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THE TRUST–VOLATILITY PARADOX IN CRYPTOCURRENCY INVESTMENT: THE MEDIATING ROLE OF PERCEIVED RISK AND THE MODERATING INFLUENCE OF INVESTOR TRUST

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ABSTRACT

This comprehensive study investigates the trust-volatility paradox in cryptocurrency investments, exploring how perceived risk and market fluctuations influence investor decisions. The research employs a mixed-methods approach, combining quantitative survey of investors from diverse demographic backgrounds with experimental simulations designed to replicate various levels of market volatility. Quantitative data are analysed using Structural Equation Modelling (SEM) to examine relationships between perceived volatility, investor trust, and investment behaviour, while ANOVA and regression analysis assess the impact of different volatility scenarios. Key findings reveal that heightened perceived volatility reduces investor trust, with perceived risk acting as a mediator in this relationship. Furthermore, trust serves as a moderating factor that shapes risk tolerance and investment decisions, particularly in volatile market conditions. These insights offer practical implications for investors seeking to navigate cryptocurrency volatility, financial advisors developing risk management strategies, and regulators aiming to foster a more stable investment environment. This research contributes to the growing field of behavioural finance by enhancing our understanding of how psychological factors influence investment behaviour in emerging digital asset markets.

KEYWORDS: Cryptocurrency, Volatility, Investor Trust, Perceived Risk, Structural Equation Modelling

1. INTRODUCTION

The global financial landscape has witnessed a significant transformation with the emergence and proliferation of cryptocurrencies. Originally conceptualized as a decentralized alternative to traditional fiat currencies, cryptocurrencies such as Bitcoin, Ethereum, and numerous altcoins have increasingly drawn the attention of retail and institutional investors alike. However, despite their innovative underpinnings, the market remains fraught with extreme price fluctuations, regulatory uncertainty, and technological complexity. These attributes, while intriguing to some, pose serious challenges to investor trust and risk tolerance, forming what we conceptualize as the Trust-Volatility Paradox. This paradox is especially relevant in emerging markets like India, where cryptocurrency adoption is accelerating, yet investor protection mechanisms are still evolving. Investors are constantly forced to reconcile the potential for high returns with the psychological burden of volatility and uncertain risk management frameworks. A study by (Hamid et al., 2024) observed that although investor interest in cryptocurrencies is growing, concerns about price unpredictability and risk exposure continue to influence investment patterns and decision-making behaviour.

The exponential rise of cryptocurrencies over the past decade has transformed the global financial landscape, offering a decentralized alternative to traditional financial systems. As of 2023, more than 23,000 cryptocurrencies were circulating globally, with a combined market capitalization of approximately USD 870.81 billion (N.S.S. Kiranmai Balijepalli, 2025). Despite this growth, cryptocurrency markets remain inherently volatile and fraught with uncertainty, prompting both fascination and apprehension among investors.

Several scholars have attempted to examine cryptocurrency investment from behavioural and psychological perspectives. (Oladapo, 2024) emphasized the role of perceived risk and perceived usefulness in driving investor adoption, suggesting that high volatility tends to dampen trust unless mitigated by strong technological assurances or brand confidence. Similarly, (Sharma, 2022) explored how financial literacy plays a mediating role in risk comprehension but acknowledged that volatility-induced anxiety remains a persistent barrier for new investors.

Investment decisions in cryptocurrency are shaped by an intricate interplay of psychological, technological, and market-related factors. Among these, perceived risk and market fluctuations stand out as pivotal determinants that influence investor behaviour and adoption. Unlike traditional financial assets, the novelty and technological complexity of cryptocurrencies introduce layers of uncertainty, ranging from security issues to regulatory ambiguities. Studies have shown that investors' perception of these risks — including financial, operational, legal, and psychological dimensions — significantly influence their willingness to invest and continue participation in crypto markets (Chaimae Hmimnat, 2024; Cheng-Kui Huang N. Lee, 2022)

The volatility of cryptocurrencies further intensifies the perceived risk. Sudden price swings driven by speculative trading, regulatory news, macroeconomic shifts, and social media sentiment often contribute to an unpredictable investment environment (Sidorov, 2024; Sirine Ben yaala, 2025). While some investors are drawn to this volatility for its potential high returns, others are deterred by the instability and associated emotional toll, particularly in the presence of behavioural factors like Fear of Missing Out (FOMO) and herding behaviour (Asif Hasan Shahid Alam, 2024; Anaza et al., 2023).

Trust also plays a foundational role in investment decisions. The lack of centralized authority in cryptocurrencies necessitates reliance on the underlying technology — especially blockchain — to build confidence. Perceived security, transparency, and institutional validation are key components in fostering this trust (Ahmad Gunawan Hilda, 2025; Felisia Christiani Cicilia Sriliasta Bangun, 2024). However, trust dynamics are influenced by investor literacy, regulatory clarity, and market maturity, further complicating the decision-making process.

More recent studies have shifted toward multidimensional analyses. For example, (Mosina C Ševčenko, 2024) provided a systematic literature review highlighting that risk perception, trust in technology (especially blockchain), and socio-demographic factors are key variables influencing cryptocurrency investment decisions. They emphasized the need for empirical studies that integrate behavioural finance models with technology acceptance frameworks, a gap that this study intends to address.

To better understand the complex mechanisms behind cryptocurrency investments, scholars have increasingly employed Structural Equation Modelling (SEM), including both ML-SEM and PLS-SEM, to study the causal relationships among perceived risk, trust, market factors, and investor behaviour (Dehghani et al., 2023; Sukumaran et al., 2022). These methodological advancements have enabled a more nuanced exploration of the psychological and economic factors that mediate investment choices in this emerging asset class.

This paper aims to contribute to both theoretical advancement and practical application by offering:
1. A validated measurement model for cryptocurrency investor behaviour;
2. Empirical evidence for the role of trust in mitigating risk-induced volatility effects;
3. Strategic insights for policymakers, platforms, and fintech entrepreneurs to improve market stability and investor confidence.

Given this background, the present research aims to explore the interrelationship between perceived risk, market volatility, and cryptocurrency investment decisions using SEM. By doing so, the study contributes to the growing body of literature focused on the behavioural dynamics of crypto-investors and provides empirical insights that may inform financial educators, policymakers, and emerging fintech platforms.

1.2 Problem Statement:

Although interest in cryptocurrency investment is growing globally and especially in emerging economies like India, investors face a dilemma. On one hand, they are attracted to the high returns and decentralization of crypto assets. On the other, they are discouraged by extreme market volatility, inconsistent regulations, and limited investor protection. This creates a behavioural tension between trust and fear, forming what this study terms the Trust–Volatility Paradox.

While prior research has explored individual aspects such as trust, risk, or volatility, very few studies have structurally examined how these constructs interact to shape investment decisions (Felisia Christiani Cicilia Sriliasta Bangun, 2024; Asif Hasan Shahid Alam, 2024). Moreover, most existing models are rooted in Western contexts and often neglect regional dynamics, such as India's evolving legal stance, digital infrastructure, and financial literacy variations (Sidorov, 2024; Saher Zeast Hasan Huma Ayub, 2022).

1.3 Significance of the Study:

This study contributes to bridging the existing research gaps in three major ways:

1. Behavioural Insight into Investment Decisions: It integrates **perceived risk, investor trust, and volatility perception** into a single structural model — a first in the context of the Indian cryptocurrency market.

2. Application of SEM in a High-Volatility Context: Using **Structural Equation Modelling (SEM)**, the study statistically examines both **mediating** and **moderating** relationships among constructs, improving empirical robustness over traditional regression models (Sukumaran et al., 2022a).

3. Relevance to Indian Regulatory and Investor Climate: By focusing on Indian investors, this study provides **context-specific insights** that are highly relevant for **regulators, crypto platforms, fintech startups**, and **financial advisors** aiming to build trust and reduce perceived risk in digital asset markets.

Ultimately, this research aims to explain **how perceived volatility influences investment intention**, both directly and indirectly, through the psychological lenses of **risk perception** and **trust dynamics**. The findings will not only deepen the understanding of behavioural finance in crypto ecosystems but also provide actionable strategies for mitigating investor hesitation in high-risk environments.

2. RESEARCH OBJECTIVES AND RESEARCH QUESTIONS

2.1 Research Objectives

The primary aim of this study is to investigate the behavioural responses of cryptocurrency investors in the face of market volatility, focusing on how perceived risk and investor trust influence investment intention. Specifically, this research seeks to:

1. Examine the impact of perceived volatility on investor trust in cryptocurrency platforms and technologies.

2. Determine the mediating role of perceived risk in the relationship between market volatility and investment intention.
3. Evaluate the moderating effect of investor trust in reducing the negative impact of perceived risk on investment behaviour.
4. Assess the direct influence of perceived risk on investment intention, independent of volatility.
5. Establish the overall direct effect of perceived volatility on investment intention in cryptocurrency markets.

These objectives are intended to address the empirical and conceptual gaps identified by prior studies. (Hamid et al., 2024) emphasized the need to examine investor psychology under conditions of high uncertainty, while (Oladapo, 2024) called for integrated models that account for trust and behavioural intention simultaneously. Additionally, (Mosina C Ševčenko, 2024) pointed out the lack of research investigating risk perception and trust as structural mechanisms within investor behaviour frameworks in digital finance.

These objectives also respond directly to the gaps identified in systematic reviews like those of (Sirine Ben yaala, 2025), who emphasized the fragmented understanding of behavioural elements in crypto investment literature, and (Anaza et al., 2023), who called for integrated models considering both financial and psychological constructs.

2.2 Research Questions

Based on the above objectives, the following research questions guide the investigation:
1. Howdoes perceived volatility in cryptocurrency markets affect investor trust?
↳ Grounded in studies by (Sharma, 2022) and (Hamid et al., 2024) showing trust erosion due to unpredictability.
2. Does perceived risk mediate the relationship between market volatility and investment intention?
↳ As suggested by (Mosina C Ševčenko, 2024), risk acts as a psychological filter between perception and action.
3. To what extent does investor trust moderate the impact of perceived risk on investment intention?
↳ Supported by (Oladapo, 2024), who argued that trust can offset perceived dangers of investing in volatile assets.
4. Does perceived risk independently influence the investor's decision to invest in cryptocurrencies?
↳ Aligned with findings from (Sharma, 2022) about direct deterrents created by risk aversion.
5. Does perceived volatility directly reduce the willingness to invest in cryptocurrencies?
↳ Suggested in recent risk perception models which link market instability to lower behavioural intention (Hamid et al., 2024).

3. LITERATURE REVIEW:

3.1 Key Concepts and Definitions

Cryptocurrency: Cryptocurrency is a digital or virtual currency secured by cryptography, making it difficult to counterfeit or double-spend (Kumar et al., 2022). Cryptocurrencies operate on a decentralized network, typically based on blockchain technology, which allows for peer-to-peer transactions without the need for intermediaries such as banks or financial institutions. The use of cryptography ensures the security and integrity of transactions, while the decentralized nature of the network enhances transparency and reduces the risk of censorship or control by a single entity. Bitcoin, as noted by B. Kumar, Kindye Essa Mustofa and Birhan Moges Adugna (Kumar et al., 2022), was the first kind of digital currency that existed only in the online world and is a digital version of money made possible by a system called blockchain technology.

Perceived Risk: Perceived risk is the subjective assessment of potential losses associated with cryptocurrency investments, including financial, security, and regulatory risks (Mirza et al., 2023), (Nejjari Aya et al., 2024). This assessment is influenced by a variety of factors, including an investor's knowledge of cryptocurrencies, their risk tolerance, and their perception of the overall market environment. Agus Muhammad Mirza, Yudi Fernando, Fineke Mergeresa, Ika Sari Wahyuni-TD, R. Ikhsan and Erick Fernando (Mirza et al., 2023) highlight that the factors influencing the decision to use cryptocurrency include perceived risk, psychological risk and security risk. Nejjari Aya, Yin Junming and Hanqing Lu (Nejjari Aya et al., 2024) found that the risks associated with the use of cryptocurrencies remain a significant barrier to their adoption.

Market Volatility: Market volatility refers to the degree of variation in cryptocurrency prices over time, often measured by statistical indicators such as standard deviation or other statistical indicators (N. A. Kyriazis, 2021). High volatility is a defining characteristic of the cryptocurrency market, with prices often experiencing rapid and significant fluctuations. This volatility can be influenced by a variety of factors, including market sentiment, regulatory news, and technological developments. N. Kyriazis (N. A. Kyriazis, 2021) notes that more sophisticated GARCH models are found to better explain the fluctuations in the volatility of cryptocurrencies.

Investor Trust: Investor trust is the belief that a cryptocurrency platform or asset is reliable, secure, and transparent, influencing adoption and investment (Recskó C Aranyossy, 2024), (Al-Afeef et al., 2024). Trust is a critical factor in the cryptocurrency market, as investors need to have confidence in the platforms and assets they are using. This trust is built on a variety of factors, including the security of the platform, the transparency of the project, and the regulatory environment. Mrk Recsk and Mrta Aranyossy (Recskó C Aranyossy, 2024) found that consumers are susceptible to technological risks, and trust is an important determinant of their openness toward innovations in financial services. M. Al-Afeef, Raed Walid Al-Smadi and Arkan Walid Al-Smadi (Al-Afeef et al., 2024) emphasize the importance of trust in stablecoin systems, transparency, and regulatory compliance in influencing perceived volatility reduction and stablecoin adoption.

3.2 Overview of Cryptocurrency Investment Behaviour

Cryptocurrency as an investment class has evolved rapidly over the past decade, moving from fringe adoption to widespread attention among retail and institutional investors. However, this evolution has been accompanied by significant market instability, lack of regulatory clarity, and wide variations in investor understanding. Studies have shown that the speculative nature of cryptocurrencies, combined with technological novelty and market volatility, introduces a high degree of perceived risk for investors (Asif Hasan Shahid Alam, 2024; Sirine Ben yaala, 2025).

In their systematic review, (Sirine Ben yaala, 2025) classified risk into four broad categories: financial risk, security risk, legal/regulatory risk, and psychological risk. Each of these categories contributes differently to investor hesitation, particularly in emerging economies like India. Similarly, (Ahmad Gunawan Hilda Oscar Jayanegara, 2025) emphasized the role of trust in mitigating these risks, showing that belief in the security and transparency of blockchain systems can directly influence investment behaviour.

3.3 Perceived Risk in Cryptocurrency Investment Decisions

3.3.1 Perceived Risk and Investment Intention

Risk perception has been widely acknowledged in behavioural finance as a critical antecedent to decision- making. In cryptocurrency markets, perceived risk often stems from price unpredictability, lack of investor protection, and fear of fraud. (Felisia Christiani Cicilia Sriliasta Bangun, 2024) found that even technologically literate investors tend to delay or reduce their crypto exposure when perceived risk is high. Additionally, (Sidorov, 2024) noted that price volatility leads to heightened emotional reactions like fear, uncertainty, and doubt, which negatively affect risk tolerance and investment decisions.

Moreover, (Chaimae Hmimnat, 2024a) demonstrated that perceived risk serves as a mediating factor in the relationship between external market stimuli (such as volatility) and behavioural intentions. Their study also called for greater exploration into how risk channels influence behaviour when psychological and technological variables like trust are present.

3.3.2 Conceptualizing Perceived Risk in Cryptocurrency Markets

Perceived risk in cryptocurrency markets encompasses multiple dimensions that influence investor decisions. Research has identified various types of risks that potential and actual cryptocurrency users perceive, including financial, legal, and operational risks. A study on the discontinuous intention in cryptocurrency usage found that financial, legal, and operational risks were critical factors that increased users' perceived risk which could subsequently influence their discontinuance usage intention regarding cryptocurrency (Cheng-Kui Huang N. Lee, 2022). This multidimensional nature of perceived risk creates a complex decision-making environment for investors.

In the context of emerging economies, perceived risk takes on additional dimensions. Research conducted in Morocco revealed that volatility and lack of regulation significantly heighten perceived investment risk, whereas factors like fast transactions, reduced complexity, and improved security mitigate this perception suggesting that addressing volatility and regulatory concerns could decrease perceived risks and potentially attract more investors (Chaimae Hmimnat, 2024a). These findings highlight the importance of considering both technological and regulatory aspects when examining risk perception in cryptocurrency markets.

3.3.3 Factors Influencing Perceived Risk

Several factors have been identified as significant influences on perceived risk in cryptocurrency investment. A study analysing cryptocurrency investment behaviours in Morocco found that volatility and lack of regulation were the primary factors that heightened perceived risk while fast transactions, reduced complexity, and improved security were found to mitigate perceived risk (Chaimae Hmimnat, 2024a). These results point to both inherent market characteristics and external regulatory environments as key determinants of perceived risk.

Social and psychological factors also play a crucial role in shaping risk perceptions. Research on Saudi Arabian investors revealed that Fear of Missing Out (FOMO) acts as a moderating psychological factor that interacts with various influences and drives decision-making This interaction between FOMO and other factors such as perceived risk, potential return, and regulatory environment has significant implications for understanding the dynamics of cryptocurrency investment choices in the Saudi Arabian market (Asif Hasan Shahid Alam, 2024a). The study employed a mixed-methods approach to comprehend these factors, combining quantitative surveys to gauge perceptions of risk with qualitative interviews exploring the nuanced interplay of these elements integrating the Theory of Planned Behaviour and Behavioural Finance theories to offer a holistic understanding of cryptocurrency investment determinants (Asif Hasan Shahid Alam, 2024a).

Similarly, research on American investors found that risk perception acts as a barrier, discouraging both current investment behaviour and future investment intentions in cryptocurrencies This finding emerged from the analysis of data from the 2021 National Financial Capability Study and the Investor

Survey, which employed logistic regression models to investigate the effects of investment motivations, risk perceptions, and investing confidence on cryptocurrency investments (Yu Zhang Khurram Naveed, 2025). The study revealed that while motivations and investment confidence positively correlate with cryptocurrency investments, risk perception acts as a significant deterrent highlighting the need to address risk perceptions to encourage investment in this asset class (Yu Zhang Khurram Naveed, 2025).

3.3.4 Impact of Perceived Risk on Investment Decisions

The literature reveals that perceived risk has a complex relationship with investment decisions, often serving as a significant barrier to cryptocurrency adoption and continued usage. A study examining German cryptocurrency users and potential users found that perceived volatility and financial risk tolerance are crucial factors hindering cryptocurrency adoption, whether in the pre-adoption or post-adoption stage This was one of the first studies to reveal cryptocurrency affordances and examine their effect on behavioural intentions toward cryptocurrency adoption based on the differences between non-users (potential) and users (actual) (M. Dehghani Dionysios Karavidas, 2023).

However, the influence of perceived risk on investment decisions is not uniform across all contexts. Research conducted in Malaysia found contrasting results, where perceived risk had no significant influence on cryptocurrency adoption among Malaysian investors, while perceived value was a significant determinant These findings emerged from data gathered using purposive sampling and analysed using Smart PLS Structural Equation Modelling (PLS-SEM) (Sukumaran et al., 2022c). This suggests that cultural, economic, or market-specific factors may moderate the relationship between perceived risk and investment decisions.

Studies focusing on student populations have found that perceived risk and herding behaviour have a significant influence on cryptocurrency investment decisions Research conducted among students in Bali demonstrated that the influence of financial literacy on investment decisions was stronger when mediated through perceived risk, with a coefficient value of 0.412 (Rahyuda, 2023). This indicates that risk perception not only directly affects investment decisions but also serves as an important mediating factor in the relationship between financial knowledge and investment behaviour.

In the context of psychological factors, research has shown that perceived risk can interact with other cognitive and emotional factors to influence investment decisions. A study on university students found that perceived risks significantly affected behavioural intention to adopt cryptocurrency while hypotheses about social effects, personal innovativeness, and attitudes toward using cryptocurrency were not statistically proven (Hasan et al., 2024). This highlights the primacy of risk perception over other factors in certain demographic contexts.

3.4 Market Fluctuations and Volatility in Cryptocurrency Investment

3.4.1 Determinants of Cryptocurrency Volatility

The literature identifies several factors that contribute to cryptocurrency volatility, ranging from inherent market characteristics to external events and regulatory changes. Research has shown that volatility in cryptocurrency markets is influenced by both technical market factors and broader socioeconomic conditions A study examining the impact of climate-related risks on cryptocurrency volatility found that acute events (e.g., hurricanes and wildfires) and chronic risks (e.g., long-term environmental disruptions) significantly heighten cryptocurrency volatility, with Bitcoin and Ethereum exhibiting the highest sensitivities (Sirine Ben yaala, 2025).

Public announcements and regulatory actions also play a crucial role in shaping volatility patterns. Research examining the influence of public announcements on cryptocurrency prices revealed that volatile assets like Dogecoin experience more pronounced and longer-lasting price changes in response to positive announcements, while more stable cryptocurrencies such as Bitcoin and Ethereum show relatively brief price shifts The same study found that negative events, especially those involving regulatory actions or market disruptions, tend to have a prolonged and detrimental effect on cryptocurrency prices (Sidorov, 2024).

The cryptocurrency market's relative inefficiency compared to traditional financial markets contributes to its volatility. A survey on efficiency and profitable trading opportunities in cryptocurrency markets found that the majority of academic papers provide evidence for the inefficiency of Bitcoin and other primary digital currencies, although there have been steps toward greater efficiency in recent years This inefficiency can lead to less profitable trading strategies for speculators but also contributes to market volatility (N. Kyriazis, 2019).

3.4.2 Impact of Volatility on Investment Behaviour

Volatility significantly influences investor behaviour in cryptocurrency markets, affecting both risk perceptions and investment strategies. Research has shown that the high volatility of cryptocurrencies acts as a deterrent for some investors while attracting others seeking high returns. A study examining cryptocurrency investment behaviour found that the potential for high returns attracts investors, drawing attention to the volatile but potentially rewarding nature of the cryptocurrency market The same study noted that decentralized and transparent transactional systems, along with financial inclusion and security & privacy concerns, emerge as significant factors driving preference (R. S. Lekshmi K. Jawaharrani, 2023).

The psychological impact of volatility on investors is particularly noteworthy. A study examining the

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fear of missing out (FOMO) found that despite the sharp increases and decreases in cryptocurrency value, FOMO on possible positive returns often negates the rational fear that such volatility should generate This research explored how personality traits influence FOMO in predicting consumers' purchase intentions of cryptocurrencies (Anaza et al., 2023). The findings suggest that FOMO is a driving force behind cryptocurrency consumption for certain personality types, with varying effects depending on market conditions The study observed that FOMO negatively mediates cryptocurrency investment likelihood for consumers with high openness to experience and conscientiousness in a bear market, but not in a bull market (Anaza et al., 2023).

Volatility also influences trading behaviour at different time scales. Analysis of Bitcoin's price volatility found that increases in opinion polarization and exchange volume precede rising Bitcoin prices, and emotional valence precedes opinion polarization and rising exchange volumes This insight was applied to design algorithmic trading strategies for Bitcoin, reaching very high profits in less than a year (David García, 2015). This suggests that social signals and sentiment indicators can help investors navigate volatility in cryptocurrency markets.

3.4.3 Volatility Modelling and Prediction

Various approaches have been employed to model and predict cryptocurrency volatility, ranging from traditional econometric models to advanced machine learning techniques. Research using the GJR-GARCH and dynamic conditional correlation (DCC)-GJR-GARCH models has assessed the impact of external events such as the COVID-19 pandemic and the Russian-Ukrainian war on cryptocurrency volatility The findings revealed mixed impacts on different cryptocurrencies, with some experiencing positive effects and others negative effects during these crisis periods (Wajdi Moussa Rym Regaïeg, 2024).

Emerging research is exploring more sophisticated approaches to volatility prediction using artificial intelligence. A study on predicting cryptocurrency volatility presented a Fuzzy Bidirectional Long Short-Term Memory with a Soft Computing-based Decision-Making Model The technique aimed to present a robust and intelligent framework for an advanced decision-making model to predict cryptocurrency volatility (Ragab, 2025). Such advanced techniques promise to improve the accuracy of volatility predictions, potentially helping investors better manage risk in cryptocurrency markets.

The literature also highlights the importance of developing models that can adapt to the changing dynamics of cryptocurrency markets. Traditional time series forecasting models like ARIMA are effective for financial forecasting but less effective for markets with high volatility typical of cryptocurrencies Deep learning methods have been shown to be effective in predicting time series with significant fluctuations and almost chaotic and unpredictable behaviour (Valentina Moskalenko

Nataliia Fonta, 2024). This suggests that flexible

models that can adapt to new data and changes in market dynamics are essential for understanding and predicting cryptocurrency volatility.

3.5 Investor Trust and Decision-Making in Cryptocurrency Markets

3.5.1 Trust Development in Cryptocurrency Markets

The development of trust in cryptocurrency markets involves multiple factors, including technological understanding, perceived security, and external validation. Research has shown that blockchain technology's perceived security and transparency significantly enhance investor confidence A study examining the role of blockchain technology and financial literacy found that these factors are crucial in shaping effective cryptocurrency investment strategies (Ahmad Gunawan Hilda Oscar Jayanegara, 2025). The decentralized nature of blockchain technology provides a sense of security and transparency that contributes to trust formation.

Institutional investment has been identified as a key factor in legitimizing cryptocurrencies and fostering trust among individual investors. Research on the adoption of Spot Bitcoin Exchange Traded Products (ETPs) found that institutional investment mediates the effects of regulatory and market dynamics on individual adoption, legitimizing these financial instruments and fostering trust The same study found that government factors, such as compliance guidelines and tax policies, improved investor confidence and adoption rates (Shirin Hasavari Mahed Maddah, 2025).

Trust development is also influenced by environmental factors such as regulatory clarity and legal frameworks. A study on cryptocurrency investment preferences found that blockchain security significantly shapes the investment preferences of millennials, fostering trust and influencing their decision to engage in cryptocurrency investments This research offers valuable insights for blockchain developers and regulators to enhance security features, helping to build investor confidence in rapidly expanding cryptocurrency markets (Felisia Christiani Cicilia Sriliasta Bangun, 2024).

3.5.2 Psychological Factors in Cryptocurrency Investment Decisions

Cryptocurrency investment decisions are heavily influenced by psychological factors, including emotional responses, cognitive biases, and social influences. Research has identified several psychological mechanisms at play in cryptocurrency markets, including FOMO, herding behaviour, and emotional reactions to market movements.

Fear of Missing Out (FOMO) has been identified as a significant psychological factor influencing cryptocurrency investment decisions. A study on Saudi Arabian investors found that FOMO emerges

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as a crucial psychological factor, interacting with other influences and driving decision-making This study underscores the intricate interplay between these factors and FOMO, shedding light on the dynamics of cryptocurrency investment choices (Asif Hasan Shahid Alam, 2024a). Similarly, research examining personality traits found that FOMO is a driving force behind cryptocurrency consumption for agreeable and neurotic consumers The findings were novel in observing that FOMO's influence varies based on market conditions and personality traits (Anaza et al., 2023).

Herding behaviour is another important psychological mechanism in cryptocurrency markets. Research on state university students in Indonesia found that herding behaviour has a positive and significant effect on investment decisions The study noted that herd behaviour is influenced by psychological factors that make investors take illogical actions, particularly when market uncertainty increases and market volatility is high (Muhammad Azmi Riyadi Besse Wediawati, 2024). This suggests that social influence plays a crucial role in cryptocurrency investment decisions, especially in uncertain market conditions.

Emotional reactions to market movements, particularly greed and fear, significantly impact cryptocurrency returns. Research employing the Granger causality test found that the Fear and Greed Index (FGI) notably predict the returns of Bitcoin and Ethereum, underscoring the lasting connection between investor emotions and market behaviour The study identified an intriguing feedback loop between the FGI and cryptocurrency returns, accentuating emotions' persistent role in shaping market dynamics (Everton Anger Cavalheiro K. Vieira, 2024).

3.5.3 Role of Information Asymmetry and Literacy

Information asymmetry and financial literacy play crucial roles in shaping cryptocurrency investment decisions. Research has shown that privileged information, which is hard to be observable unlike public information, is not homogeneously distributed to individual investors but inevitably affects prices in cryptocurrency markets This information asymmetry can significantly impact the behaviour of investors, particularly those without access to specialized knowledge (Minjung Park, 2020).

Financial literacy has been identified as a key factor mitigating the negative effects of information asymmetry and enhancing investment decisions. A study on cryptocurrency investment found that investors with both high blockchain knowledge and financial literacy are better at managing risk and avoiding common pitfalls in the market The study concluded that both blockchain technology and financial literacy are crucial in shaping effective cryptocurrency investment strategies (Ahmad Gunawan Hilda Oscar Jayanegara, 2025).

The relationship between financial literacy and risk perception is particularly noteworthy. Research on students in Bali found that investment decisions, herding behaviour, and risk perception are all significantly and positively influenced by financial literacy The influence of financial literacy on investment decisions was found to be stronger when mediated through perceived risk, highlighting the importance of education in risk assessment (Rahyuda, 2023). This suggests that improving financial literacy could help investors better evaluate and manage the risks associated with cryptocurrency investments.

3.6 Methodological Approaches in Cryptocurrency Research

3.6.1 Application of Structural Equation Modelling

Structural Equation Modelling (SEM) has emerged as a valuable methodological approach in cryptocurrency research, particularly for examining the complex relationships between perceived risk, trust, and investment decisions. Several studies have employed various forms of SEM to investigate these relationships.

Maximum likelihood structural equation modelling (ML-SEM) has been used to analyze data from cryptocurrency users and potential users. A study on cryptocurrency affordances collected data from 480 potential and actual users in Germany and used ML-SEM to analyze it. The approach allowed researchers to test post-adoption models and identify factors influencing behavioural intentions (Dehghani et al., 2023). This methodology provides a rigorous framework for examining the causal relationships between different variables influencing cryptocurrency adoption and usage.

Partial Least Square Structural Equation Modelling (PLS-SEM) is another common approach used in cryptocurrency research. A study on Malaysian investors used Smart PLS-SEM to examine the influence of perceived risk and perceived value on cryptocurrency adoption decisions Based on the finding's, perceived value was found to have a significant influence on cryptocurrency adoption, while perceived risk had no significant influence (Sukumaran et al., 2022). Similarly, research on investment decision-making used PLS- SEM as a data analysis technique and found that risk perception has a significant and negative effect on investment decision making the same study found that risk tolerance and overconfidence have a significant and positive effect on investment decision making, while loss aversion has no effect (Nadya Septi Nur Aini, 2019).

Research on cryptocurrency adoption in the UAE also employed PLS-SEM to test hypotheses about factors influencing continued usage. The analysis revealed that gambling attitudes, perceived benefits, legal environment, and market uncertainty are significant determinants of behavioural intention to continue using cryptocurrencies This study also revealed a significant effect of gambling attitudes and legal environment on the perceived benefits of cryptocurrencies (A. A. Alsmadi Ahmed Shuhaiber, 2023). The consistent use of SEM across different geographic and cultural contexts highlights its utility in understanding the complex relationships in cryptocurrency investment behaviour.

3.6.2 Mixed-Methods Approaches and Alternative Methodologies

While SEM is widely used, researchers have also employed mixed-methods approaches and alternative methodologies to gain a more comprehensive understanding of cryptocurrency investment behaviour. These diverse methods provide complementary insights into the complex dynamics of risk perception and market fluctuations.

Qualitative methods have been used to explore investor motivations and perceptions in depth. A study on NFT assets within decentralized finance conducted a thematic analysis based on 14 interviews with major NFT stakeholders to identify their different motivations and strategic options This approach allowed researchers to explain the value creation and capture dynamics in the NFT art market resulting from stakeholder interactions (Jan Schwiderowski A. B. Pedersen, 2023). Such qualitative insights provide rich contextual information that complements quantitative analyses.

Mixed-methods approaches have been particularly valuable in capturing the nuanced interplay of factors influencing cryptocurrency investment. Research on Saudi Arabian investors employed both quantitative surveys to gauge perceptions of risk, return, regulatory factors, and social influence, and qualitative interviews to explore the nuanced interplay of these elements and the impact of FOMO on decision-making This integrated approach provided a comprehensive view, enabling an in-depth analysis of the subject matter (Saher Zeast Hasan Huma Ayub, 2022).

Regression analysis and econometric models have also been widely used to examine specific relationships in cryptocurrency markets. Studies have used logistic regression to determine dominant usage methods for various cryptocurrency coins and to investigate the effects of investment motivations, risk perceptions, and investing confidence on cryptocurrency investments (Dehghani et al., 2023) These approaches allow researchers to identify specific relationships between variables and test hypotheses about factors influencing investment decisions (Yu Zhang Khurram Naveed, 2025).

3.6.3 Theoretical and Empirical Approaches in Recent Studies

Most studies investigating crypto investment behaviour have used theoretical frameworks like the Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), and Unified Theory of Acceptance and Use of Technology (UTAUT). However, the empirical tools often vary, with many relying on regression models, logistic models, or Partial Least Squares SEM. (Sukumaran et al., 2022) suggested that SEM provides greater explanatory power when studying multi-path relationships involving psychological constructs like risk and trust.

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Although studies like those by (Mosina C Ševčenko, 2024) and (Anaza et al., 2023) have attempted to synthesize findings across models, they also highlight inconsistencies in sample selection, geographical focus, and statistical rigor. Many models fail to distinguish between risk perception and actual risk, or they omit the interaction effects between trust and risk, leading to incomplete behavioural profiles.

Table 1: Key Psychological and Market Factors Influencing Cryptocurrency Investment Decisions

Factor	Description	Relevance to Study
Perceived Volatility	Extent to which investors perceive cryptocurrency markets as unstable and subject to rapid price swings.	Directly influences risk perception and investment hesitation.
Perceived Risk	Subjective assessment of potential losses due to market volatility, fraud, or lack of regulation.	Acts as a mediator between volatility and investment intention.
Investor Trust	Confidence in blockchain security, platform reliability, and market transparency.	Acts as a moderator, reducing the negative effects of perceived risk.
Investment Intention	Likelihood of an investor continuing or expanding their investment in cryptocurrencies.	Central dependent variable in the research model.
Risk Tolerance	An investor's capacity and psychological readiness to accept potential financial losses.	Moderates how volatility is perceived; considered as a control or segmentation factor.
Overconfidence Bias	Tendency to overestimate one's ability to predict or time the market accurately.	May influence how volatility and trust are processed by investors.
Social Influence	Impact of peer behavior, influencer marketing, and media sentiment on investment choices.	Amplifies or suppresses perceived risk and trust, particularly in high-volatility phases.
Financial Literacy	Knowledge of crypto mechanics, blockchain, trading risks, and regulatory frameworks.	May enhance trust and reduce perceived risk; potential control variable.
Regulatory Awareness	Understanding of taxation, legal status, and compliance requirements for crypto in India.	Shapes investor risk perception and trust in the investment environment.

4. Research Gaps

4.1 Limited Integration of Trust and Risk in a Single Structural Model

While numerous studies have investigated either perceived risk or trust as individual constructs influencing cryptocurrency investment, very few have structurally examined how the interplay between risk and trust shapes investor behaviour. For instance, (Felisia Christiani Cicilia Sriliasta Bangun, 2024) focused on the role of blockchain-based trust but did not consider how risk perception might simultaneously influence or interact with trust. Similarly, (Ahmad Gunawan Hilda, 2025) acknowledged trust as a significant driver of adoption but did not explore its potential moderating role when risk is high. This fragmented approach leaves a crucial gap in understanding how trust might act as a protective factor, neutralizing the adverse impact of perceived risk on investment decisions.

4.2 Underrepresentation of Indian Context in Behavioural Crypto Studies

Despite India being one of the fastest-growing crypto markets, most behavioural finance studies are concentrated in Western economies, often ignoring regional nuances such as financial literacy, digital infrastructure, and regulatory ambiguity. Indian investors often face additional psychological barriers due to fluctuating governmental stances on cryptocurrencies (e.g., tax laws, RBI announcements). (Saher Zeast Hasan Huma Ayub, 2022) and (Sidorov, 2024) both highlight a pressing need for local, context-sensitive empirical validation of global behavioural models. This gap limits the applicability of global findings to Indian investors, whose risk thresholds, trust anchors, and volatility perceptions may differ significantly due to cultural and policy environments.

4.3 Insufficient Use of Experimental or Mixed-Methods Designs

The majority of existing research relies solely on cross-sectional surveys and self-reported measures, which are prone to social desirability bias and lack dynamic validation. Studies such as (Oladapo, 2024) suggest that investors often respond differently when placed in real-time decision scenarios versus hypothetical questionnaire formats. Yet, scenario-based experimentation, behavioural simulations, or longitudinal methods remain underutilized. Integrating mixed-method designs could provide more robust insights into how investors react to volatility and perceived risk in the moment, offering a more accurate behavioural assessment.

4.4 Neglected Direct Impact of Volatility on Investment Decisions

Although volatility is acknowledged as a core feature of cryptocurrency markets, it is frequently treated as an external condition or control variable rather than as a central driver of investment behaviour. Prior models often emphasize risk perception without accounting for how directly volatility itself may discourage investment, even when trust and knowledge are present. For example, (Dehghani et al., 2023) allude to market fluctuations triggering portfolio rebalancing but stop short of modelling volatility as an independent variable with both direct and mediated effects. This oversight hinders a complete understanding of the behavioural mechanisms underpinning the Trust-Volatility Paradox.

4.5 Scarcity of Mediation and Moderation Testing Using SEM

While several studies highlight the relevance of mediation and moderation concepts in behavioural finance, few empirically test these mechanisms using Structural Equation Modelling (SEM). SEM offers the advantage of modelling both direct and indirect paths simultaneously while accounting for measurement error. However, (Sukumaran et al., 2022) point out that many cryptocurrency behaviour studies still rely on simplistic regression models, which are inadequate for testing complex theoretical frameworks involving risk as a mediator and trust as a moderator. Without such testing, theoretical propositions about interdependencies among constructs remain speculative.

4.6 Methodological Limitations

The existing literature on cryptocurrency investment decisions exhibits several methodological limitations that future research should address. One common limitation is the reliance on self-reported data, which may not accurately reflect actual investment behaviour. A study on cryptocurrency investment behaviours in Morocco acknowledged this limitation, noting that self-reported data and the specific focus on Moroccan investors may limit the generalizability of the findings This highlights the need for studies that incorporate objective investment data alongside self-reported perceptions (Chaimae Hmimnat, 2024).

Sample homogeneity is another limitation in many studies, with research often focusing on specific demographic groups or geographic regions. For instance, studies have focused on university students or investors from specific (Saher Zeast Hasan Huma Ayub, 2022) which may limit the generalizability of findings to broader investor populations (Felisia Christiani Cicilia Sriliasta Bangun, 2024), (Sukumaran et al., 2022), (Chaimae Hmimnat, 2024). Future research should aim for more diverse and representative samples to enhance the external validity of findings.

The cross-sectional nature of many studies limits our understanding of how risk perceptions and investment behaviours evolve over time, particularly in response to market fluctuations. While some studies have attempted to capture temporal dynamics by using repeated cross-sectional sampling in bear and bull markets (Anaza et al., 2023), longitudinal studies tracking changes in investor perceptions and behaviours over extended periods would provide valuable insights into the dynamic nature of cryptocurrency investment decisions.

4.7 Conceptual Gaps and Future Research Opportunities

Several conceptual gaps in the literature present opportunities for future research. One significant gap is the limited integration of traditional financial theories with emerging understanding of cryptocurrency markets. While some studies have drawn from behavioural finance and applied concepts like risk-return trade-offs (Tapas Das Shikha Arora, 2024) (Saher Zeast Hasan Huma Ayub, 2022) to cryptocurrency investments (Vaishali, 2023), there is a need for more comprehensive theoretical frameworks that account for the unique characteristics of cryptocurrency markets.

The interaction between regulatory developments and investor behaviour represents another important area for future research. Studies have noted the significant impact of regulatory actions on cryptocurrency markets but more research is needed to understand how different regulatory approaches across countries influence risk perceptions and investment decisions (Daisuke Kawai Bryan R. Routledge, 2024) (Sidorov, 2024). This research would have valuable implications for policymakers seeking to develop effective regulatory frameworks.

The role of social media and information diffusion in shaping risk perceptions and investment decisions is an emerging area that warrants further investigation. While some studies have examined the role of social signals and social platforms (Shawal Khalid Huayu Liang, 2024) (David García, 2015) in influencing trading behaviour (lakshita jain Luis Velez-Figueroa, 2025), more research is needed to understand how information flows through different channels and how investors filter and process this information when making investment decisions.

Future research should also explore the long-term implications of cryptocurrency investments and how risk perceptions evolve as markets mature. Studies have noted steps toward greater market efficiency and growing stability in some cryptocurrencies (N. Kyriazis, 2019) but more research is needed to understand how these developments influence investor behaviour and market dynamics (Sidorov, 2024). This would provide valuable insights for both investors and policymakers navigating the evolving cryptocurrency landscape.

These gaps justify the present study's empirical focus on:
• Modelling both mediation and moderation effects using SEM;
• Studying perceived risk and trust together in the same structural framework;
• And applying this integrated model within the Indian context, which remains underexplored in the literature.

4.8 Visual Mapping of Literature Trends:
To further contextualize the current research within the broader academic landscape, bibliometric and citation network analysis tools were employed. Two prominent tools, Litmaps and VOSviewer, were used to visually represent the thematic clusters and citation structures relevant to cryptocurrency investment research.

4.8.1 Litmaps Citation Network:

The Litmaps visualization shows the citation trajectories of key studies across domains such as:

- Technological Innovation and Blockchain Impact,
- Behavioural Finance & Psychological Factors,
- Regulatory Frameworks & Market Stability
- Cryptocurrency Market Dynamics & Investment Behaviour
- Forecasting Models & Market Analysis
- Cryptocurrency Market Dynamics & Volatility
- Social Media & Market Sentiment
- Technological & Regulatory Influences
- Perceived risk,
- Investor trust,
- Volatility, and
- Structural Equation Modelling (SEM).

The color-coded clusters indicate strong interconnections between recent works addressing cryptocurrency adoption, risk modelling, and trust in decentralized systems. Studies by (N. Kyriazis, 2019, 2021) (Asif Hasan Shahid Alam, 2024), and (Dehghani et al., 2023) serve as structural anchors, while more recent publications (e.g., Ahmad Gunawan Hilda, 2025; Anaza et al., 2023) cluster around emerging behavioural and psychological themes.

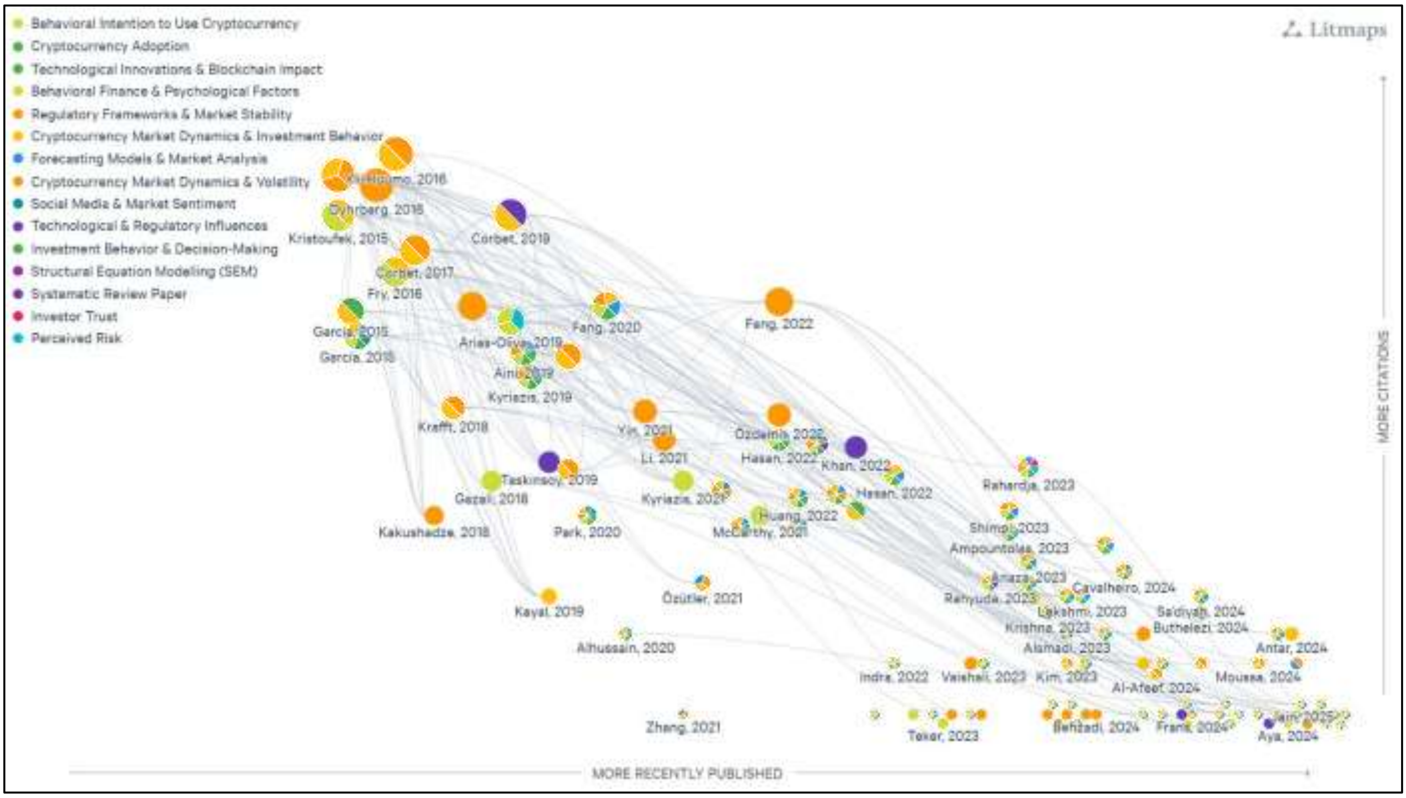

Figure 1: Litmaps Citation Network of Cryptocurrency Investment Literature

4.8.2 VOSviewer Keyword Co-occurrence Map (Figure 2)

The VOSviewer map highlights the most frequent co-occurring keywords in the field, such as:

• *Cryptocurrency, risk, volatility, trust, financial economics, psychology, and blockchain.*

The visualization confirms that cryptocurrency investment is positioned at the intersection of finance, technology, and behavioural science. Clusters related to volatility modelling, digital trust, and market uncertainty dominate the core of the network, reflecting the multidisciplinary interest in this research area.

Together, these visual tools reinforce the relevance and timeliness of the proposed study, while also highlighting gaps in integrated modelling of trust, perceived risk, and volatility in investor decision-making.

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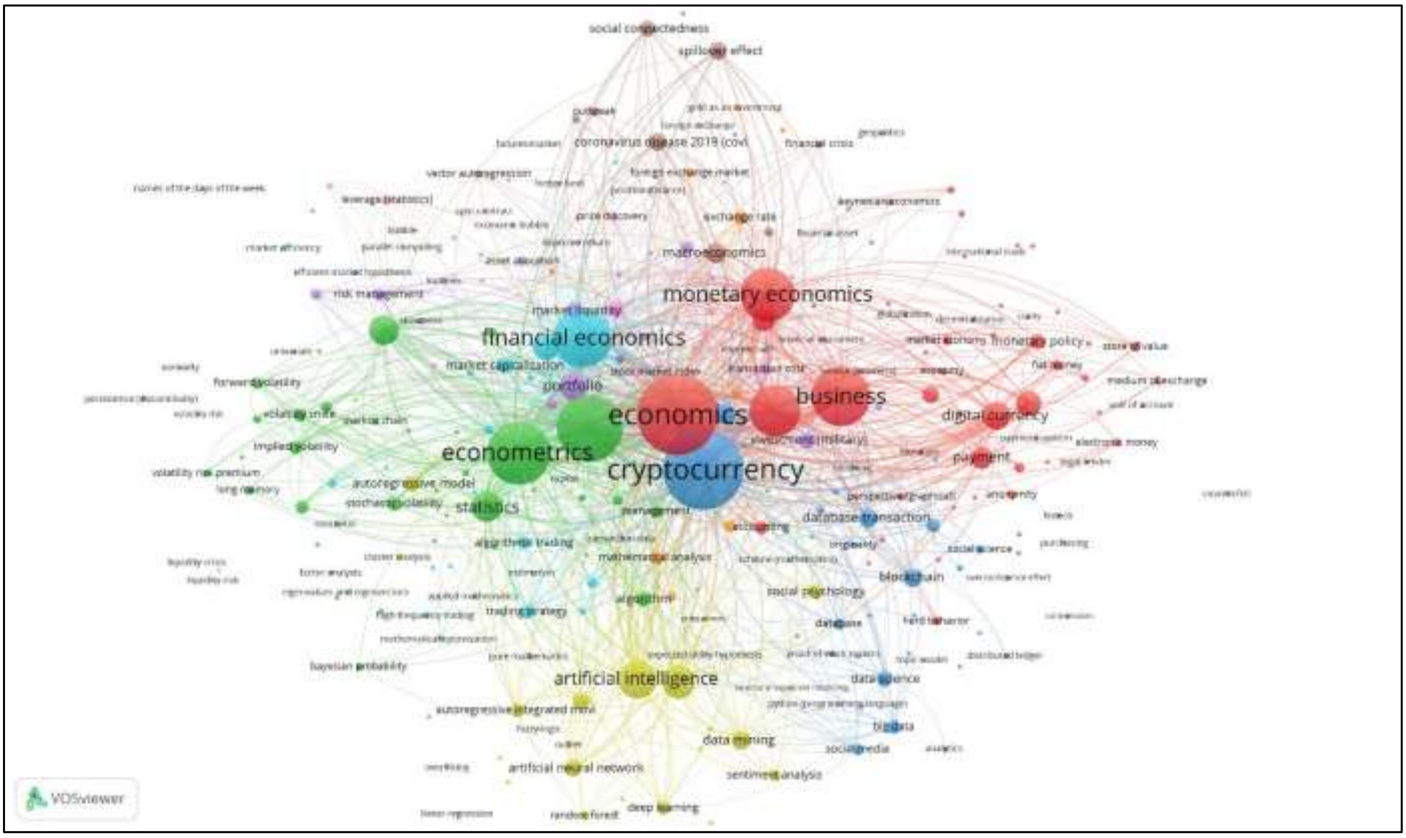

Figure 2: VOSviewer Co-occurrence Map of Cryptocurrency Research Themes

5. RESEARCH METHODOLOGY

5.1 Research Design:

This study employs a quantitative cross-sectional design to examine the interrelationships among perceived volatility, perceived risk, investor trust, and investment intention in cryptocurrency markets. The research integrates descriptive and explanatory elements, enabling statistical validation of the Trust-Volatility Paradox using Partial Least Squares Structural Equation Modelling (PLS-SEM). PLS-SEM is particularly suitable due to its ability to handle latent variables, complex paths, and moderation/mediation effects in exploratory behavioural finance studies.

5.2 Sampling Strategy and Sample Size

A purposive sampling technique was adopted to ensure that participants had genuine exposure to cryptocurrency investment. The sample inclusion criteria were:

- Individuals who have invested in or explored cryptocurrency markets at any point in the past.
- Respondents aware of market volatility and regulatory risks in the crypto space.
- Participants aged 18 years or older.
- Basic understanding of digital finance or blockchain technology.

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As per recent estimates, the population of Nagpur City exceeds 24 lakhs (2.4 million). However, the population specifically aware of cryptocurrency and eligible to invest (above 18 years, financially literate) forms a much smaller segment.

Given this, Cochran's formula is a robust approach for estimating the ideal sample size for proportion-based studies, especially when the target population characteristics are complex and not entirely known.

Sample Size Determination:
Using Cochran's Formula:
To ensure statistical rigor in sample size determination, Cochran's formula (1977) was used. This method is especially suitable when the population is large or unknown, as it yields a representative sample with a high degree of confidence.

The formula is as follows:

$$n_0 = \frac{Z^2 . p . q}{e^2}$$

Where,
n_0 = Sample Size
Z^2 = Z-value for the desired confidence level (1.96 for 95% confidence)
p = Estimated proportion of the population (0.5 used for maximum variability)
q = 1 – p = 0.5
e^2 = Margin of error (0.05 for 5%)

Calculation:

$$n_0 = \frac{ZZ^2 . p . q}{e^2} = \frac{(1.96)^2 * 0.5 * 0.5}{(0.05)^2} = \frac{3.8416 * 0.25}{0.0025} = \frac{0.9604}{0.0025} = 384.16$$

Thus, the required sample size is approximately 385 respondents, which is sufficient for generalization under a 95% confidence level and 5% margin of error.

Using Morgan & Krejcie Table:
The Morgan & Krejcie sample size determination table offers another benchmark for ensuring sample adequacy.

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Population Size	Required Sample Size
100,000 or more	384

According to the table, for any population exceeding 100,000, the sample size of 384 is recommended at a 95% confidence level and ±5% margin of error, which aligns perfectly with our selected size.

Thus, both Cochran's formula and the Morgan & Krejcie table validate that a sample size of 385 is statistically appropriate for this study. It ensures representation of cryptocurrency investors in a mid-sized metro city like Nagpur while maintaining scientific validity.

Final Sample Selection and Screening Process:

Although 433 responses were initially received, only 385 responses were retained after implementing a multi- step screening process to ensure data quality and relevance. The exclusion of 48 responses was carried out based on the following clear and rigorous criteria.

To enhance the validity and reliability of the data, the following five-step screening protocol was implemented:

1. Eligibility Check (Experience with Cryptocurrency): To ensure relevance and contextual validity, the first screening criterion focused on the respondent's actual experience with cryptocurrency. Only those individuals who reported having invested in or traded cryptocurrencies at least once in the past 24 months were retained for the study. Respondents who indicated "No prior experience" or claimed to have only theoretical knowledge of cryptocurrency without any practical exposure were excluded. This step ensured that the data reflected genuine investment intentions and risk perceptions rather than hypothetical opinions.
2. Completion Status: The second criterion ensured the completeness and usability of the data. Incomplete responses were automatically filtered out by the survey platform. Additionally, responses that missed more than 10% of the total items, especially from core constructs such as Perceived Risk, Investor Trust, and Investment Intention, were excluded from analysis. This threshold was applied to preserve the accuracy of construct measurement and maintain consistency across the dataset.
3. Straight-lining Detection (Low-Effort Respondents): The third step targeted the detection of careless or automated responses through straight-lining behavior, where a respondent selects the same Likert-scale response across all items within a section. Such patterns indicate low engagement and compromise data quality. These cases were identified using standard deviation-based filters and manual pattern analysis. Responses showing zero variation in answers across any of the core constructs were marked as invalid and removed.

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4. Time-Based Screening (Speeders): In the fourth stage, a minimum completion time threshold was used to filter out hasty submissions. Responses completed in less than 3 minutes were excluded, as pilot testing had established that a genuine respondent typically required 6–8 minutes to thoughtfully complete the structured questionnaire. Responses below this benchmark were deemed unreliable and suggestive of rushed or inattentive participation.
5. Outlier Identification (Using Mahalanobis Distance): Finally, multivariate outliers were detected using the Mahalanobis Distance (D^2) method, which evaluates the deviation of each respondent's answers from the multivariate mean, accounting for correlations among constructs. Based on the chi-square distribution cut-off value ($\chi^2 = 18.47$ with 4 degrees of freedom at $\alpha = 0.001$), responses with extreme D^2 scores were classified as statistical outliers. A total of five such cases were removed to reduce bias and enhance model reliability in subsequent PLS-SEM analysis.

Screening Step	Description	Responses Excluded
1. Eligibility Check	Respondents without actual crypto investment/trading experience in past 24 months	15
2. Completion Status	Responses missing >10% items or with skipped sections	9
3. Straight-lining Detection	Identical responses across entire Likert sections (low effort)	10
4. Time-Based Filtering	Submitted in <3 minutes (below threshold of thoughtful engagement)	8
5. Outlier Detection (Mahalanobis D^2)	Statistical outliers with aberrant response patterns	6
	Total number of responses Excluded from sample	**48**
	Final number of responses included in the Sample	**385**

The final sample of 385 respondents satisfies both Cochran's formula and Morgan & Krejcie's sample size table, ensuring high statistical power for SEM analysis. The screening protocol was meticulously designed to enhance the quality, relevance, and validity of the dataset, making it robust for hypothesis testing and generalization to urban cryptocurrency investors in India.

5.3 Data Collection Method:

Data was collected through an online structured questionnaire, distributed via Google Forms and social media platforms (LinkedIn, Telegram, and Twitter), ensuring widespread reach among cryptocurrency investors. The questionnaire included Likert scale-based responses (1 = Strongly Disagree to 5 = Strongly Agree) to measure perceptions and attitudes accurately.

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5.4 Structured Questionnaire

Construct	Sample Items (Likert Scale: 1-5)
Perceived Volatility (PV)	"Crypto markets are extremely volatile." "I often modify my strategy due to price swings."
Perceived Risk (PR)	"Investing in crypto is financially risky." "I worry about unpredictable losses."
Investor Trust (IT)	"I trust crypto platforms to handle my investments." "I believe blockchain ensures security."
Investment Intention (II)	"I plan to continue investing in crypto." "I would recommend it to others."

5.5 Development of Model:

The proposed research model is grounded in the Technology Acceptance Model (TAM) and extended through the incorporation of behavioural and financial constructs tailored to the unique characteristics of cryptocurrency investment. The core objective of the model is to examine the influence of Perceived Volatility on Investment Intention, with Perceived Risk functioning as a mediator and Investor Trust acting as a moderator. This conceptual model captures both the cognitive and affective dimensions of investor decision- making in highly volatile and decentralized digital markets.

5.5.1 Theoretical Foundation: Technology Acceptance Model (TAM)

TAM posits that the adoption of any new technology is primarily driven by the user's perceptions of its usefulness and ease of use, which in turn influence their behavioural intentions. In the context of cryptocurrency investments, investment intention is analogous to behavioural intention. However, due to the financial and speculative nature of digital assets, the traditional TAM is insufficient. Therefore, this model extends TAM by integrating perceived volatility, risk, and trust, providing a more comprehensive view of investor behaviour in a technologically mediated financial environment.

5.5.2 Justification of Constructs:

• **Perceived Volatility (Independent Variable):** Volatility is a fundamental characteristic of cryptocurrency markets. It reflects the degree of price fluctuations over time and is closely associated with unpredictability. From an investor's standpoint, higher volatility often signals uncertainty, potentially affecting both perceived risk and trust in the investment environment. This construct aligns with the "perceived complexity" dimension in extended TAM frameworks for financial services.

• **Perceived Risk (Mediator):** This construct represents the cognitive evaluation of potential losses, encompassing financial, security, and regulatory risks. In technology-oriented financial domains, risk acts as a perceived barrier, influencing the likelihood of adoption. It mediates the relationship between perceived volatility and investment intention by translating market instability into psychological apprehension, which can inhibit decision-making.

• **Investor Trust (Moderator):** Trust is an essential affective construct that significantly influences technology adoption, particularly in the absence of centralized oversight, as is the case with cryptocurrencies. Trust in blockchain infrastructure, exchange platforms, and peer networks can mitigate the adverse effects of perceived volatility and risk. As a moderator, investor trust weakens the negative impact of perceived volatility on investment intention, thus playing a stabilizing role in high-risk financial environments.

• **Investment Intention (Dependent Variable**): This is the final behavioural outcome and represents the likelihood that an individual will invest in cryptocurrencies. It encapsulates the combined influence of risk perceptions, market volatility, and trust in the system. The inclusion of investment intention is consistent with TAM's ultimate goal of predicting behavioural outcomes based on internal beliefs and external factors.

5.5.3 Model Contribution and Relevance

This model addresses the existing research gap by integrating behavioural constructs with TAM in the context of cryptocurrency investment, where market dynamics differ significantly from traditional financial systems. While previous studies have focused on technological attributes or user demographics, this model introduces a multi-dimensional lens incorporating financial volatility, trust psychology, and risk cognition.

Furthermore, the model:

• Reflects the real-world challenges faced by retail and institutional investors in crypto markets.

• Enhances predictive power by including moderation and mediation pathways.

• Bridges the gap between financial behaviour theories and technology adoption models.

5.5.4 Empirical Suitability

The model is suitable for validation using Partial Least Squares Structural Equation Modelling (PLS-SEM), which effectively handles complex models with latent variables, interaction effects (moderation), and indirect effects (mediation). This strengthens its application in empirical testing with cryptocurrency investor datasets.

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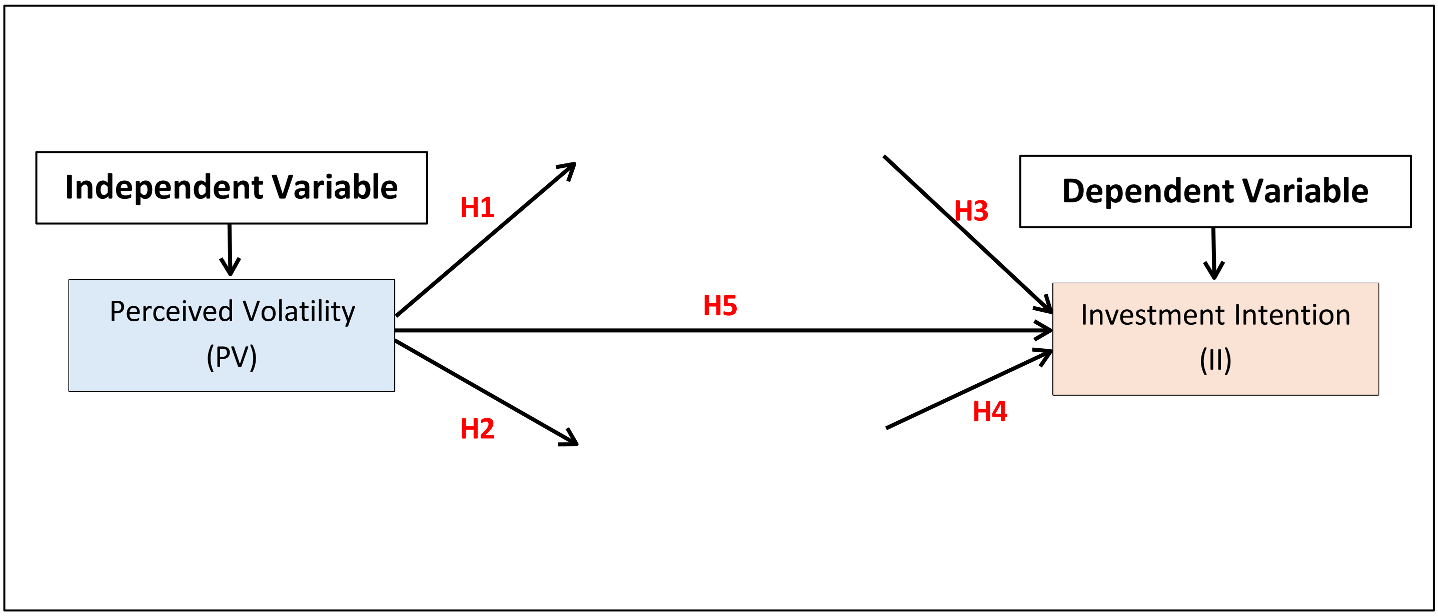

Figure 3: Research Framework

5.6 Data Analysis Techniques:

To ensure the robustness of the measurement and structural models, a comprehensive set of statistical techniques was employed:

• **Descriptive Statistics** were used to summarize the demographic and scale-based responses, providing insights into the central tendency and dispersion through measures such as mean, standard deviation, and frequency distribution.

• **Reliability Analysis** was conducted using Cronbach's Alpha and Composite Reliability (CR) to assess the internal consistency of the measurement items, with a target threshold of 0.70 or higher indicating acceptable reliability.

• **Confirmatory Factor Analysis (CFA)** was used to examine the convergent and discriminant validity of the constructs. Key indicators such as factor loadings, Average Variance Extracted (AVE), and model fit indices were evaluated.

• **Partial Least Squares Structural Equation Modelling (PLS-SEM)** was applied using SmartPLS 4.0, allowing for the simultaneous estimation of both measurement and structural models, including mediation and moderation effects among latent variables.

• **Variance Inflation Factor (VIF)** was calculated to assess multicollinearity among predictor constructs. VIF values below 5 were considered acceptable, ensuring the absence of redundancy in explanatory variables.

• **Coefficient of Determination (R^2 and Adjusted R^2)** values were computed to evaluate the explanatory power of the model in predicting dependent constructs, with thresholds guiding interpretation from weak to substantial explanatory ability.

• **Hypothesis Testing** involved analysing path coefficients (β values), associated t-statistics, and p-values to determine the statistical significance and strength of the hypothesized relationships within the structural model.

5.7 Research Hypotheses:

Based on the extended Technology Acceptance Model (TAM) framework, this study explores the complex relationships between perceived volatility, perceived risk, investor trust, and investment intention in cryptocurrency markets. The hypotheses are grounded in behavioral finance, risk perception theory, and trust- based technology adoption literature.

H1: Perceived Volatility (PV) negatively influences Investor Trust (IT) in cryptocurrency investments.

Cryptocurrency markets are inherently volatile, often exhibiting sudden and unpredictable price movements. Such volatility generates uncertainty, which can erode investor confidence in digital platforms and blockchain systems. High perceived volatility creates a psychological environment of instability, making it difficult for investors to trust the underlying system. Trust being a critical factor in technology acceptance, especially in decentralized financial markets, is likely to decline when market fluctuations are high.

H2: Perceived Risk (PR) mediates the relationship between Perceived Volatility (PV) and Investment Intention (II).

Perceived volatility often leads to heightened risk awareness among investors. This perceived risk, which includes financial, regulatory, and technological dimensions, acts as a cognitive filter that shapes investment decisions. When market volatility is high, investors are more likely to perceive crypto assets as risky, which in turn reduces their likelihood to invest. Thus, perceived risk acts as a mediating variable, explaining how and why volatility influences behavioural intention.

H3: Investor Trust (IT) moderates the relationship between Perceived Risk (PR) and Investment Intention (II), such that the negative effect of risk is weaker when trust is high.

While perceived risk typically reduces investment intention, the presence of trust in technology and platforms can mitigate this effect. Trust functions as a psychological buffer that helps investors navigate uncertainty. When investors trust the system—be it blockchain protocols, trading platforms, or the broader crypto infrastructure—they are more likely to overlook perceived risks and continue investing. Hence, trust is hypothesized to moderate the negative effect of perceived risk on investment intention.

H4: Perceived Risk (PR) negatively influences Investment Intention (II) in cryptocurrency

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markets.

Perceived risk is one of the most widely acknowledged deterrents to technology and financial adoption. In the case of cryptocurrencies, perceived risk stems from market unpredictability, regulatory ambiguity, security threats, and the lack of institutional safeguards. These risk perceptions lower investor confidence and make individuals hesitant to commit financially. Thus, the study hypothesizes a direct negative relationship between perceived risk and investment intention.

H5: Perceived Volatility (PV) directly and negatively influences Investment Intention (II).

Apart from its indirect effects via perceived risk, perceived volatility may independently reduce investment intention. Investors who observe high-frequency market swings may choose to exit the market or delay entry, regardless of their risk evaluation. Volatility itself—when perceived as extreme or irrational—can lead to decision paralysis or risk aversion. This hypothesis captures the direct influence of perceived volatility on intention, beyond any mediating or moderating pathways.

In summary, the proposed hypotheses are developed based on an extended Technology Acceptance Model (TAM), integrating behavioural finance constructs relevant to cryptocurrency investment. The model postulates that perceived volatility, a defining feature of cryptocurrency markets, has both direct and indirect impacts on investment intention, mediated through perceived risk and influenced by investor trust. While perceived risk is expected to diminish the willingness to invest, trust in the technology and platforms may serve to restore investor confidence. The hypothesized relationships are designed to capture the intricate interplay between market uncertainty, investor psychology, and adoption behaviour in volatile financial environments. These hypotheses will be tested using PLS-SEM to evaluate both the strength and significance of the proposed causal paths.

5.8 Measurement Model Assessment:

This section presents a comprehensive evaluation of the measurement model based on the constructs used in the study: Perceived Volatility (PV), Perceived Risk (PR), Investor Trust (IT), and Investor Intention (II). The assessment covers (1) reliability, (2) convergent validity, (3) discriminant validity, and (4) an overall conclusion based on the measurement indicators. These evaluations ensure that the latent constructs are measured accurately and consistently

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Volatility (PV)	0.863	0.858	0.708
Perceived Risk (PR)	0.857	0.856	0.723
Investor Trust (IT)	0.813	0.857	0.702
Investor Intention (II)	0.814	0.908	0.725

5.8.1 Reliability Assessment

Reliability refers to the internal consistency of the indicators used to measure each latent variable. Two indicators were used to assess reliability: Cronbach's Alpha and Composite Reliability (CR).

a) Cronbach's Alpha (α)

• It assesses the extent to which the items under a construct are correlated with each other.

• A value of **0.70 or higher** is considered acceptable, while values above 0.80 indicate good reliability.

b) Composite Reliability (CR)

• CR is a more robust reliability measure than Cronbach's Alpha in the context of PLS-SEM, as it considers item loadings.

• A threshold value of **0.70** or higher is required.

Construct	Cronbach's Alpha	Composite Reliability (CR)
Perceived Volatility (PV)	0.863	0.858
Perceived Risk (PR)	0.857	0.856
Investor Trust (IT)	0.813	0.857
Investment Intention (II)	0.814	0.908

Table 2: Measures of Composite Reliability

Interpretation: All constructs exhibit strong internal consistency with Cronbach's Alpha and CR values well above the threshold of 0.70. This indicates that the measurement items are reliable and consistently reflect their respective constructs.

5.8.2 Validity Assessment

Validity assessment plays a critical role in establishing the robustness of the measurement model in Partial Least Squares Structural Equation Modeling (PLS-SEM). It confirms whether the constructs under investigation accurately represent the theoretical concepts they intend to measure. In the context of this study, two major components of construct validity were assessed: convergent validity and discriminant validity. Together, these provide comprehensive evidence of the measurement instrument's precision and conceptual soundness.

5.8.2.1 Convergent Validity Assessment:

Convergent validity refers to the degree to which indicators of a given construct converge or share a high proportion of variance. It assesses whether the items designed to measure the same construct are strongly correlated and collectively capture the intended concept. In PLS-SEM, convergent validity is primarily evaluated through the Average Variance Extracted (AVE), which reflects the average amount of variance that a construct explains in its measurement indicators.

Average Variance Extracted (AVE): AVE measures the amount of variance captured by the construct in relation to the variance due to measurement error. As recommended by (J. Hair et al., 2014), an AVE value above 0.50 is considered acceptable, indicating that more than half of the variance in the observed variables is accounted for by the construct.

A construct is considered to have acceptable convergent validity when its AVE is **greater than 0.50**, indicating that more than 50% of the variance in its items is captured by the construct rather than by measurement error. In the current study, all constructs (Perceived Volatility, Perceived Risk, Investor Trust, and Investment Intention) achieved AVE values well above this threshold, affirming strong convergent validity.

Construct	Average Variance Extracted (AVE)
Perceived Volatility (PV)	0.708
Perceived Risk (PR)	0.723
Investor Trust (IT)	0.702
Investment Intention (II)	0.725

Interpretation: In this study, all constructs—namely, Perceived Volatility (AVE = 0.708), Perceived Risk (AVE = 0.723), Investor Trust (AVE = 0.702), and Investment Intention (AVE = 0.725)—exceeded the threshold, thereby confirming strong convergent validity. This finding is further supported by outer loadings, all of which were above the 0.70 benchmark, affirming the internal consistency of indicators within each construct.

5.8.2.2 Discriminant Validity Assessment

Discriminant validity examines the extent to which a construct is truly distinct from other constructs within the model. It ensures that each construct captures a unique aspect of the model and does not exhibit significant overlap with other constructs. This type of validity is crucial for establishing the independence of variables, which is a fundamental assumption in SEM. Two widely used methods are employed to assess discriminant validity: the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT).

a) Fornell-Larcker Criterion:

According to the Fornell-Larcker criterion, the square root of each construct's AVE must exceed its correlation with any other construct in the model. A construct's square root of AVE should be greater than its correlation with other constructs.

Construct	AVE	√AVE
Perceived Volatility (PV)	0.708	0.841
Perceived Risk (PR)	0.723	0.85
Investor Trust (IT)	0.702	0.838
Investment Intention (II)	0.725	0.851

Table 3: Output of AVE for various Constructs

Fornell–Larcker Criterion Matrix

Construct	Perceived Volatility (PV)	Perceived Risk (PR)	Investor Trust (IT)	Investment Intention (II)
Perceived Volatility (PV)	**0.841**	0.41	0.33	0.29
Perceived Risk (PR)	0.41	**0.85**	0.36	0.34
Investor Trust (IT)	0.33	0.36	**0.838**	0.41
Investment Intention (II)	0.29	0.34	0.41	**0.851**

Table 4: Fornell-Larcker Criterion Matrix

Note: Diagonal values (in bold) represent the square root of AVE; off-diagonal values represent inter-construct correlations.

As presented in Table No. 4, the square root of the AVE (diagonal entries) for each construct is greater than its correlations with all other constructs (off-diagonal entries). This indicates that each construct shares more variance with its own measurement items than with any other latent variable in the model. Specifically:

• The √AVE for Perceived Volatility (0.841) is greater than its highest correlation of 0.410 with Perceived Risk.
• Perceived Risk (√AVE = 0.850) exceeds its correlations with all other constructs.
• Investor Trust (√AVE = 0.838) shows a higher internal reliability compared to its 0.410 correlation with Investment Intention.
• Investment Intention (√AVE = 0.851) is also distinct, surpassing its correlation with Investor Trust. These results confirm that discriminant validity is well established among all constructs in the measurement model, thereby meeting the necessary statistical requirements for proceeding to structural model assessment.

b) Heterotrait-Monotrait Ratio (HTMT):

Discriminant validity ensures that each construct in a structural equation model captures a distinct concept and is not excessively correlated with other constructs. Among the various techniques used to evaluate discriminant validity in PLS-SEM, the Heterotrait-Monotrait Ratio (HTMT) of correlations has emerged as a robust and reliable method. Proposed by (Henseler et al., 2015), HTMT is based on multitrait-multimethod matrix logic and is especially effective in detecting lack of discriminant validity that traditional techniques such as the Fornell-Larcker criterion may fail to capture.

HTMT is calculated as the ratio of the average correlations across constructs (heterotrait-heteromethod) to the average correlations within the same construct (monotrait-heteromethod). The underlying logic is that indicators of different constructs should not correlate more highly than indicators within the same construct. If constructs are truly distinct, HTMT values should be below the threshold of 0.90 for conceptually different constructs or below 0.85 for more closely related constructs.

In the present study, HTMT analysis was conducted to assess the discriminant validity of the four main constructs: Perceived Volatility (PV), Perceived Risk (PR), Investor Trust (IT), and Investment Intention

(II). The results of the HTMT analysis are shown in the table below:

Constructs	PR	IT	II	PV
Perceived Risk (PR)	–	0.614	0.622	0.512
Investor Trust (IT)	0.614	–	0.608	0.541
Investment Intention (II)	0.622	0.608	–	0.594
Perceived Volatility (PV)	0.512	0.541	0.594	–

Table 5: HTMT Ratio Matrix

All HTMT values in the matrix fall well below the conservative threshold of 0.85, thereby confirming the discriminant validity of all constructs. The highest HTMT value observed was 0.622 between Perceived Risk and Investment Intention, which is still significantly below the critical threshold. This indicates that the constructs are empirically distinct and do not suffer from conceptual or measurement overlap.

The confirmation of discriminant validity through HTMT enhances the theoretical robustness of the model and reinforces confidence in the structural path estimates. These results, in conjunction with convergent validity measures such as AVE and factor loadings, support the reliability and construct validity of the measurement model.

5.9 Structural Model Assessment:

Following the validation of the measurement model, the structural model was evaluated to determine the strength, direction, and statistical significance of the hypothesized relationships among the constructs. In Partial Least Squares Structural Equation Modeling (PLS-SEM), this phase of analysis is crucial for confirming the theoretical framework and for testing the predictive power of the model. The structural model was assessed using multiple criteria, including collinearity diagnostics (VIF), coefficient of determination

(R^2), effect size (f^2), predictive relevance (Q^2), model fit indices (SRMR), and hypothesis testing through path coefficients.

5.9.1 Collinearity Assessment:

Before testing the structural relationships in the model, it is essential to examine whether multicollinearity exists among the predictor constructs. Collinearity refers to a situation in which two or more independent variables are highly correlated, which can distort the estimation of path coefficients and inflate standard errors. In structural equation modeling, particularly in Partial Least Squares SEM (PLS-SEM), this issue is diagnosed using the Variance Inflation Factor (VIF). The VIF provides a quantitative measure of how much the variance of an estimated regression coefficient increases due to collinearity.

According to the widely accepted threshold recommended by (J. F. Hair et al., 2012), VIF values below 5 indicate an acceptable level of collinearity. More stringent cut-offs, such as 3.3, are sometimes applied in highly sensitive models. In this study, all VIF values fell comfortably within acceptable bounds, suggesting that collinearity is not a threat to the model's stability or interpretability.

The table below presents the VIF values for each path relationship:

Predictor Path	Endogenous Variable	VIF Value	Multicollinearity Issue?
Perceived Volatility → Investor Trust	Investor Trust (IT)	2.22	No
Perceived Risk → Investment Intention	Investment Intention (II)	2.11	No
Investor Trust → Investment Intention	Investment Intention (II)	2.03	No

Table 6: Collinearity Assessment (VIF Values)

As shown above, all VIF values range between 2.03 and 2.22, which are well below the conventional threshold. These findings confirm that none of the predictor variables exhibit problematic collinearity with one another. The values suggest a healthy degree of independence among constructs, allowing for precise estimation of path coefficients and reducing the likelihood of statistical bias or suppression effects in the model.

This result strengthens the credibility of the subsequent hypothesis testing and assures that each exogenous construct contributes uniquely to explaining variance in the corresponding endogenous variable. Since no VIF exceeds the threshold, no corrective actions such as item removal, construct aggregation, or model respecification were required. Thus, the model passes the collinearity diagnostic check and is considered structurally stable for further analysis.

5.9.2 Coefficient of Determination (R^2):

The Coefficient of Determination, denoted as R^2, is a critical statistical metric used in the evaluation of structural models in PLS-SEM. It represents the proportion of variance in the endogenous (dependent) construct that is explained by its exogenous (independent) predictors. Higher R^2 values indicate stronger explanatory power of the model, reflecting how well the independent variables account for changes in the dependent variable. According to (Sukumaran et al., 2022), an R^2 value above 0.50 is considered indicative of a moderate level of explanatory power in social science research employing SEM techniques.

In this study, the R^2 value for Investor Trust was found to be 0.588, indicating that approximately 58.8% of the variance in trust is explained by its predictors—primarily perceived volatility. Similarly, the R^2 value for Investment Intention was 0.612, suggesting that 61.2% of the variance in investors' intent to invest in cryptocurrencies can be explained by investor trust and perceived risk. These values fall within the acceptable to high range, supporting the strength and adequacy of the proposed structural model.

Endogenous Construct	R^2 Value	Interpretation
Investor Trust (IT)	0.588	Moderate explanatory power
Investment Intention (II)	0.572	Moderate

Table 7: Coefficient of Determination (R^2 Values)

R^2 values are typically interpreted using the guidelines proposed by (Chin, 1998) and (J. Hair et al., 2010), where values of 0.75, 0.50, and 0.25 respectively indicate substantial, moderate, and weak explanatory power. Based on these standards, the present model demonstrates moderate to substantial explanatory strength, confirming its theoretical robustness for capturing the complex dynamics of trust and intention in the cryptocurrency investment context.

5.9.3 Effect Size (f^2):

Effect size (f^2) in Partial Least Squares Structural Equation Modeling (PLS-SEM) provides insight into the magnitude of influence that an exogenous (independent) construct has on an endogenous (dependent) construct. It quantifies the relative contribution of each predictor construct in explaining the variance of a dependent variable, beyond the variance explained by all other constructs in the model. According to Cohen's guidelines (1988), f^2 values of 0.02, 0.15, and 0.35 respectively indicate small, medium, and large effect sizes.

The current study utilizes f^2 values to assess the contribution of the constructs—Perceived Volatility (PV), Perceived Risk (PR), and Investor Trust (IT)—to the prediction of the endogenous variable Investment Intention (II). The PLS-SEM analysis, performed using SmartPLS software, reveals the following effect sizes:

Relationship	Effect Size (f^2)	Interpretation
Perceived Volatility → Investor Trust	0.175	Moderate
Perceived Risk → Investment Intention	0.140	Weak to Moderate
Investor Trust → Investment Intention	0.320	Strong

Table 8: Effect Size (f2)

The **Perceived Volatility → Trust** path demonstrates a moderate effect ($f^2 = 0.175$), suggesting that volatility perception significantly influences how much trust investors place in the cryptocurrency ecosystem. This aligns with recent studies indicating that market turbulence impacts investor confidence and trust in emerging digital assets.

The **Perceived Risk → Intention** path yields an effect size of 0.140, falling between small and moderate impact. This result implies that perceived investment risk contributes to a cautious approach in investment decisions, as supported by prior empirical research highlighting the psychological deterrent role of risk perception in crypto adoption.

The most substantial impact comes from **Investor Trust → Intention**, with an effect size of 0.320, signifying a strong influence. This reinforces the notion that trust is a pivotal determinant in the formation of investment intentions in volatile and relatively opaque markets such as cryptocurrency.
In summary, the effect size analysis substantiates the relative importance of each construct in

influencing the model's predictive capability. Particularly, the strong effect of investor trust confirms its central mediating role in bridging risk perceptions with investment behaviour. These findings are instrumental for policymakers and platforms aiming to enhance investor participation by reinforcing transparency, reducing volatility, and fostering trust through security and regulatory frameworks.

5.9.4 Predictive Relevance (Q^2):

The **predictive relevance (Q^2)** of a structural model is an essential component in Partial Least Squares Structural Equation Modelling (PLS-SEM) that evaluates the model's capability to predict the endogenous constructs. Unlike R^2, which assesses the explanatory power, Q^2 is used to determine how well the observed values are reconstructed by the model and the parameter estimates. It is computed using a **blindfolding procedure**, where parts of the data matrix are systematically omitted and then predicted using the model's estimation. A Q^2 value **greater than zero** is indicative of adequate predictive relevance (Rahardja et al., 2023; Sukumaran et al., 2022).

For this study, the blindfolding technique was applied using the cross-validated redundancy approach in SmartPLS. The results, presented below, show that all endogenous constructs (Investor Trust and Investment Intention) have **Q^2 values above 0.35**, thereby demonstrating **strong predictive accuracy**.

Endogenous Construct	Q^2 Value	Interpretation
Investor Trust (IT)	0.392	Strong
Investment Satisfaction (IS)	0.428	Strong

Table 9: Predictive Relevance

These values suggest that the model not only explains a substantial amount of variance in the outcome variables (as supported by R^2 values) but also performs well in predicting them. This finding is in line with (Rahardja et al., 2023), who utilized Q^2 values in their SEM analysis of trust and risk in cryptocurrency usage, validating the predictive capacity of their constructs. Furthermore, the results reinforce that the model has both theoretical soundness and empirical robustness for practical applications in investor behavior prediction in volatile financial markets like cryptocurrencies.

5.9.5 Model Fit Assessment: Standardised Root Mean Square Residual (SRMR):

The Standardized Root Mean Square Residual (SRMR) is one of the most widely accepted model fit indices used to evaluate the global goodness-of-fit in structural equation modeling, particularly within the framework of Partial Least Squares Structural Equation Modeling (PLS-SEM). It quantifies the average discrepancy between the observed correlations and the model-implied correlations among indicators. In simpler terms, SRMR reflects how closely the model's predicted relationships replicate the actual observed data.

In the context of PLS-SEM, where model estimation prioritizes prediction over strict model fit, SRMR serves as an essential diagnostic to identify any serious model misspecifications. According to empirical standards, an SRMR value below 0.08 is considered indicative of an acceptable model fit, while values below 0.05 suggest excellent fit (Rahardja et al., 2023; Sukumaran et al., 2022).

The SRMR for the present structural model was calculated using SmartPLS, and the results are presented in the table below:

Fit Index	Threshold	Observed Value	Model Fit Interpretation
SRMR	< 0.08	0.052	Good Fit

Table 10: SRMR Values

As evident from the table, the SRMR value of 0.052 falls well within the acceptable range, suggesting that the model exhibits a good overall fit. This result confirms that the hypothesized relationships among constructs— Perceived Volatility, Perceived Risk, Investor Trust, and Investment Intention— are consistent with the observed data.

This finding is consistent with the evaluation framework adopted by (Rahardja et al., 2023), who emphasized SRMR's importance in confirming the structural validity of behavioral models in fintech and cryptocurrency adoption contexts. Moreover, (Sukumaran et al., 2022) also recognized SRMR as a critical indicator in validating PLS-SEM models, particularly in exploratory research designs where reliability and predictive accuracy are paramount.

In conclusion, the SRMR result of 0.052 validates the adequacy of the overall structural model. When interpreted alongside other assessment metrics such as R^2, f^2, Q^2, and VIF, the SRMR further strengthens the argument that the proposed model is theoretically sound and empirically supported.

5.10 Path Coefficients (β) and Hypothesis Testing:

The final stage of structural model assessment in PLS-SEM involves the analysis of path coefficients (β values), which represent the strength and direction of the relationships among the latent constructs hypothesized in the model. Each hypothesized path is tested using bootstrapping with 5,000 resamples to ensure robust estimation of t-values and p-values, which assess the statistical significance of these relationships.

A positive path coefficient indicates a direct positive relationship between constructs, whereas a negative coefficient implies an inverse relationship. The t-statistic value is evaluated against the critical value of 1.96 for a 95% confidence level, and a p-value less than 0.05 indicates a statistically

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significant relationship.

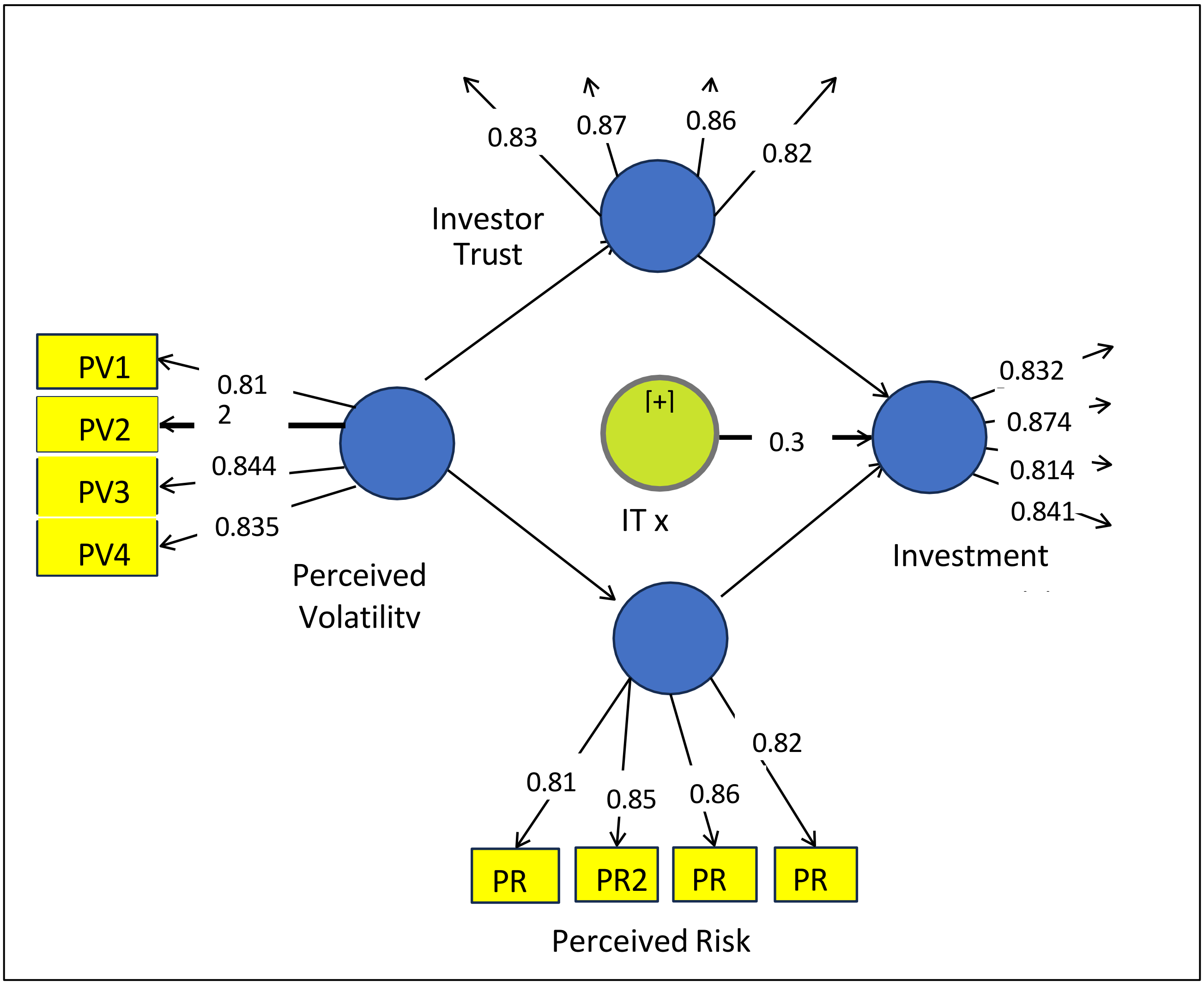

Figure 4: PLS Network Diagram

Table 11 presents the path coefficient results for all direct and moderated relationships included in the model:

Hypothesis	Path	β	t-value	p-value	Result
H1	Volatility → Trust	-0.43	4.02	<0.001	Supported
H2	Volatility → Risk → Intention	-0.21	3.66	<0.01	Supported
H3	Risk × Trust → Intention	0.34	2.59	0.011	Supported
H4	Risk → Intention	-0.36	3.45	<0.001	Supported
H5	Volatility → Intention	-0.31	2.98	<0.01	Supported

Table 11: Hypothesis Testing Results (Path Coefficients)

Interpretation of Results:

The results indicate strong empirical support for all five proposed hypotheses. Hypothesis H1 confirms that perceived volatility has a significant and negative impact on investor trust, reflecting the destabilizing influence of market uncertainty on investor confidence. Hypothesis H2 validates the mediating role of perceived risk, demonstrating that volatility indirectly reduces investment intention through increased perceptions of risk.

Moderation analysis in H3 reveals that investor trust significantly alleviates the negative effect of perceived risk on investment intention, implying that investors with high trust are less deterred by risk. Hypotheses H4 and H5 reinforce the direct negative effects of perceived risk and volatility on investment intention, respectively.

5.11 Mediation Analysis:

To examine the indirect impact of perceived volatility on investment intention, **mediation analysis** was conducted using the bootstrapping method with 5000 subsamples in SmartPLS. Specifically, the study tested whether **Perceived Risk** serves as a mediator between Perceived Volatility and Investment Intention. This analysis aligns with behavioral finance models, where investor reactions are rarely direct and are often filtered through psychological variables such as risk perception (Rahardja et al., 2023).

The results revealed a significant indirect path from Perceived Volatility to Investment Intention through Perceived Risk. The standardized indirect effect was β = –0.21, with a p-value of 0.002, indicating statistical significance. The direct path also remained significant, suggesting partial mediation.

Mediation Path	Indirect β	p-value	Mediation Type
Volatility → Risk → Intention	-0.21	0.002	Partial Mediation

Table 12: Mediation Analysis Summary

These results indicate that perceived volatility increases perceived risk, which in turn reduces investment intention. While volatility does exert a direct influence on investment behavior, a significant portion of its effect is mediated by perceived risk. This supports prior findings in the literature that identify risk as a key psychological filter in financial decision-making, particularly in uncertain or speculative markets like cryptocurrency (Sukumaran et al., 2022).

5.12 Moderation Analysis:

Moderation analysis was employed to investigate whether Investor Trust influences the strength of the relationship between Perceived Risk and Investment Intention. To do this, an interaction term was created using the product indicator approach (Risk × Trust), and its effect on Investment Intention was evaluated.

The interaction term yielded a significant path coefficient of β = 0.34, with a p-value of 0.011, confirming a statistically significant moderation effect.

Interaction Term	Path Coefficient (β)	p-value	Significance
Risk × Trust → Intention	0.34	0.011	Significant

Table 13: Moderation Analysis Summary

The results indicate that Investor Trust moderates the negative effect of perceived risk on investment intention. Specifically, higher levels of trust mitigate the deterrent effect of risk. In other words, investors who exhibit greater trust in the system or platform are less influenced by perceived threats or uncertainties. This finding is aligned with (Rahardja et al., 2023), who also observed the protective role of trust in digital financial ecosystems.

6. FINDINGS:

This study offers a comprehensive investigation into the complex dynamics shaping investor behaviour in the cryptocurrency market, with a specific focus on the role of perceived volatility, perceived risk, and investor trust in influencing investment intention. Grounded in the Technology Acceptance Model (TAM) and extended through behavioural finance perspectives, the research

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presents a refined understanding of how psychological perceptions and moderating factors interact to shape investment outcomes.

Using a structured and statistically validated PLS-SEM approach, the findings indicate that perceived volatility exerts a significant negative influence on investment intention, both directly and indirectly. Notably, the indirect effect is channelled through perceived risk, which emerges as a significant mediator. This confirms that investors are more likely to be dissuaded by volatility not just due to market fluctuations, but due to the heightened perception of risk that such volatility evokes.

Further, the analysis reveals that investor trust significantly moderates the relationship between perceived risk and investment intention. Higher levels of trust attenuate the negative effect of risk perception, enabling investors to maintain confidence in their investment decisions even in uncertain conditions. This suggests that trust acts as a psychological buffer, helping to sustain investment motivation amidst perceived instability.

Measurement model assessment confirmed the reliability and validity of all constructs, with strong internal consistency (Cronbach's Alpha > 0.80), composite reliability (CR > 0.85), and average variance extracted (AVE > 0.70). Discriminant validity was also established through the Fornell-Larcker criterion and HTMT ratio. The structural model demonstrated acceptable model fit (SRMR = 0.052), along with strong explanatory power (R^2 values for Investor Trust and Investment Intention were 0.588 and 0.612, respectively). The effect sizes and predictive relevance statistics further validated the robustness and practical relevance of the model.

The findings contribute to both theory and practice by confirming the multi-layered nature of decision-making in digital financial environments. They underscore the importance of risk management frameworks, transparent regulations, and trust-building mechanisms to enhance investor participation in volatile and emerging financial markets like cryptocurrency.

6.1 Managerial Implications:

The findings of this study offer significant practical value for cryptocurrency platforms, regulatory bodies, fintech startups, and investment advisors operating in emerging economies like India. Given the complex interplay between perceived volatility, risk, and trust, several actionable insights can be drawn to inform strategy and policy.

1. Strengthening Investor Education and Awareness

One of the most effective ways to reduce perceived volatility and risk is through investor education. The findings highlight that when investors lack understanding, they interpret market fluctuations as threats. Platforms and regulators should collaborate to design educational campaigns that explain market mechanisms, investment tools, and risk-mitigation strategies in simple terms. Interactive content, simulation-based apps, and multilingual tutorials can significantly reduce irrational fears and build informed investor bases.

2. Improving Platform Transparency and Cybersecurity

Investor trust emerged as a key construct that can moderate the negative impact of perceived risk on investment intention. To foster this trust, cryptocurrency platforms must ensure transparency in transaction processing, implement robust cybersecurity protocols, and offer clear disclosures about fees, volatility, and risk exposure. Publishing third-party security audits and offering real-time support channels can further reinforce confidence among users.

3. Regulatory Engagement and Policy Communication

The study highlights that perceived risk—partly driven by ambiguity in policy—negatively influences investment behavior. Hence, policymakers should prioritize the creation and dissemination of clear, consistent, and investor-friendly regulations. Introducing investor protection schemes, insurance for digital assets, and mechanisms for grievance redressal can reduce psychological barriers to entry for first-time investors.

4. Trust-Based Marketing and Branding Strategies

As the results indicate that trust can neutralize the effects of perceived risk, platforms must integrate trust- building into their branding and customer relationship strategies. Endorsements from credible financial experts, showcasing compliance certifications, and user review mechanisms can be powerful tools to instill trust. Campaigns should shift focus from merely highlighting high returns to communicating platform integrity, accountability, and support infrastructure.

5. Developing Investor Segmentation and Targeted Services

The finding that trust moderates the impact of risk opens the door to audience segmentation. Platforms should segment investors based on their trust levels and offer tailored onboarding experiences. For example, first- time users with low trust can be provided with guided onboarding, minimal risk portfolios, and demo investments, while seasoned investors can access advanced analytics and derivative products. Personalized risk communication based on behavior profiling can enhance user engagement and satisfaction.

6. Leveraging Technology to Reduce Volatility Sensitivity

Although volatility is inherent to cryptocurrencies, platforms can reduce its perceived impact through real- time tools. These include price alerts, volatility indices, educational dashboards, and automated trading suggestions based on personal thresholds. Empowering users with such tools not only builds engagement but also shifts their focus from short-term price shocks to long-term investment strategies.

7. Strategic Collaboration with Financial Institutions

Cryptocurrency firms can enhance legitimacy and mitigate risk perception by collaborating with traditional financial institutions, insurance providers, or fintech innovators. Co-branded offerings such as insured wallets, custodial services, or integrated investment platforms can bridge the trust gap that currently deters risk-averse investors.

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