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Research Article

Understanding Cryptocurrency Adoption: The Role of Technology, Users, and Trust in Unregulated Markets

Tran Le Nguyen[1,2] **Van Kien Pham**[3] **and Thi Thuy Dung Pham**[4]

[1]*Faculty of Management and Economics, Tomas Bata University in Zlín (UTB), Zlín, Czech Republic*
[2]*Faculty of International Economics, Ho Chi Minh City University of Banking, Ho Chi Minh City, Vietnam*
[3]*Smart Green Transformation Center, VinUniversity Da Ton, Hanoi, Vietnam*
[4]*Department of Science, Technology and International Projects, Ho Chi Minh City University of Economics and Finance, Ho Chi Minh City, Vietnam*

Correspondence should be addressed to Van Kien Pham; vankien.pham87@gmail.com

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The rise of cryptocurrencies, powered by blockchain technology, shifts trust from centralized institutions to technology itself. However, the drivers of trust in cryptocurrency adoption (CA) remain unclear, with existing models like commitment-trust theory, trust in technology, and digital trust insufficiently addressing decentralized systems. To bridge this gap, this study integrates the task-technology fit (TTF) framework and five-factor theory (FFT) into a comprehensive cryptocurrency trust model. TTF explains how blockchain features—security, transparency, traceability, price value, and transaction speed—impact technology characteristics (TCs), while FFT captures user characteristics (UCs), including psychological and behavioral dimensions, essential for trust development. Analyzing survey data from 200 participants using structural equation modeling (SEM), the findings highlight the mediating role of crypto trust (CT) between TC, UC, and external environmental factors (EX) in driving CA. CT mitigates concerns about fraud, security breaches, and reliability, transforming technological and individual readiness into adoption, particularly in unregulated markets like Vietnam. This study updates trust frameworks by integrating TTF and FFT, emphasizing the need for trust-building strategies, technological transparency, and regulatory clarity. In particular, the findings underscore that clear, supportive, and consistent regulatory policies are essential for legitimizing cryptocurrency use, reducing uncertainty, and indirectly fostering user trust. These insights provide concrete policy directions for governments seeking to enhance adoption in decentralized financial systems while ensuring public protection and market stability.

Keywords: blockchain technology; crypto trust; cryptocurrency adoption; decentralized finance; five-factor theory; task-technology fit

1. Introduction

The intersection of technology and financial markets has catalyzed the emergence of innovative digital financial instruments, with cryptocurrencies leading the charge [1, 2]. Unlike traditional financial assets that depend on centralized institutions such as banks and regulators, cryptocurrencies operate on decentralized networks powered by blockchain technology [3, 4]. This fundamental shift transfers the basis of trust from institutional structures to the technology itself [5, 6]. However, while behavioral finance models like the theory of reasoned action (TRA) and the theory of planned behavior (TPB) have been effective in explaining user behavior in regulated environments, they fall short when addressing the complexities inherent in decentralized systems such as cryptocurrencies [7–10]. In these decentralized landscapes, trust in technology becomes a crucial determinant of adoption [11].

Furthermore, many studies have explored trust in cryptocurrency adoption (CA), treating it as a variable [12–18], a mediator [5, 19–21] or a moderator [11]. However, despite this extensive focus, the specific components or drivers of trust remain unclear. Although some studies summarize factors influencing trust [22–24], a comprehensive model of trust in the context of cryptocurrencies has yet to be clearly developed and tested.

1.1. Problem Statement. Current research lacks an integrated framework that explains how trust is formed and how it influences CA within decentralized systems. Specifically, there is no model that simultaneously considers the influence of technology characteristics (TCs), individual user traits, and external environmental factors (EX), particularly in underregulated markets where traditional institutional safeguards are absent. This absence of a comprehensive trust model limits the ability of scholars, developers, and regulators to understand and predict adoption behavior in contexts shaped by technological risk and legal ambiguity.

To bridge this gap, existing trust models, such as the commitment-trust theory [25], trust in technology [26], and digital trust [17], provide useful frameworks. Nevertheless, trust in cryptocurrencies lies at the intersection of trust in technology and digital trust, reflecting the dual complexity of blockchain technology and digital currencies. Importantly, a shared component in Shin [17] and Müller [26] models is the role of contextual factors related to legal regulations, which emphasizes that external influences must be represented in any model of trust. These EX include legal frameworks, market stability, and societal attitudes, which significantly shape user trust by providing contextual assurances. For example, regulatory clarity or even the anticipation of future regulation often serves as a proxy for institutional trust, fostering a sense of stability and encouraging adoption [20, 23].

Moreover, in underregulated markets like Vietnam, the absence of comprehensive regulatory oversight further highlights the importance of crypto trust (CT) [27]. Users are acutely aware of risks such as financial scams and technology failures [28, 29], making trust a cornerstone for CA. Research underscores that trust serves as a stabilizing force in these markets, compensating for insufficient institutional and legal assurances [5, 30]. In such contexts, CT acts as a psychological safety net, alleviating concerns about fraud, security breaches, and transaction reliability [31].

Given these theoretical and contextual gaps, this study incorporates the task-technology fit (TTF) framework [32] and five-factor theory (FFT) [33] into a comprehensive cryptocurrency trust model. Specifically, TTF effectively defines TCs, encompassing blockchain attributes like security, transparency, traceability, price value, and transaction speed ([34] a; [5]). Similarly, FFT provides a robust framework for examining user characteristics (UCs) by explaining human behavior through basic tendencies, characteristic adaptations, and interactions with the environment—critical for understanding individual trust in cryptocurrencies. This study is guided by three research questions:

1. How do TCs, UCs, and EX influence CT?
2. How does CT mediate the relationship between TC, UC, EX, and CA?
3. In underregulated markets such as Vietnam, how do external regulatory conditions shape the role of trust in CA?

To address these questions, the study employs structural equation modeling (SEM) with data from 200 participants, offering a robust analysis of how trust mediates the influence of technical, personal, and contextual factors on adoption behavior. Ultimately, the findings provide actionable insights for developers, policymakers, and regulators, emphasizing the need for trust-building strategies, regulatory clarity, and technological transparency to foster adoption in underregulated environments.

There is a pressing need for this study due to the lack of an integrated, empirically tested model that captures the complex interplay between technology, user traits, and external regulatory factors in shaping trust and adoption behavior within decentralized financial systems. As cryptocurrencies continue to grow in underregulated markets like Vietnam, understanding how trust is formed becomes essential for fostering responsible adoption. Existing models fail to address this complexity, underscoring the necessity of a framework that reflects the sociotechnical realities of blockchain-based finance.

2. Literature Review

2.1. CA. The intention to adopt and use cryptocurrencies is influenced by various factors that shape user confidence and willingness to engage with digital currencies [35]. Familiarity with cryptocurrency plays a foundational role in this process [36]. Research highlights that users who are more familiar with how cryptocurrencies operate are likely to have higher trust levels and readiness to engage in trading and investment activities [37, 38]. Familiarity reduces the uncertainty associated with new financial technologies, equipping users to navigate the complexities of cryptocurrency markets more confidently [39].

Confidence in using cryptocurrency is another critical driver of adoption. Studies emphasize that users with greater confidence in their understanding of cryptocurrencies are more likely to adopt these technologies [35, 36]. Positive experiences, perceived financial benefits, and reduced transaction costs significantly enhance confidence [40]. Regulatory clarity also encourages adoption, as it provides users with the security and legitimacy required to engage with cryptocurrencies [41].

2.2. Digital Trust Theory and CA. Digital trust has emerged as a critical factor in CA. While institutional trust is central in traditional financial systems, cryptocurrencies require users to trust the underlying blockchain technology instead of institutions [17, 42]. Trust in decentralized systems depends on users' perceptions of security, privacy, and transparency—qualities intrinsic to blockchain technology [43].

Trust in technology [26] and digital trust [17] frameworks offer foundational perspectives on trust in technological systems. However, these models lack granularity in defining the role of specific technological attributes, such as blockchain's unique features, in shaping user trust. Research by Norbu et al. [23] and Marella et al. [22] highlights that security, transparency, and traceability significantly influence trust in blockchain systems, but further empirical validation is required. Additionally, user awareness and technological literacy are critical factors in fostering trust, as emphasized by Ku-Mahamud et al. [44].

Although earlier research has examined trust as a variable [13, 14], as a mediator [5, 20], or as a moderator [11], the factors and processes underlying trust in decentralized technologies remain inadequately understood. This study addresses these gaps by integrating theoretical insights into user and technological characteristics, as well as EX, to provide a more comprehensive model of trust in CA.

By synthesizing insights from TTF and FFT, this study underscores the interplay between technology and individual traits in fostering trust. These characteristics are particularly significant in underregulated markets, where trust in the technology itself must compensate for the absence of institutional protections.

2.2.1. UCs. The FFT [33] provides a robust framework for analyzing UCs, including behavioral tendencies and interactions with the environment. This theory allows for a nuanced understanding of how individual traits influence trust in decentralized technologies. Key characteristics such as technological literacy, digital finance experience, and risk tolerance play pivotal roles in shaping users' perceptions and behavior [24, 45]. For instance, users with high technological proficiency are more likely to trust blockchain's mechanisms and feel confident engaging with cryptocurrencies [46].

Psychological factors, including excitement about trading opportunities and fear of financial loss, further influence trust. While users motivated by the potential for substantial financial rewards may exhibit higher engagement, anxiety and market volatility can hinder adoption [47]. This highlights the complexity of trust formation, as both positive and negative emotions coexist in shaping user behavior.

2.2.2. TCs. The TTF framework by Goodhue and Thompson [32] offers a comprehensive lens to analyze how blockchain's features contribute to trust. TTF defines knowledge of technology as "TCs," encompassing attributes such as security, transparency, traceability, price value, and transaction speed [5, 34]. Blockchain's transparency ensures verifiable transactions, reducing fraud risks and enhancing user confidence [48]. Its security features, such as encryption and immutability, safeguard user assets, providing reassurance in environments that lack institutional safeguards [34].

2.2.3. Contextual/EX. Shin [17] and Müller [26] emphasize the role of contextual factors, particularly legal regulations, in shaping trust. Both models suggest that external factors, such as regulatory clarity, societal attitudes, and market stability, should be represented in trust frameworks.

2.2.3.1. Legal Regulations. Legal regulations are critical for fostering trust by legitimizing cryptocurrencies and providing protections against fraud [20, 23]. Regulatory clarity not only reduces perceived risks but also enhances societal acceptance of cryptocurrencies, normalizing their use in financial transactions. Anticipation of future regulation can serve as a proxy for institutional trust, reassuring users about the security and stability of the system [16].

2.2.3.2. Facilitating Conditions. Facilitating conditions, such as access to resources, information, and technical support, further influence trust [11]. These factors ensure that users, particularly those with less technical expertise, can confidently engage with cryptocurrency platforms [49]. The availability of user-friendly mobile platforms has also significantly reduced barriers to adoption, making cryptocurrencies more accessible to a broader audience [46].

In unregulated environments like Vietnam, the absence of robust institutional safeguards makes EX particularly important. Users rely heavily on signals such as government endorsements, societal attitudes, and the perceived legitimacy of cryptocurrency markets to build trust. This study incorporates these factors as critical components in a comprehensive trust model for CA.

2.3. Key Theories Informing the Research Model. This study is grounded in multiple theoretical frameworks to explain the dynamics of trust and CA in underregulated markets. Prior models such as the technology acceptance model (TAM), TRA, and TPB have provided foundational insights into technology adoption but fall short in capturing the complexities of decentralized and trust-dependent systems like cryptocurrencies.

The TAM developed by Davis [7] argues that users adopt technologies primarily based on perceived ease of use and perceived usefulness. While TAM has been extensively applied in digital adoption studies, it does not account for trust, perceived risk, or the decentralized nature of blockchain systems, making it less effective in explaining cryptocurrency behavior.

The TRA proposed by Fishbein and Ajzen [8] explains behavior through the lens of attitudes and subjective norms. Similarly, the TPB [50] adds the dimension of perceived behavioral control. While useful in understanding behavioral intentions, both theories were designed for regulated environments and do not adequately address the uncertainty and lack of institutional oversight characteristic of cryptocurrency ecosystems.

Ryu [10] extends these models by incorporating psychological variables like financial literacy and control perceptions, illustrating that users with high cognitive and behavioral self-regulation are better able to manage crypto-related risks. This aligns with the current study's emphasis on user traits as critical but insufficient without trust.

To address these limitations, the current study adopts a multitheoretical approach.

TTF [32] is used to define TCs. TTF captures how blockchain attributes—such as transparency, traceability, transaction speed, and security—align with user needs and task requirements, which is essential for building trust.

FFT [33] explains UCs through psychological dimensions such as risk tolerance, technological literacy, and emotional stability. These traits influence how users assess and respond to trust-related signals in decentralized systems.

Trust in technology [26] and digital trust theory [17] form the basis for CT, acknowledging the role of both system reliability and contextual assurance in shaping user confidence.

Moreover, although institutional trust theory [51] and regulatory focus theory [52] offer insights into external environmental influences, they are primarily designed for regulated, institution-centric contexts rather than decentralized systems like blockchain. Therefore, this study acknowledges that EX—including legal regulations, societal norms, and resource accessibility—play a mediating role in shaping trust. These factors are particularly salient in markets like Vietnam, where institutional safeguards are minimal. Studies such as Mashatan et al. [20] and Norbu et al. [23] highlight how regulatory support and social acceptance can bridge the trust gap in decentralized finance.

In summary, while traditional models (TAM, TRA, TPB) offer foundational insights, they are inadequate for capturing the unique sociotechnical landscape of CA. These models typically overlook the dynamic interplay between emerging technologies and user trust, especially in underregulated environments where institutional support is lacking. By integrating TTF, FFT, and trust-based frameworks with recent empirical research, this study presents a more nuanced and comprehensive model suited for unregulated and decentralized contexts.

To address these limitations, recent advances in financial technology highlight the growing role of generative artificial intelligence (AI) and the Internet of Things (IoT) in shaping user trust within decentralized finance ([53, 54]. Specifically, generative AI enhances system transparency and security through advanced fraud detection, real-time risk modeling, and personalized service delivery ([55, 56]). Concurrently, IoT-integrated blockchain platforms offer continuous data validation and autonomous transaction verification, which reinforce trust through enhanced automation, real-time monitoring, and decentralized control [53].

These developments reinforce the technological foundation of the TTF framework, suggesting that user trust is increasingly mediated by the effectiveness of intelligent and interconnected systems. Zada et al. [54] emphasize that while generative AI accelerates innovation and efficiency in fintech, it also introduces new ethical challenges—necessitating stronger mechanisms for transparency and governance. Similarly, Andronie et al. [57] demonstrate that AI–blockchain applications significantly enhance fraud prevention and customer satisfaction, thereby reinforcing the reliability dimension of trust. Balcerzak and Valaskova [58] contribute by showing that AI–blockchain infrastructures support sustainable finance through enhanced transparency and ESG compliance. Furthermore, studies on edge computing and IoT-based blockchain systems ([54, 57, 58]) point to increased system resilience and decentralized security—further strengthening the case for trust-building technologies in decentralized finance.

To synthesize these theoretical contributions and recent insights, Table 1 provides a comparative overview of the core frameworks supporting the conceptual model.

This theoretical integration sets the foundation for the study's hypotheses and conceptual framework.

2.4. Hypothesis and Model Development. This study proposes a comprehensive conceptual model that integrates TCs, UCs, and EX, with CT serving as a mediating element that influences CA. This model addresses critical gaps in understanding how trust operates in underregulated markets like Vietnam, where formal government oversight is minimal. By incorporating insights from the TTF framework and the FFT, the model offers a nuanced perspective on the interplay between technology, user traits, and contextual factors in driving trust and adoption.

2.4.1. Hypothesis Development. To enhance the robustness of the proposed hypotheses, this study incorporates both classical and contemporary sources of theoretical support. For instance, the relationship between TCs and trust is well established in the literature on system design and user acceptance (Goodhue [60]; Müller [26]; Asaithambi et al. [53]). Similarly, user traits such as technological literacy and risk tolerance have been shown to influence trust in decentralized systems (Costa Jr and McCrae [33]; Albayati et al. [45]; Ryu [10]). EX, such as regulatory clarity and facilitating conditions, further reinforce trust and adoption (Shin [17]; Zucker [51]; Mashatan et al. [20]). By drawing on this diverse body of knowledge, each hypothesis is grounded in both theoretical and empirical precedent.

Based on the theoretical foundations and empirical insights outlined above, the following hypotheses are proposed.

2.4.1.1. TCs and CT

Hypothesis 1. *TCs positively impact CT.*

This hypothesis is grounded in the TTF theory [32], which posits that a good fit between technology features and task requirements improves user outcomes. TCs, encompassing attributes such as transparency, security, decentralization, traceability, and transaction speed, are pivotal in building CT. For example, blockchain's transparency ensures verifiable transactions, reducing fraud risks [48]. Security, achieved through encryption and immutability, reassures users about the safety of their assets, compensating for the lack of regulatory safeguards in unregulated environments [17, 34].

2.4.1.2. TCs and CA. TCs can also directly influence CA by enhancing user perceptions of the platform's utility. Features such as faster transaction speeds, lower fees, and robust security provide significant incentives for tech-savvy users to adopt cryptocurrencies [61, 62]. In regions with inefficient financial systems, blockchain's efficiency and user empowerment further motivate adoption [17]. Drawing from the arguments presented, the study posits this hypothesis:

TABLE 1: Summary of theories applied to the conceptual model.

Theory	Key contribution	Limitation in crypto context
TAM [59]	Explains adoption via ease of use and usefulness	Lacks focus on trust and risk in decentralized systems
TRA [8]	Behavioral intention via attitudes and norms	Assumes rational decisions in regulated settings
TPB [50]	Adds perceived control to TRA	Does not address technology-specific trust or contextual factors
Ryu [10]	Adds financial literacy and self-control traits	Supports individual differences but lacks broader environmental scope
TTF [32]	Matches tech features with user tasks	Captures tech relevance but needs trust integration
FFT [33]	Explains behavioral tendencies via personality traits	Useful for UC but not sufficient without trust mediation
Trust in technology model [26]; digital trust [17]	Identify trust as key to tech adoption	Best suited for trust modeling in decentralized systems

Hypothesis 2. *TCs have a direct influence on CA.*

2.4.1.3. UCs and CT. UCs, as defined by the FFT framework, include traits such as technological literacy, risk tolerance, and previous digital finance experience. Drawing from the FFT [33], this hypothesis proposes that individual traits enhance the likelihood of trusting decentralized systems. Users with high technological literacy are better equipped to understand blockchain mechanisms, increasing their confidence in decentralized systems ([11, 24, 63]). However, psychological factors such as fear, anxiety, or trading addiction underscore the complexity of trust formation [47]. In light of the insights discussed, the following hypothesis is suggested:

Hypothesis 3. *UCs positively affect CT.*

2.4.1.4. UCs and CA. UCs also directly influence adoption. Individuals with strong digital literacy and familiarity with financial technology are better positioned to assess the risks and benefits of cryptocurrencies, leading to higher adoption rates [45]. Additionally, psychological motivators, such as excitement from trading and the allure of financial gains, drive adoption [10]. Grounded in the analysis above, the study formulates this hypothesis:

Hypothesis 4. *UCs have a direct impact on CA.*

2.4.1.5. EX and CT. The trust models proposed by Shin [17] and Müller [26] identify contextual factors such as legal regulations and societal attitudes as critical for trust building. Regulatory signals, even when incomplete, can foster perceptions of legitimacy and security, enhancing CT [20, 23]. Societal attitudes and media coverage also play a role in normalizing cryptocurrency use, further reinforcing trust [16]. Based on the preceding discussion, this study proposes the following hypothesis:

Hypothesis 5. *EX positively influence CT.*

2.4.1.6. EX and CA. External factors such as government support, regulatory clarity, and accessible resources can significantly influence adoption. These factors reduce barriers by creating a stable environment that encourages user engagement [39, 46]. Facilitating conditions, such as technical support and mobile-friendly platforms, further enhance usability and adoption [49]. Reflecting on the key points discussed, the study advances the following hypothesis:

Hypothesis 6. *EX directly impact CA.*

2.4.1.7. Mediating Role of CT. CT plays a critical mediating role in the relationships between TCs, UCs, EX, and CA ([64, 65]). While blockchain technology offers advanced features such as transparency, security, and decentralization, these attributes alone are insufficient to guarantee adoption. Users must trust that these features consistently deliver on their promises to feel secure enough to engage with cryptocurrencies. Trust serves as the psychological assurance that bridges the gap between perceived technological advantages and actual user behavior. For instance, while users may acknowledge blockchain's transparency or immutability, they are unlikely to adopt the technology unless they trust that these features will safeguard their assets and ensure reliable transactions [17, 19, 34].

Similarly, user traits such as technological literacy, digital finance experience, and risk tolerance influence adoption only when users trust the technology to meet their expectations. Even individuals with high digital literacy or extensive experience in financial technology may hesitate to adopt cryptocurrencies if they lack trust in the system's security or reliability. Trust transforms favorable UCs into actionable engagement by mitigating concerns about fraud, security breaches, and market instability [24, 63]. Psychological factors like excitement and fear coexist in shaping trust, highlighting its role as a balancing mechanism that enables users to feel confident in their decision-making [46, 47].

EX, such as regulatory clarity, societal attitudes, and market stability, also require trust to translate into adoption [64]. While regulatory signals or government endorsements may create a sense of legitimacy, trust ensures that users perceive these signals as reliable safeguards against risks. In underregulated markets like Vietnam, where formal oversight is minimal, trust becomes even more crucial in enabling users to rely on these external cues to navigate the uncertainties of CA. Societal attitudes and facilitating conditions, such as accessible resources and support, further reinforce trust by normalizing cryptocurrency use and reducing entry barriers [20, 23, 49]. These perspectives align with trust in technology [26] and digital trust theory [17], which emphasize the importance of contextual conditions in shaping trust in digital and decentralized systems. Based on these discussions, the study proposes the following mediating hypotheses:

Hypothesis 7. *CT mediates the relationship between UCs and CA.*

Hypothesis 8. *CT mediates the relationship between TCs and CA.*

Hypothesis 9. *CT mediates the relationship between EX and CA.*

2.4.1.8. CT and CA. Trust serves as a pivotal mechanism in shaping user behavior, particularly in high-risk and decentralized systems where institutional oversight is limited. When users perceive blockchain platforms as secure, transparent, and reliable, their likelihood of adopting cryptocurrencies increases significantly [11, 23]. Trust mitigates concerns related to fraud, system reliability, and privacy, thereby fostering a sense of confidence in engaging with digital assets. This hypothesis aligns with prior theoretical assertions that position trust as a fundamental determinant of behavioral intention (Shin [17]; Anagnostopoulos [42]). Empirical research further supports this association, demonstrating that trust not only facilitates adoption but also enhances long-term user engagement in blockchain ecosystems (Toufaily [24]; Zada et al. [54]; Balcerzak and Valaskova [58]). Considering the findings discussed, this study puts forward the following hypothesis:

Hypothesis 10. *CT has a direct and significant effect on CA.*

These hypotheses collectively reflect the multidimensional nature of trust in the adoption of cryptocurrency and guide the empirical analysis presented in subsequent sections.

2.4.2. Conceptual Model. Figure 1 presents the conceptual framework developed to investigate the factors influencing CA. The model identifies three core antecedents: TCs, UCs, and EX. These factors are hypothesized to influence users' CT—a central mediating construct—through Hypotheses 1, 3, and 5, respectively. In turn, CT is proposed to significantly affect CA (Hypothesis 10). The model also posits direct relationships between the antecedents and CA (Hypothesis 2 for TC, Hypothesis 4 for UC, and Hypothesis 6 for EX), suggesting that certain factors may impact adoption both directly and indirectly. Furthermore, trust itself is hypothesized to be shaped by multiple influences (Hypotheses 7, 8, and 9), reinforcing its role as a mediating mechanism. This integrative framework reflects a multidimensional perspective, emphasizing the importance of technological readiness, user perception, environmental support, and, critically, trust in driving adoption behavior.

2.5. Methodology

2.5.1. Measures. After finalizing the research framework, this study adopted a structured approach to develop the measurement scales for the constructs: UCs, TCs, EX, CT, and CA. The constructs were grounded in an extensive review of the literature and aligned with established theories in trust and technology adoption.

2.5.2. Common Method Bias. To minimize the risk of common method bias, several procedural remedies were applied during the survey design. First, the questionnaire was carefully pretested with 15 cryptocurrency users of varying experience levels to refine the wording, reduce ambiguity, and ensure conceptual clarity. Additionally, the anonymity of responses was assured to reduce social desirability bias. Procedurally, items measuring different constructs were separated and mixed throughout the questionnaire to minimize the likelihood of method-related variance [66].

2.5.3. Nonresponse Bias. Nonresponse bias was assessed by comparing early and late respondents, following Armstrong and Overton [67]'s method. No significant differences were observed between the two groups across key demographic variables and main constructs, suggesting that nonresponse bias was unlikely to threaten the validity of the findings. Furthermore, incomplete responses were excluded during data cleaning, enhancing the quality and integrity of the dataset [68].

2.5.4. Research Design Used. A cross-sectional survey design was employed, which is suitable for studies aiming to collect data at a single point in time to analyze relationships among variables [69]. The survey was designed to capture perceptions of cryptocurrency users regarding technological attributes, individual characteristics, EX, trust, and adoption behavior. To ensure the measurement instruments were reliable and valid, a pilot study was conducted from March 1 to March 15, 2023, involving 60 cryptocurrency users. After removing incomplete questionnaires, 50 valid responses were retained for analysis.

The pilot study followed best practices in survey research methodology [70]. Three refinement processes were undertaken:

1. Correlation matrix analysis: A correlation matrix was generated to identify highly correlated items (correlation coefficients > 0.9). Items exhibiting such high correlations were either merged or removed to avoid redundancy, thereby ensuring that each item contributes uniquely to the construct being measured [71].

2. Internal consistency assessment: The internal consistency of the items was assessed by comparing high-score and low-score groups. Items lacking discriminant power—those that did not significantly differentiate between these groups—were removed. This method is consistent with the recommendations of Nunnally and Bernstein [72], who advocate for the use of this comparative approach to enhance the reliability of measurement instruments.

3. Commonality check: A commonality analysis was performed to evaluate the shared variance among

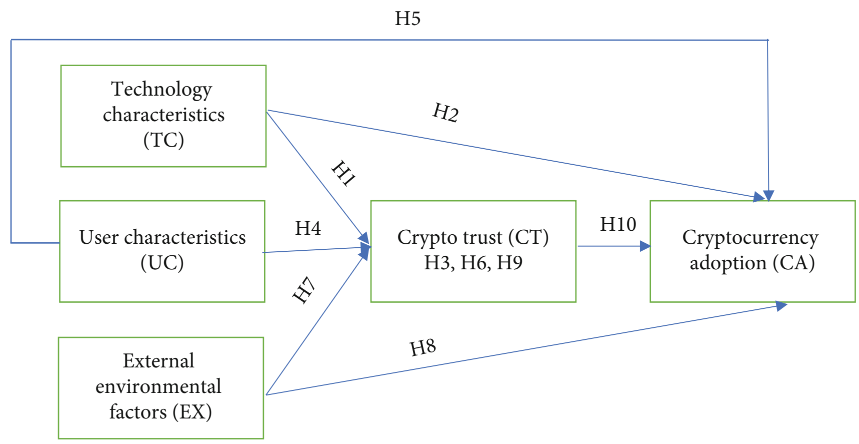

Figure 1: The conceptual model.

the items. Items with commonalities below the threshold of 0.5 were excluded, as they were deemed to contribute insufficiently to the constructs. This step is crucial for ensuring that the retained items possess adequate explanatory power [69].

2.5.5. Sampling Approach and Sample Size Calculation. The sampling approach adopted was purposive sampling, targeting cryptocurrency users who had engaged in transactions or investments within the past year. A sample size calculation was guided by the requirements for SEM, which suggests a minimum of 5–10 participants per parameter estimated [69]. Given the model complexity, the study targeted a sample size of at least 200 participants to ensure adequate statistical power and robustness in subsequent analyses.

The final reliability results for each construct, assessed using Cronbach's alpha, are summarized in Table 2. All constructs achieved alpha values above 0.7, indicating acceptable internal consistency [72].

The reliability results for each construct are summarized in Table 2, reflecting the internal consistency as measured by Cronbach's alpha, with values above 0.7 indicating acceptable reliability [72].

The pilot study results demonstrate strong reliability with all Cronbach's alpha values exceeding the recommended threshold of 0.7 [72].

2.5.5.1. Finalized Measurement Scale. The finalized scales, informed by the pilot study results, are reliable, ensuring the robustness of the survey instrument for measuring the relationships among UC, TC, EX, CT, and CA. The final measurement items and their sources are outlined in Table 3.

Each item was measured using a 5-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). This scale is widely used in studies of trust and adoption in digital environments, ensuring comparability with existing literature [7, 75].

2.5.6. Participants and Procedures. This study employed a structured, cross-sectional survey design to examine CA behaviors in Vietnam. The target population consisted of individuals with varying levels of exposure to and experience with cryptocurrencies. A nonprobability purposive sampling method was adopted, which is suitable for exploratory studies focusing on specific user groups [76]. Participants were recruited through cryptocurrency-related online platforms, including blockchain forums, Facebook groups, Telegram channels, and relevant social media communities.

TABLE 2: Pilot study for construct reliability.

Construct	Number of items	Cronbach's alpha
User characteristics (UCs)	7	0.86
Technology characteristics (TCs)	5	0.89
External environment (EX)	8	0.91
Crypto trust (CT)	4	0.92
Cryptocurrency adoption (CA)	6	0.87

A total of 400 questionnaires were distributed electronically over a 4-week period. Out of these, 240 responses were returned, resulting in a response rate of 60%. After applying data cleaning protocols—excluding responses with excessive missing data, uniform answers, or clear patterns of inattentiveness—a final sample of 200 valid responses was retained for further analysis. This sample size satisfies the minimum threshold for partial least squares structural equation modeling (PLS-SEM), which recommends 5–10 cases per estimated path coefficient ([77, 78]).

To ensure relevance and data quality, participants were required to be over 18 years of age and to possess at least a basic awareness of cryptocurrency technologies. Moreover, the survey instrument was pretested with a small group of users, and their feedback was used to refine the wording and structure of the questionnaire, thereby enhancing its clarity and contextual relevance prior to full deployment.

2.5.6.1. Sample Characteristics. The demographic characteristics of the respondents provide insight into the composition of cryptocurrency users in Vietnam. As summarized

TABLE 3: Measurement scale.

Category	Subcategory	Sample statements	Source
User characteristics (UC)	Psychological and personal factors	- Trading cryptocurrency is exciting based on vicarious experience. - There is an addiction to trading cryptocurrency. - Fear and anxiety are felt during cryptocurrency trading.	[47]
Technology characteristics (TCs)	Transparency, security, and reliability	- Cryptocurrency supply chain processes are transparent. - Cryptocurrency trading platforms are dependable. - Private information is secure.	(Chen et al., 2022; [48]; [73]; [17])
External environment (EX)	EX1: Government regulation and support EX2: Facilitating conditions	EX1: - Government regulation of cryptocurrency would reduce risks. - Illegal cryptocurrency trading undermines trust. EX2: - Resources and support are available for cryptocurrency use. - Smartphones make trading easier.	EX1: [63] EX2: ([49]; [46])
Crypto trust (CT)	Trust in cryptocurrency	- Blockchain is a trustworthy service. - Investing in cryptocurrency has benefits. - Cryptocurrency is reliable and secure.	([49]; [15]; [16]; [11])
Cryptocurrency adoption (CA)	Adoption and intention to use	- Intention to use cryptocurrencies when legally regulated. - Familiarity with cryptocurrencies promotes adoption. - Cryptocurrency benefits personal finances.	([46]; [74])

in Table 4, the largest age group was 21–30 years (51%), reflecting the predominance of younger, digitally literate individuals in early-stage adoption. Additionally, 65% of participants reported less than 1 year of trading experience, suggesting that the Vietnamese market remains in an early development phase with many novice users.

In terms of education, 58% were university students or graduates, and 25% held postgraduate degrees (Master's or PhD), indicating a relatively well-educated user base. Regarding occupation, 51% were students, followed by 33% working professionals or employees and 16% entrepreneurs or managers, reflecting a diverse but knowledge-oriented participant pool.

These demographic insights align with existing literature that associates CA with younger, educated, and digitally proficient populations ([12, 63]), particularly in emerging markets where regulatory clarity is still evolving. A detailed demographic breakdown is provided below.

The structured survey was administered between June 1, 2023, and August 31, 2023, and participants completed the questionnaire in approximately 10–15 min. The sample was diverse in terms of age, gender, education, occupation, and trading experience, ensuring a comprehensive view of CA behaviors.

While convenience sampling facilitated efficient data collection from a geographically dispersed population, it also introduced limitations in terms of generalizability [79]. Future studies should consider employing stratified random sampling or similar probabilistic techniques to improve representativeness and ensure the broader applicability of findings [80].

This approach aligns with established practices in emerging research domains, providing an exploratory foundation for understanding CA in underregulated markets like Vietnam.

2.5.7. Data Analysis Technique: SmartPLS. This study employed PLS-SEM using SmartPLS software to analyze the data. PLS-SEM was chosen due to its suitability for exploratory research and theory development, which aligns with the study's objective of proposing and validating a new trust-based model of CA [77, 78, 81]. The conceptual model includes multiple latent variables (UCs, TCs, EX, CT, and CA); some of which involve formative constructs and mediating relationships—conditions under which PLS-SEM is especially appropriate.

Moreover, PLS-SEM is flexible in handling complex models with moderate sample sizes, making it well suited to this study's sample of 200 respondents. It also enables robust estimation of both direct and indirect effects, which is particularly important for testing the mediating role of CT. Its emphasis on maximizing explained variance further strengthens its predictive capabilities in modeling user behavior in decentralized environments.

To complement this approach, the study integrates necessary condition analysis (NCA), a novel technique designed to identify variables that are not only influential but also essential for the desired outcome to occur [82]. While PLS-

TABLE 4: Demographics of respondents.

Criteria	Description	Number of respondents	Percentage
Gender	Female	114	57%
	Male	86	43%
Age	< 20	38	19%
	21–30	102	51%
	31–40	40	20%
	41 and above	20	10%
Education	Bachelor/university students	116	58%
	Master/PhD	50	25%
	High school or equivalent	34	17%
Job title	Students	102	51%
	Employees/professionals	66	33%
	Entrepreneurs/managers	32	16%
Trading experience	Less than 1 year	130	65%
	1–2 years	36	18%
	More than 2 years	34	17%

SEM explains how much a factor contributes, NCA determines whether a factor is indispensable—providing a sharper diagnostic view of causal asymmetry. This dual-method approach enhances both the predictive power and theoretical rigor of the study, offering a comprehensive understanding of the critical and sufficient conditions underlying CA.

2.5.8. Measurement Model Evaluation. To ensure the reliability and validity of the measurement model, a comprehensive assessment was conducted. Content validity was confirmed through expert reviews, ensuring the survey items accurately represented the constructs of CT, TCs, and CA. Construct validity was verified using factor analysis, while convergent validity was established with average variance extracted (AVE) values above 0.5, indicating adequate convergence.

Reliability was measured using Cronbach's alpha and composite reliability (CR), both requiring values over 0.7 to demonstrate strong internal consistency. Discriminant validity was assessed using the Fornell–Larcker criterion, which ensured that the square root of each construct's AVE was greater than its correlations with other constructs, confirming the distinctiveness of each construct [83]. These evaluations collectively validated the robustness of the measurement model.

2.5.9. Structural Model Evaluation. Following the validation of the measurement model, the structural model was assessed by examining the path coefficients and R^2 values to evaluate the model's predictive power. Bootstrapping was used to estimate the standard errors and test the significance of the path coefficients, ensuring robust hypothesis testing [78].

Mediation analysis: Since several hypotheses involve mediation (Hypotheses 7, 8, and 9), SmartPLS was employed to calculate the indirect effects and assess whether CT mediates the relationship between UCs, TCs, external environment, and CA. The bootstrapping method was also used to test the significance of these indirect effects [84, 85].

2.5.10. NCA. To complement the sufficiency-oriented PLS-SEM, this study incorporated NCA using the integrated module in SmartPLS 4. While PLS-SEM estimates how much predictors contribute to an outcome, NCA identifies whether a predictor is indispensable—that is, a necessary condition that must be present at a certain level for the outcome to occur [82].

NCA was conducted using the ceiling envelopment–free disposal hull (CE-FDH) technique with 5000 bootstrap samples. This method allowed us to test whether TCs, UCs, EX, and CT were necessary conditions for high CA. Effect sizes (d) and statistical significance were used to interpret the necessity level of each predictor.

3. Findings

3.1. Validity and Reliability Test. The reliability and validity of the constructs were evaluated using Cronbach's alpha, CR, AVE, heterotrait–monotrait ratio (HTMT), and the Fornell–Larcker criterion.

Cronbach's alpha values for all constructs exceeded 0.7, indicating high reliability [86]. Similarly, CR values also surpassed the threshold of 0.7, demonstrating consistency in the measurement scales. Convergent validity was confirmed as the AVE values for all constructs met the required threshold of 0.5 [83], as shown in Table 5.

Discriminant validity was assessed through the HTMT values and the Fornell–Larcker criterion. All HTMT values for construct pairs fell below the strict threshold of 0.85 [87], ensuring sufficient discriminant validity. These results are detailed in Table 6.

Furthermore, the Fornell–Larcker criterion was satisfied, as the diagonal values (square root of AVE) were greater

TABLE 5: Construct reliability and validity.

Construct	Cronbach's alpha	Composite reliability (ρc)	Average variance extracted (AVE)	Threshold
CA	0.900	0.923	0.667	≥ 0.7 (Cronbach's alpha, composite reliability); ≥ 0.5 (AVE)
CT	0.870	0.911	0.720	Same
EX	0.887	0.909	0.526	Same
TC	0.897	0.924	0.709	Same
UC	0.708	0.818	0.530	Same

TABLE 6: Heterotrait–monotrait ratio (HTMT).

	CA	CT	EX	TC	UC	Threshold
CA	—	0.652	0.666	0.542	0.663	≤ 0.85
CT	0.652	—	0.725	0.696	0.652	≤ 0.85
EX	0.666	0.725	—	0.619	0.621	≤ 0.85
TC	0.542	0.696	0.619	—	0.733	≤ 0.85
UC	0.663	0.652	0.621	0.733	—	≤ 0.85

TABLE 7: Fornell–Larcker criterion.

	CA	CT	EX	TC	UC
CA	0.817	0.590	0.606	0.499	0.557
CT	0.590	0.849	0.646	0.623	0.524
EX	0.606	0.646	0.725	0.568	0.525
TC	0.499	0.623	0.568	0.842	0.584
UC	0.557	0.524	0.525	0.584	0.728

than the off-diagonal correlations between constructs. This further validated discriminant validity, as presented in Table 7 [83].

Together, these results affirm the robustness and reliability of the measurement model, confirming its appropriateness for further analysis.

3.2. Hypothesis Testing. The hypothesis testing results confirm various relationships within the research model, focusing on the direct and mediating effects of TCs, UCs, external environment, and CT on CA. Table 8 and Figure 2 summarize the path coefficients, T-statistics, and p values for the 10 hypotheses tested.

3.2.1. Hypothesis 1: TCs Positively Impact CT. The results show that TCs, such as decentralization, security, transparency, and immutability, have a significant positive effect on CT (path coefficient: 0.361, p value: 0.005). This confirms that users tend to rely on the technological reliability of cryptocurrencies, especially in environments where institutional trust is weak, such as Vietnam. The robustness of blockchain technology, particularly its transparency and security, helps to foster trust among users.

3.2.2. Hypothesis 2: TCs Directly Impact CA. The direct effect of TCs on CA was not significant (path coefficient: 0.029, p value: 0.784). This suggests that while features like security and efficiency might attract early adopters, they are insufficient on their own to drive mass adoption. The findings indicate that most users still require trust in the system before they are willing to adopt the technology.

3.2.3. Hypothesis 3: CT Mediates the Relationship Between TCs and CA. The mediation effect of CT between TCs and CA is supported (path coefficient: 0.216, p value: 0.026). Even if users recognize the strengths of cryptocurrency technology, they are unlikely to adopt it without developing trust in the system. This is particularly important in unregulated markets, where the absence of institutional guarantees makes trust in technology itself crucial for adoption.

3.2.4. Hypothesis 4: UCs Positively Impact CT. The impact of UCs on CT was not supported (path coefficient: 0.114, p value: 0.253). This suggests that personal traits like technological proficiency or risk tolerance do not directly contribute to trust in cryptocurrency. Instead, users might need additional reassurances from the external environment, such as regulatory support, to fully develop trust in technology.

3.2.5. Hypothesis 5: UCs Directly Impact CA. The results show that UCs have a significant positive impact on CA (path coefficient: 0.266, p value: 0.020). Users with greater technological literacy or risk tolerance are more likely to adopt cryptocurrencies, as they are better equipped to evaluate and understand the benefits and risks of decentralized technology.

3.2.6. Hypothesis 6: CT Mediates the Relationship Between UCs and CA. CT was found to mediate the relationship between UCs and CA (path coefficient: 0.266, p value: 0.020). Even users with high technological proficiency or risk tolerance require trust in the system before adopting cryptocurrencies. This highlights the central role of trust as a mediator, especially in high-risk environments where users must rely on the system's ability to protect their investments.

3.2.7. Hypothesis 7: EX Positively Impact CT. The results support the hypothesis that EX significantly influence CT (path coefficient: 0.345, p value: 0.001). Factors such as government regulation, societal attitudes, and market stability play a crucial role in shaping user trust in cryptocurrencies. In unregulated markets, users often look for signals that regulatory support will be forthcoming, which can significantly enhance their trust in the technology.

TABLE 8: Summary of hypothesis testing.

Hypothesis	Relationship	Path coefficient	*p* value	Conclusion
Hypothesis 1	TC → CT	0.361	0.005	Supported
Hypothesis 2	TC → CA	0.029	0.784	Not supported
Hypothesis 7	TC → CT → CA	**0.216**	0.026	Supported
Hypothesis 3	UC → CT	0.114	0.253	Not supported
Hypothesis 4	UC → CA	0.266	0.020	Supported
Hypothesis 8	UC → CT → CA	**0.266**	0.020	Supported
Hypothesis 5	EX → CT	0.345	0.001	Supported
Hypothesis 6	EX → CA	0.301	0.016	Supported
Hypothesis 9	EX → CT → CA	**0.301**	0.016	Supported
Hypothesis 10	CT → CA	0.216	0.026	Supported

Note: Path coefficients in bold indicate significant indirect (mediated) effects in the structural model.

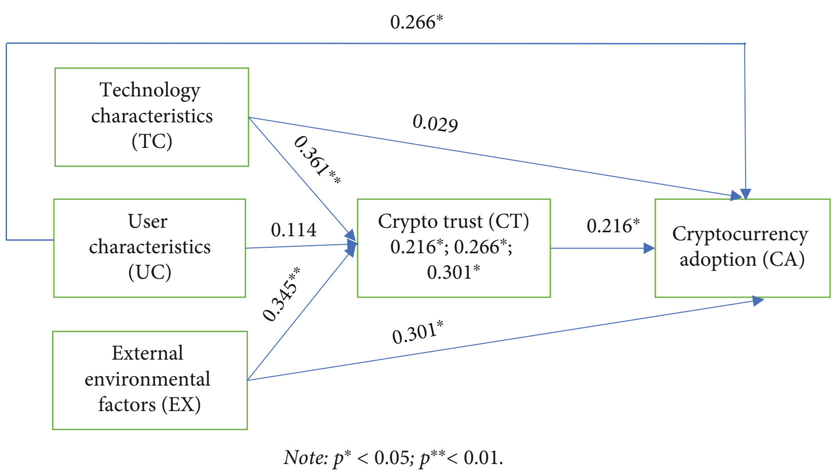

Figure 2: The research findings. *Note:* $^{*}p < 0.05$; $^{**}p < 0.01$.

3.2.8. Hypothesis 8: EX Directly Impact CA. The direct effect of EX on CA is supported (path coefficient: 0.301, *p* value: 0.016). Users may adopt cryptocurrencies if they perceive that the market is stabilizing or that government regulations are likely to be implemented. This suggests that external factors, such as anticipated regulation or societal acceptance, can drive adoption even in the absence of full trust.

3.2.9. Hypothesis 9: CT Mediates the Relationship Between External Environment and CA. The mediation effect of CT between EX and CA is supported (path coefficient: 0.301, *p* value: 0.016). External factors like regulatory support create a climate where users can build trust in cryptocurrencies, which in turn drives adoption. This underscores the role of trust as a bridge between external factors and actual adoption behaviors.

3.2.10. Hypothesis 10: CT Directly Impacts CA. The results confirm that CT has a direct and significant impact on CA (path coefficient: 0.216, *p* value: 0.026). Users who trust the reliability and security of cryptocurrency technology are more likely to adopt it. This highlights the importance of trust in fostering user engagement with cryptocurrency markets, particularly in emerging economies like Vietnam.

In summary, the findings show that while technological features like decentralization and security enhance trust in cryptocurrencies, they do not directly lead to adoption. Trust must first be established, especially in environments with low institutional trust, such as Vietnam.

UCs, including tech proficiency and risk tolerance, encourage adoption but do not significantly build trust. Even skilled users rely on external reassurance to feel confident using crypto.

External factors, such as regulatory signals and social acceptance, influence both trust and adoption. These factors help create the conditions for trust, which then supports user engagement.

Trust is the essential mediator connecting technology, user traits, and the external environment to adoption behavior. This highlights the need to go beyond technical development by focusing on regulation, transparency, and trust building to enable broader cryptocurrency use.

3.3. Structural Model Evaluation. The *R*-square and *R*-square adjusted values provide insights into the proportion of variance in the dependent variables explained by the independent variables in the model. Specifically, *R*-square represents the explanatory power of the predictors, while the adjusted R-square refines this value by accounting for the number of predictors and the sample size, thereby preventing overestimation [85].

As illustrated in Table 9, for CA, the R-square value of 0.481 indicates that 48.1% of the variance in CA is explained by the predictors. Moreover, the adjusted R-square value of 0.469 accounts for potential overfitting, resulting in a slightly reduced variance explained. Similarly, for CT, the R-square value of 0.524 shows that 52.4% of the variance is explained by the predictors. Furthermore, the adjusted R-square of 0.516 performs a similar correction for overfitting.

In conclusion, these results emphasize that the model exhibits slightly greater explanatory power for CT compared to CA. Nonetheless, both constructs demonstrate substantial variance explained by the predictors, reflecting the robustness of the model.

TABLE 9: R-square and R-square adjusted results.

Construct	R -square	R -square adjusted
CA	0.481	0.469
CT	0.524	0.516

3.4. NCA Results. Table 10 presents the effect sizes and p values obtained from the NCA. The analysis shows that CT is a statistically significant necessary condition for achieving high levels of CA, with an effect size of $d = 0.312$ ($p < 0.05$). This indicates that without a certain threshold level of trust in cryptocurrency systems, high adoption is unlikely to occur—regardless of other favorable factors.

EX also demonstrated a moderate necessity effect ($d = 0.165$, $p < 0.10$), suggesting that regulatory signals and facilitating conditions may serve as secondary constraints to adoption, although with lower impact.

In contrast, TCs and UCs did not meet the significance threshold for necessity, with effect sizes of $d = 0.123$ and $d = 0.076$, respectively (both $p > 0.10$). These findings confirm that while TC and UC contribute to sufficiency in the PLS-SEM model, they are not required at minimum levels to achieve adoption.

These results reinforce the role of CT as a noncompensatory precondition for adoption and enrich our interpretation of trust as both a necessary and sufficient condition in decentralized financial contexts.

4. Discussion and Implication

4.1. Discussion

4.1.1. CT as a Necessary and Sufficient Condition. The inclusion of NCA further clarifies the central role of CT in CA. Beyond acting as a mediating and sufficient condition, CT also emerged as a necessary condition. This means that even when other factors such as favorable technology features or user traits are present, high levels of adoption cannot occur unless a baseline level of trust is achieved.

This finding is particularly salient in underregulated environments such as Vietnam, where institutional support is weak. In these contexts, users require a minimum threshold of trust to justify engagement with cryptocurrency systems. This aligns with earlier work by Shin [17] and Anagnostopoulos [42], who highlight trust as a prerequisite for adoption in high-risk financial ecosystems. Moreover, our findings expand on Marella et al. [22] and Norbu et al. [23], who also found that transparency and regulatory assurance enhance trust. However, our study adds a methodological distinction by using NCA to confirm that trust is not just influential—it is indispensable.

The dual role of CT—as both necessary and sufficient—-strengthens the theoretical foundation of the model and underscores the urgency for developers and policymakers to prioritize trust-building measures. In essence, CT is the gatekeeper to CA in uncertain market environments like Vietnam.

4.1.2. TCs, Trust, and Adoption. The results affirm that TCs—including decentralization, security, transparency, and immutability—significantly contribute to CT. In alignment with the TTF theory [60], these attributes help compensate for institutional voids. This finding corroborates studies by Arli et al. [5], Chen et al. [34], and McKnight et al. [48], who underscore the role of perceived system qualities in fostering trust.

Interestingly, our findings contrast with those in more regulated markets. While prior studies (e.g., Morosan and DeFranco [73]; Toufaily [24]) have observed a direct relationship between TC and adoption in institutionally mature environments, our study shows that such a direct path is absent in underregulated settings. Instead, trust must first mediate the relationship—reinforcing the idea that in environments lacking strong oversight, system-level features alone are insufficient.

4.1.3. UCs, Trust, and Adoption. Contrary to conventional wisdom and earlier findings (e.g., Costa Jr and McCrae [33]; Toufaily [24]), our data reveals that UCs such as technological literacy and risk tolerance do not directly foster CT, as indicated by Hypothesis 3. This suggests that in volatile, unregulated markets, personal traits are secondary to contextual cues in trust formation. However, Hypothesis 4 does confirm a direct link between UC and CA, consistent with Albayati et al. [63] and Folkinshteyn and Lennon [12], who identified a strong association between tech-savviness and digital asset engagement.

This divergence from prior findings may be attributed to differences in regulatory environments. In developed markets, trust may be more internalized through personal capability; in emerging markets, it depends more on external validation. This nuanced distinction adds to the FFT's application in fintech contexts by situating UC within broader socioenvironmental interactions.

4.1.4. External Environment, Trust, and Adoption. Our results validate the strong impact of EX on both CT and CA. Regulatory clarity, societal norms, and facilitating conditions were all found to significantly influence trust. This aligns with commitment-trust theory Morgan [25] and

TABLE 10: NCA effect sizes and significance for cryptocurrency adoption.

Predictor variable	Necessity effect size (*d*)	*p* value	Interpretation
Crypto trust (CT)	0.312	< 0.05	**Necessary condition**
External environment (EX)	0.165	< 0.10	Possibly necessary (moderate)
Technology characteristics (TCs)	0.123	> 0.10	Not necessary
User characteristics (UCs)	0.076	> 0.10	Not necessary

Note: Bold entries highlight the main necessary condition(s) identified.

builds on empirical findings by Prakosa and Sumantika [16] and Mashatan et al. [20].

Notably, our findings diverge from traditional views where external validation is seen as only complementary. Here, EX emerged as both a direct and indirect driver of adoption, even bypassing trust in some cases. This echoes recent work by Prasetyo and Kurniasari (2023), who found that perceived governmental support alone could stimulate adoption behavior. Our findings extend this by showing how external cues not only influence behavior but also mediate through trust, offering a comprehensive view of how regulatory and social environments shape adoption dynamics.

4.2. Theoretical Implications. This study contributes to theory by integrating TTF and FFT within a trust-centric framework tailored for decentralized finance. It empirically demonstrates that while TCs are foundational in shaping trust, they do not independently lead to adoption—highlighting CT as a necessary mediator.

By contrasting findings in underregulated markets like Vietnam with those from institutionally mature settings, this research also broadens the contextual relevance of theories such as TTF and digital trust theory. Specifically, the observed mediation effects and contextual dependencies offer deeper insights into how environmental and technological dimensions coproduce user behavior in decentralized ecosystems.

Moreover, the study contributes methodologically through the dual application of PLS-SEM and NCA. While PLS-SEM captures the sufficiency logic underlying complex variable relationships, NCA identifies the necessary conditions for outcomes to occur. This combination enhances the explanatory power and diagnostic utility of trust-centric models—an innovation that can inform future fintech research designs.

4.3. Practical Implications. The findings of this study offer several important practical implications for developers, policymakers, and other stakeholders seeking to enhance CA, particularly in underregulated markets. Strengthening CT should be a priority, especially in contexts where institutional trust is weak. Developers are encouraged to improve system-level security, ensure transactional transparency, and design user-friendly interfaces. These measures can significantly enhance user confidence by reducing perceived technological risks and making cryptocurrency systems more accessible.

In addition to technological enhancements, the role of regulatory clarity is highlighted as a critical enabler of both trust and adoption. In countries like Vietnam, where regulatory ambiguity persists, the establishment of clear, consistent, and supportive policies can offer legitimacy to cryptocurrency activities. Such regulatory frameworks not only mitigate uncertainty but also function as indirect signals of institutional support, which are vital for building user trust in decentralized systems.

The study also underscores the need for targeted user education initiatives. Although technological literacy is positively associated with adoption, it does not inherently foster trust. Therefore, educational programs should be aimed at improving users' understanding of blockchain security features, operational risks, and practical applications. By addressing knowledge gaps and demystifying the technology, these efforts can foster greater inclusion, empowering a broader segment of the population—beyond early adopters and tech-savvy individuals—to engage with cryptocurrency platforms confidently.

4.4. Limitations. While this study offers valuable insights into the dynamics of CA, several limitations should be acknowledged. First, the geographic focus on Vietnam restricts the generalizability of the findings to other markets with distinct cultural, economic, and regulatory contexts. Future research could extend this framework to other emerging and developed markets to compare and contrast adoption behaviors. Additionally, the study's cross-sectional design provides a snapshot of user perceptions at a single point in time, making it challenging to capture how trust and adoption evolve over time. Longitudinal studies could address this limitation by exploring the impact of regulatory changes or technological advancements on adoption trends.

The reliance on self-reported data introduces potential response bias, as participants may overstate or understate their trust levels or adoption intentions. To enhance reliability, future studies could incorporate behavioral data, such as actual cryptocurrency usage records or transaction patterns. Moreover, this study emphasizes CT as the central mediator, potentially overlooking other influential factors such as perceived usefulness, ease of use, or satisfaction with cryptocurrency systems. Incorporating these additional variables in future research could provide a more comprehensive understanding of adoption drivers.

4.5. Future Directions. Future research should consider extending the model across diverse geographic and regulatory contexts to assess its broader applicability. Longitudinal designs could offer insights into how trust and adoption behaviors evolve over time, especially in response to regulatory or technological changes. Incorporating behavioral data, such as transaction logs, would enhance data validity beyond self-reported measures. Additionally, examining variables like usability, satisfaction, and psychological factors—such as trust propensity or financial anxiety—could deepen understanding of adoption drivers. Segmented analyses by demographic groups may also reveal important differences in user behavior, supporting more targeted adoption strategies.

4.6. Conclusion. This study deepens our understanding of CA by proposing and empirically validating a trust-based model incorporating user, technological, and environmental determinants. The findings reveal that CT is not only a powerful mediator but also a necessary precondition for adoption—particularly in underregulated markets like Vietnam.

The theoretical contributions lie in combining TTF, FFT, and trust theories with empirical rigor, while the methodological innovation of using both PLS-SEM and NCA offers robust and actionable insights. Practically, the study emphasizes the need for transparency, regulation, and user empowerment as key levers in enhancing trust and fostering widespread adoption.

For a broader readership, the study offers a template for understanding how trust, shaped by both systemic and individual factors, underpins digital transformation in financial ecosystems. Whether in emerging markets or established economies, trust remains the cornerstone of technology adoption—especially in contexts where decentralization replaces traditional authority structures.

Future research should explore longitudinal effects of trust and investigate cross-national differences, potentially incorporating qualitative data to capture evolving user perceptions. By addressing these avenues, scholars can further refine the trust–adoption nexus and contribute to more inclusive and trustworthy digital finance landscapes.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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