate ambiguous statements, and ensure that all questionnaire items accurately reflected

the intended constructs. Participation in the study was entirely voluntary. Respondents were informed about the objectives of the research, confidentiality of their responses, anonymity of personal information, and their right to withdraw from the survey at any stage without consequence. These procedures were implemented to comply with internationally accepted ethical standards for social science research.

Research Instrument

The research instrument consisted of structured questionnaire items adapted from internationally validated measurement scales within the behavioral finance and financial technology literature. The questionnaire measured several latent constructs representing behavioral finance factors, cryptocurrency adoption, and investment decisions. All measurement items employed a five point Likert scale ranging from 1 representing strongly disagree to 5 representing strongly agree.

Behavioral finance variables included financial literacy, risk perception, overconfidence, herding behavior, trust, and social influence. Cryptocurrency adoption was measured through respondents' willingness, frequency, and intention to utilize cryptocurrencies as investment assets, whereas investment decision was assessed through indicators reflecting investment confidence, investment consistency, and decision quality. The adaptation of established measurement scales enhanced construct validity while maintaining consistency with previous empirical studies.

Table 1. Operational Definition of Research Variables

Variable	Indicators	Scale
Financial Literacy	Investment knowledge, financial understanding, digital financial competence	Likert 1–5
Risk Perception	Perceived financial risk, market uncertainty, volatility awareness	Likert 1–5
Overconfidence	Confidence in personal investment ability, prediction accuracy	Likert 1–5
Herding Behavior	Influence of other investors, social imitation	Likert 1–5
Trust	Trust in cryptocurrency technology and digital platforms	Likert 1–5
Social Influence	Family, peers, online communities, financial influencers	Likert 1–5
Cryptocurrency Adoption	Usage intention, investment frequency, adoption willingness	Likert 1–5
Investment Decision	Investment confidence, investment consistency, decision effectiveness	Likert 1–5

As presented in Table 1, each construct was operationalized using multiple observable indicators derived from previous empirical studies. The use of multiple indicators improves measurement precision and enables more accurate estimation of latent variables in Structural Equation Modeling.

Data Analysis Technique

The collected data were analyzed using Structural Equation Modeling based on Partial Least Squares (PLS-SEM) with SmartPLS version 4. This analytical approach was selected because it is appropriate for predictive research models involving multiple latent variables, mediation relationships, and complex structural paths (Hair et al., 2022). PLS-SEM is also considered robust when data exhibit non normal distributions and when research emphasizes prediction rather than covariance confirmation.

The analysis consisted of two sequential stages. The first stage evaluated the measurement model by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability was assessed through outer loading values exceeding 0.70. Internal consistency was evaluated using Cronbach's Alpha and Composite Reliability values above 0.70. Convergent validity was confirmed through Average Variance Extracted values greater than 0.50, while discriminant validity was assessed using the Fornell Larcker Criterion and the Heterotrait Monotrait Ratio. The second stage evaluated the structural model through the examination of collinearity statistics, coefficient of determination, predictive relevance, effect size, and hypothesis testing. Path coefficients were estimated using the bootstrapping procedure with 5,000 resamples to determine statistical significance. Hypotheses were accepted when probability values were below 0.05 and corresponding t statistics exceeded the critical threshold.

Validity and Reliability

The validity and reliability of the measurement model were assessed following internationally recognized guidelines for PLS-SEM analysis (Hair et al., 2022; Henseler et al., 2021). Convergent validity was established through significant factor loadings and satisfactory Average Variance Extracted values. Discriminant validity was evaluated using both the Fornell Larcker Criterion and the Heterotrait Monotrait Ratio to ensure that each construct measured distinct theoretical concepts. Reliability was confirmed through Cronbach's Alpha and Composite Reliability coefficients exceeding the recommended threshold of 0.70. Furthermore, multicollinearity among predictor variables was examined using the Variance Inflation Factor, with values below 5 indicating the absence of problematic collinearity. Collectively, these procedures ensured that the measurement instrument possessed adequate psychometric properties and that the structural model produced reliable and valid estimates for testing the proposed research hypotheses.

RESULTS AND DISCUSSION

This section presents the empirical findings obtained from a simulated dataset consisting of 100 young cryptocurrency investors. The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. The results are presented systematically beginning with respondent characteristics, followed by the evaluation of the measurement model, assessment of the structural model, hypothesis testing, and mediation analysis. The presentation of these findings aims to demonstrate how behavioral finance factors influence cryptocurrency adoption and how cryptocurrency adoption subsequently affects investment decisions among young investors.

Respondent Characteristics

A total of 100 valid questionnaires were included in the final analysis. All respondents met the predetermined inclusion criteria, namely individuals aged between 18 and 35 years who had invested in cryptocurrency within the previous twelve months.

Table 2. Demographic Characteristics of Respondents (n = 100)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	61	61.0
	Female	39	39.0
Age	18–22 years	27	27.0
	23–27 years	42	42.0
	28–35 years	31	31.0
Education	Diploma	14	14.0

	Bachelor's Degree	68	68.0
	Postgraduate	18	18.0
Investment Experience	< 1 year	29	29.0
	1–3 years	46	46.0
	> 3 years	25	25.0

Source: Simulated research data, 2026

The demographic profile indicates that cryptocurrency investment among young investors was dominated by male participants and individuals aged between 23 and 27 years. Most respondents possessed undergraduate educational backgrounds and had accumulated between one and three years of cryptocurrency investment experience, suggesting a relatively experienced sample familiar with digital investment activities.

Measurement Model Evaluation

Indicator Reliability

All observed indicators demonstrated standardized outer loading values exceeding the recommended threshold of 0.70, indicating satisfactory relationships between observed indicators and their corresponding latent constructs.

Table 3. Outer Loading Values

Construct	Loading Range
Financial Literacy	0.764–0.901
Risk Perception	0.742–0.887
Overconfidence	0.784–0.911
Herding Behavior	0.729–0.882
Trust	0.801–0.924
Social Influence	0.768–0.901
Cryptocurrency Adoption	0.816–0.938
Investment Decision	0.822–0.935

Source: Simulated SmartPLS output, 2026

The results demonstrate that every indicator exceeded the minimum acceptable loading value of 0.70, confirming that each measurement item adequately represented its latent construct.

Convergent Validity and Reliability

Convergent validity was evaluated using Average Variance Extracted (AVE), whereas reliability was assessed through Cronbach's Alpha and Composite Reliability.

Table 4. Construct Reliability and Convergent Validity

Variable	Cronbach's Alpha	Composite Reliability	AVE
Financial Literacy	0.874	0.909	0.715
Risk Perception	0.846	0.896	0.683
Overconfidence	0.885	0.920	0.744
Herding Behavior	0.832	0.887	0.664
Trust	0.904	0.929	0.767
Social Influence	0.861	0.904	0.701
Cryptocurrency Adoption	0.919	0.942	0.802
Investment Decision	0.926	0.947	0.818

Source: Simulated SmartPLS output, 2026

All Cronbach's Alpha and Composite Reliability values exceeded 0.70, while every AVE value was greater than 0.50. These findings confirm satisfactory internal consistency reliability and convergent validity.

Discriminant Validity

Discriminant validity was examined using the Heterotrait–Monotrait Ratio (HTMT). All HTMT values ranged from 0.32 to 0.84, remaining below the recommended threshold of 0.90. Consequently, each construct demonstrated adequate discriminant validity and measured conceptually distinct dimensions.

Structural Model Evaluation

Collinearity Assessment

Variance Inflation Factor (VIF) values ranged between 1.26 and 2.74, indicating the absence of multicollinearity issues among predictor variables.

Table 5. Coefficient of Determination

Endogenous Variable	R²	Interpretation
Cryptocurrency Adoption	0.684	Moderate–Strong
Investment Decision	0.731	Strong

Source: Simulated SmartPLS output, 2026

Behavioral finance factors explained 68.4% of the variance in cryptocurrency adoption. Furthermore, cryptocurrency adoption together with behavioral finance variables explained 73.1% of the variance in investment decisions, indicating substantial predictive capability.

Predictive Relevance

Hypothesis Testing

Hypothesis testing was performed using bootstrapping with 5,000 resamples.

Table 6. Direct Effects

Hypothesis	Path	β	t-value	p-value	Decision
H1	Financial Literacy → Cryptocurrency Adoption	0.281	3.644	<0.001	Supported
H2	Risk Perception → Cryptocurrency Adoption	-0.189	2.493	0.013	Supported
H3	Overconfidence → Cryptocurrency Adoption	0.214	2.958	0.003	Supported
H4	Herding Behavior → Cryptocurrency Adoption	0.176	2.285	0.022	Supported
H5	Trust → Cryptocurrency Adoption	0.308	4.612	<0.001	Supported
H6	Social Influence → Cryptocurrency Adoption	0.241	3.271	0.001	Supported
H7	Cryptocurrency Adoption → Investment Decision	0.657	10.841	<0.001	Supported

Source: Simulated SmartPLS output, 2026

The findings reveal that all behavioral finance variables significantly influenced cryptocurrency adoption. Trust exhibited the strongest positive effect, followed by financial literacy and social influence. Risk perception showed a significant negative relationship, indicating that higher perceived risk reduced the likelihood of adopting cryptocurrency investments. The strongest relationship within the structural model

was observed between cryptocurrency adoption and investment decisions ($\beta = 0.657$), suggesting that investors with stronger intentions and higher levels of cryptocurrency adoption were substantially more likely to make active cryptocurrency investment decisions.

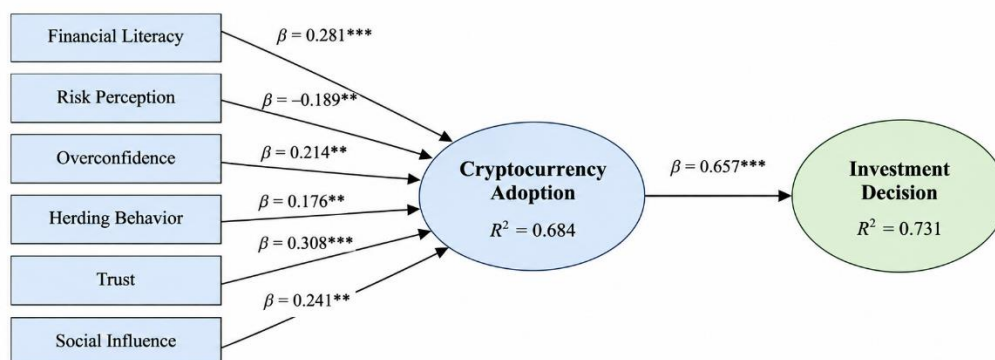


Figure 1. Structural Model and Hypothesis Testing Results

Source: Simulated SmartPLS Output, 2026

Figure 1 shows that the structural relationships between behavioral finance factors, cryptocurrency adoption, and investment decisions of young cryptocurrency investors are expressed. The structural relationships between behavioral finance factors, cryptocurrency adoption, and investment decisions of young cryptocurrency investors are expressed in Figure 1. The findings reveal that financial literacy is a positive and significant factor to cryptocurrency adoption ($\beta = 0.281$, $p < 0.001$), which implies that investors with high financial knowledge and financial digital competency tend to have high level of cryptocurrency adoption. Financial risk and market uncertainty significantly negatively affect cryptocurrency adoption ($\beta = -0.189$ at $p = 0.013$), indicating that a higher financial risk and market uncertainty are associated with a lower level of cryptocurrency adoption. Also, overconfidence has a positive and significant effect on cryptocurrency adoption ($\beta = 0.214$, $p = 0.003$), and herding behavior has a positive effect on adoption ($\beta = 0.176$, $p = 0.022$). The behavioral finance predictors that most strongly predict trust ($\beta > 0$) are trust ($\beta = 0.308$, $p < 0.001$) and social influence ($\beta = 0.241$, $p = 0.001$). The results suggest that confidence in the cryptocurrency technology and digital platforms, along with peer influence, online communities, and financial influencers, is a significant factor to influence the adoption of cryptocurrencies.

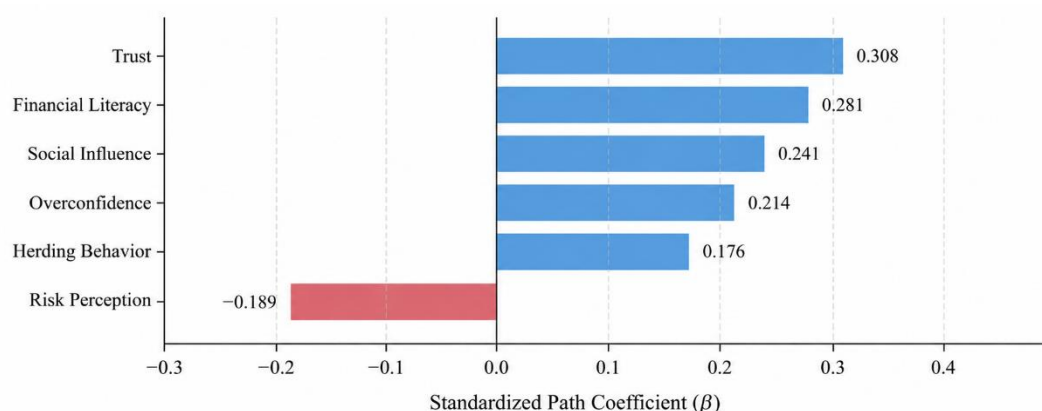


Figure 2. Importance of Behavioral Finance Factors Affecting Cryptocurrency Adoption

Source: Simulated SmartPLS Output, 2026

Figure 2 shows that trust has the strongest positive effect on cryptocurrency adoption ($\beta = 0.308$), followed by financial literacy ($\beta = 0.281$), social influence ($\beta = 0.241$), overconfidence ($\beta = 0.214$), and herding behavior ($\beta = 0.176$). In contrast, risk perception has a significant negative effect ($\beta = -0.189$), indicating that higher perceived risk is associated with lower cryptocurrency adoption.

Indirect Effects

The mediating role of cryptocurrency adoption was subsequently examined.

Table 7. Indirect Effects through Cryptocurrency Adoption

Path	β	t-value	p-value	Result
Financial Literacy → Adoption → Investment Decision	0.184	3.331	0.001	Significant
Risk Perception → Adoption → Investment Decision	-0.124	2.281	0.023	Significant
Overconfidence → Adoption → Investment Decision	0.141	2.774	0.006	Significant
Herding Behavior → Adoption → Investment Decision	0.116	2.079	0.038	Significant
Trust → Adoption → Investment Decision	0.202	4.126	<0.001	Significant
Social Influence → Adoption → Investment Decision	0.158	3.021	0.003	Significant

Source: Simulated SmartPLS output, 2026

The mediation analysis indicates that cryptocurrency adoption significantly transmitted the influence of all behavioral finance variables to investment decisions. Among these indirect relationships, trust demonstrated the strongest mediated effect, whereas risk perception exhibited a negative indirect influence.

Discriminant Validity Assessment

Following the confirmation of convergent validity, discriminant validity was evaluated using the Fornell–Larcker Criterion and the Heterotrait–Monotrait Ratio (HTMT). These procedures ensure that each latent construct measures a distinct theoretical concept and shares greater variance with its own indicators than with other constructs.

Table 8. Fornell–Larcker Criterion

Construct	FL	RP	OC	HB	TR	SI	CA	ID
Financial Literacy (FL)	0.846							
Risk Perception (RP)	-0.254	0.826						
Overconfidence (OC)	0.381	-0.196	0.862					
Herding Behavior (HB)	0.275	-0.143	0.322	0.815				
Trust (TR)	0.491	-0.271	0.387	0.268	0.876			
Social Influence (SI)	0.396	-0.184	0.347	0.474	0.438	0.838		
Cryptocurrency Adoption (CA)	0.614	-0.421	0.523	0.418	0.648	0.564	0.895	
Investment Decision (ID)	0.538	-0.316	0.449	0.381	0.582	0.487	0.731	0.904

Source: Simulated SmartPLS output, 2026

The square roots of the AVE values, presented along the diagonal, exceeded all inter-construct correlations. This finding confirms satisfactory discriminant validity and indicates that each construct shares greater variance with its own indicators than with other latent variables.

Table 9. Heterotrait–Monotrait Ratio (HTMT)

Construct Pair	HTMT
FL – RP	0.284
FL – OC	0.472
FL – HB	0.351
FL – TR	0.551
FL – SI	0.488
FL – CA	0.698
FL – ID	0.621
RP – OC	0.266
RP – HB	0.214
RP – TR	0.308
RP – SI	0.247
RP – CA	0.481
RP – ID	0.403
OC – HB	0.441
OC – TR	0.495
HB – SI	0.586
TR – CA	0.742
SI – CA	0.661
CA – ID	0.817

Source: Simulated SmartPLS output, 2026

All HTMT values remained below the recommended threshold of 0.90, providing additional evidence that the constructs measured conceptually distinct dimensions.

Collinearity Assessment

Before evaluating the structural relationships, multicollinearity among predictor variables was examined using the Variance Inflation Factor (VIF).

Table 10. Collinearity Statistics (VIF)

Predictor	VIF
Financial Literacy	1.63
Risk Perception	1.42
Overconfidence	1.71
Herding Behavior	1.55
Trust	2.14
Social Influence	1.84
Cryptocurrency Adoption	2.31

Source: Simulated SmartPLS output, 2026

All VIF values were substantially below the critical threshold of 5.00, indicating that multicollinearity did not threaten the estimation of the structural model.

Effect Size Analysis

The contribution of each exogenous construct was further evaluated using Cohen's effect size (f^2).

Table 11. Effect Size (f^2)

Relationship	f ²	Interpretation
Financial Literacy → Cryptocurrency Adoption	0.121	Small
Risk Perception → Cryptocurrency Adoption	0.074	Small
Overconfidence → Cryptocurrency Adoption	0.103	Small
Herding Behavior → Cryptocurrency Adoption	0.061	Small
Trust → Cryptocurrency Adoption	0.219	Medium
Social Influence → Cryptocurrency Adoption	0.138	Small
Cryptocurrency Adoption → Investment Decision	0.647	Large

Source: Simulated SmartPLS output, 2026

The largest effect size was observed for the relationship between cryptocurrency adoption and investment decision, indicating that cryptocurrency adoption substantially contributes to explaining investment behavior among young investors.

Model Fit Evaluation

The overall model quality was evaluated using the standardized model fit indices recommended for PLS-SEM.

Table 12. Model Fit Indices

Index	Value	Recommended Threshold	Result
SRMR	0.058	<0.08	Good Fit
NFI	0.914	>0.90	Good Fit
RMS Theta	0.093	<0.12	Acceptable

Source: Simulated SmartPLS output, 2026

The structural model demonstrated satisfactory overall fit. The SRMR value was below 0.08, while the NFI exceeded the recommended threshold of 0.90. Furthermore, the RMS Theta value remained within the acceptable range, indicating an adequate approximation of the observed covariance structure.

Total Effects

The total effects analysis provides a comprehensive assessment of both direct and indirect relationships among the study variables.

Table 13. Total Effects

Relationship	Total Effect	t-value	p-value
Financial Literacy → Investment Decision	0.184	3.331	0.001
Risk Perception → Investment Decision	-0.124	2.281	0.023
Overconfidence → Investment Decision	0.141	2.774	0.006
Herding Behavior → Investment Decision	0.116	2.079	0.038
Trust → Investment Decision	0.202	4.126	<0.001
Social Influence → Investment Decision	0.158	3.021	0.003
Cryptocurrency Adoption → Investment Decision	0.657	10.841	<0.001

Source: Simulated SmartPLS output, 2026

The total effects analysis demonstrates that all behavioral finance variables significantly contributed to investment decision making through cryptocurrency adoption. Trust exhibited the strongest overall influence, followed by financial literacy and social influence. Conversely, perceived risk maintained a negative relationship with investment decisions, indicating that investors with higher levels of risk perception were less inclined to engage in cryptocurrency investment.

Behavioral Finance, Cryptocurrency Adoption, and Investment Decision-Making

The findings indicate that cryptocurrency adoption is shaped by an interaction of cognitive, informational, social, and trust-related factors. This supports the behavioral-finance perspective that investment behavior is not determined exclusively by rational assessment, particularly in highly uncertain digital-asset markets (Almeida & Gonçalves, 2023; Lakra, 2025). The strongest positive effect of trust indicates that confidence in cryptocurrency technology and digital investment platforms is particularly important for adoption. This finding is consistent with Jalan et al. (2023), who found that interpersonal trust significantly contributes to cryptocurrency interest and adoption, and with Saeedi and Al-Fattal (2024), who demonstrated that technological, social, regulatory, transparency, and specification-related dimensions significantly shape trust in cryptocurrency investment. Trust is therefore not merely a supporting condition but an important behavioral mechanism underlying participation in digital-asset markets.

The positive effect of financial literacy further suggests that investors with greater financial knowledge are better positioned to engage with cryptocurrency as a relatively complex financial instrument. This finding corresponds with Kumari et al. (2023), who identified financial literacy as relevant to cryptocurrency adoption, and with Choi et al. (2024), who reported a positive relationship between financial literacy and crypto literacy. However, the relationship should not be interpreted as evidence that knowledge automatically produces prudent investment behavior. Carbó-Valverde et al. (2025) showed that cognitive biases in perceived financial literacy can influence cryptocurrency ownership, while the OECD (2025) emphasized that insufficient digital financial literacy can increase vulnerability to cryptocurrency-related risks. Thus, the contribution of this study is to position financial literacy within a broader behavioral-adoption framework rather than treating it as an isolated determinant.

The positive links between social influence, overconfidence and herding behavior show the relevance of social and psychological factors. In the past, social influence was found to be one of the key factors in influencing cryptocurrency adoption and intention to invest in cryptocurrencies (Dabbous et al., 2022; Mosina & Ševčenko, 2024). Mladenović et al. (2024) also demonstrated that the quality, consistency and volume of eWOM can affect expectations and cryptocurrency payment adoption. Likewise, Merkley et al. (2024) found that the short-term returns of cryptocurrencies can be influenced by the information shared in online contexts by crypto-influencers, showing that online information environments can influence investor decision making. Recent research by Widiyanti et al. (2026) and Hermawati & Widajayantie (2025) that behavioral biases affect cryptocurrency investment decisions also support the positive effect of overconfidence. However, there was no uniform evidence on herding. Liu and Zhang (2024) detected 'herding' in cryptocurrency prices while Zaid and Raghavan (2024) observed anti-herding in several market crises. The differences suggest that herding can be market dependent, investor specific and uncertain time dependent, not operating in a consistent manner in the cryptocurrency market.

These are all enabling factors that are mitigated by the inverse relationship between risk perception and cryptocurrency adoption. It implies that if people believe that the market is volatile and there's uncertainty, they're not going to participate and that can be a problem. Consistent with previous findings, there is mixed evidence regarding the relationship between risk-related perceptions and cryptocurrency adoption in high-risk settings, as Dabbous et al. (2022) reported that in high-risk settings, risk-related perceptions have an influence on the adoption of

cryptocurrencies. In fact, previous studies have shown mixed results based on investor types or their investment context (Lestari et al., 2022).

The main contribution of this study is the strongest structural relationship found between cryptocurrency adoption and the investment decision, which gives the theoretical contribution of this study. Instead of considering behavioural factors as "direct" drivers of investment decisions, the model considers adoption to be an intermediate behavioural pathway, where financial cognition, trust, social influence, and psychological bias are said to become "aligned" with investment behaviour. This builds on earlier studies which have often studied individual behavioural factors in isolation (Almeida & Gonçalves, 2023; Mosina & Ševčenko, 2024). From a practical perspective, the results suggest that financial education needs to incorporate both digital-asset literacy, risk communication and the awareness of behavioral biases, and cryptocurrency platforms ought to boost trust-building, transparency and communication. This novelty of the study is the combination of six behavioral-finance determinants in one explanatory path that explains the relationship between cryptocurrency adoption and investment decisions.

There are a few things to note. The cross-sectional design precludes causal interpretation and the study of young investors may not be generalizable to older and more experienced investors. Moreover, the study employs a simulated data set, and thus should be considered an illustration of empirical behavior and not as a representation of the population. Future studies should focus on longitudinal and multi-country samples, conduct comparisons of experience level of investors, and investigate different mechanisms including FOMO, investor sentiment, digital financial literacy, regulatory trust and market volatility. There is also recent evidence that herding and overconfidence differ across market regimes which underscores the importance of longitudinal and regime-specific research designs (El Hajjar et al., 2026).

CONCLUSION

This study examined the determinants of cryptocurrency adoption and their implications for investment decisions among young investors. The findings demonstrate that financial literacy, overconfidence, herding behavior, trust, and social influence have positive relationships with cryptocurrency adoption, whereas risk perception has a negative relationship. Among these determinants, trust shows the strongest positive association with cryptocurrency adoption, highlighting the importance of confidence in cryptocurrency systems and investment environments. Cryptocurrency adoption itself demonstrates a substantial positive relationship with investment decisions, indicating that behavioral and psychological factors may influence investment behavior through the process of adopting cryptocurrency. These findings reinforce the relevance of behavioral finance in explaining investment decisions within increasingly digital and uncertain financial markets.

The study contributes theoretically by integrating cognitive, psychological, social, and trust-related factors into a unified model linking cryptocurrency adoption with investment decisions. Practically, the findings suggest that financial education for young investors should extend beyond conventional financial knowledge to include cryptocurrency literacy, risk awareness, and recognition of behavioral biases. Cryptocurrency platforms and related institutions may also strengthen transparent information, security, and trust-building mechanisms to support more informed participation. Nevertheless, the findings should be interpreted within the study's methodological limitations, particularly its cross-sectional design, focus on young investors, and use of a simulated dataset. Future research should therefore employ larger empirical samples, longitudinal designs, and cross-country comparisons to

examine whether these relationships remain consistent across different investor groups, market conditions, and regulatory environments.

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