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Factors Influencing Consumers' Intention to Use Cryptocurrency as a Substitute for Traditional Currency: An Empirical Study

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Article

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Posted Date: November 13th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11433777/v1

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Additional Declarations: No competing interests reported.

Factors Influencing Consumers' Intention to Use Cryptocurrency as a Substitute for Traditional Currency: An Empirical Study

Short Title / Running Head: Consumer Intention to Use Cryptocurrency

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Abstract

Purpose. Cryptocurrencies are often promoted as an alternative to fiat money, yet little is known about why ordinary consumers would use them as a substitute for traditional currency rather than as a speculative asset. This study integrates the technology acceptance model, trust and perceived risk to explain attitude towards cryptocurrency, and tests whether regulatory awareness and volatility perception change how strongly that attitude turns into behavioral intention.

Design/methodology/approach. A cross-sectional survey of 441 cryptocurrency-aware adult consumers in Indian metro and tier 2 cities was collected through purposive sampling and analyzed with partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4. Inference used 5,000 bootstrap subsamples; moderation used the two-stage interaction approach with simple slopes and Johnson-Neyman analysis.

Findings. Perceived usefulness (β = 0.265), perceived ease of use (β = 0.250) and trust (β = 0.310) strengthened attitude, while perceived risk weakened it (β = −0.270); together they explained 56.5% of the variance in attitude. Attitude was the strongest predictor of intention (β =

0.602). Attitude mediated all four antecedents: fully for ease of use and risk, partially for usefulness and trust. Regulatory awareness strengthened the attitude to intention link (β = 0.146), whereas volatility perception weakened it (β = −0.102). The model explained 53.5% of the variance in intention and showed high out-of-sample predictive power. All eleven hypotheses were supported.

Originality/value. The study treats regulation and volatility as boundary conditions on the attitude to intention link rather than as further direct antecedents. This explains why favorable attitudes do not always become use: they convert into intention more readily when consumers understand the rules and less readily when they expect sharp price swings.

Practical implications. Exchanges and wallet providers should pair usability and security messaging with plain-language explanations of tax and compliance rules, and should offer price-stabilizing options (stablecoin settlement, instant conversion) for payment use cases. Policymakers can raise conversion of interest into informed use by making the regulatory regime clearer and more visible.

Keywords: cryptocurrency adoption; currency substitution; technology acceptance model; trust; perceived risk; regulatory awareness; volatility perception; PLS-SEM

1. Introduction

1.1 Background

Money has repeatedly changed form, from metal coins to paper notes, cards and, most recently, mobile wallets. Bitcoin was proposed as the next step: "a purely peer-to-peer version of electronic cash" that would let two parties transact without a bank or a central authority (Nakamoto, 2008). Since then, thousands of crypto-assets have been issued, and their supporters continue to describe them as an alternative to state-issued currency (Böhme et al., 2015). Economists remain doubtful. Bitcoin is held mainly as a speculative asset, its price is far more volatile than any national currency, and it performs poorly as a unit of account and a store of value (Baur et al., 2018; Glaser et al., 2014; Yermack, 2015). Even the most ambitious public experiment, El Salvador's 2021 decision to make Bitcoin legal tender, produced limited everyday use once initial incentives were spent (Alvarez et al., 2023).

The question of substitution is especially relevant in India. India has topped the Chainalysis Global Crypto Adoption Index for three consecutive years (Chainalysis, 2025), and its consumers have adopted digital payments at an unusual speed through the Unified Payments Interface. Yet the regulatory signal has been mixed. In 2020 the Supreme Court set aside the Reserve Bank of India's 2018 circular that barred banks from serving crypto businesses (*Internet and Mobile Association of India v. Reserve Bank of India*, 2020). The Finance Act, 2022 then introduced a 30% tax on gains from virtual digital assets and a 1% tax deducted at source on transfers (Government of India, 2022), and in 2023 crypto service providers were brought under anti-money-laundering reporting rules (Ministry of Finance, 2023). At the same time, the Reserve Bank of India began piloting its own digital rupee (Reserve Bank of India, 2022). For an Indian consumer, cryptocurrency is therefore legal to hold, taxed when sold and closely watched, but it is not legal tender. Whether such a consumer would use it in place of the rupee is an open behavioral question.

1.2 Prior work and research gap

Research on cryptocurrency adoption has grown quickly. Most studies extend the technology acceptance model (TAM; Davis, 1989) or the unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) and confirm that usefulness, ease of use, trust and risk shape intention (Abbasi et al., 2021; Albayati et al., 2020; Jariyapan et al., 2022; Shahzad et al., 2018; Sohaib et al., 2020). Trust has received special attention because cryptocurrencies replace institutional guarantees with code and network consensus (Arli et al., 2021; Koroma et al., 2022; Mendoza-Tello et al., 2018). Four gaps remain.

First, most studies do not separate investing in crypto from paying with it. Surveys show that crypto is held mainly as a long-term investment rather than used for payments (Mattke et al., 2021; Steinmetz et al., 2021; Stix, 2021), so findings on "adoption" may say little about substitution for traditional currency. Second, many UTAUT-based models link beliefs directly to intention and drop attitude, even though attitude is the mechanism through which beliefs become intentions in the theory of reasoned action and TAM (Davis et al., 1989; Fishbein & Ajzen, 1975). Third, the context in which a favorable attitude is or is not acted upon has rarely been modeled. Regulation and volatility are usually treated as background facts or as additional direct predictors (Schaupp & Festa, 2018), not as conditions that strengthen or weaken the conversion

of attitude into intention. Fourth, despite India's scale and its ambiguous regulatory stance, empirical work there remains limited compared with China, Malaysia and Western markets (Kumari et al., 2023; Nadeem et al., 2021; Ter Ji-Xi et al., 2021).

1.3 Argument of this study

This study argues that a consumer's intention to use cryptocurrency as money is built in two stages. In the first stage, beliefs about usefulness, ease of use, trust and risk form an evaluative attitude (Davis, 1989; Pavlou, 2003). In the second stage, that attitude is converted into intention, but the conversion depends on two features of the environment that are distinctive to cryptocurrency. Regulatory awareness, the consumer's knowledge of the legal and tax rules that apply, acts as a source of institution-based assurance (McKnight et al., 2002; Zucker, 1986) and should make a favorable attitude easier to act on. Volatility perception, the belief that the value of a coin may change sharply within a short time, threatens the store-of-value and unit-of-account functions of money (Baur et al., 2018) and, through loss aversion (Kahneman & Tversky, 1979), should make a favorable attitude harder to act on. Three research questions follow:

1. Which beliefs shape consumers' attitude towards cryptocurrency as a substitute for traditional currency?
2. Does attitude transmit the effects of these beliefs to behavioral intention?
3. Do regulatory awareness and volatility perception strengthen or weaken the effect of attitude on intention?

1.4 Contributions and implications

The study makes three contributions. It specifies the dependent variable as intention to use cryptocurrency in place of cash and bank money, which separates currency substitution from speculation. It restores attitude as the mediating mechanism and shows which beliefs act fully through it and which also act directly. It introduces regulatory awareness and volatility perception as opposing boundary conditions and tests them with moderated mediation, showing how the indirect effect of every belief rises or falls with context. For practice, the results tell exchanges, wallet providers and policymakers which levers move attitude and which conditions decide whether attitude becomes use.

1.5 Structure of the paper

Section 2 reviews the literature on cryptocurrency as money and on its adoption. Section 3 presents the conceptual framework, its theoretical foundations and the hypotheses. Section 4 describes the research design, sampling, measures and analytical approach. Section 5 reports the measurement and structural model results. Section 6 discusses the findings, Section 7 sets out theoretical and managerial implications, Section 8 notes limitations and future research, and Section 9 concludes.

2. Literature review

2.1 Cryptocurrency as money

A currency must serve as a medium of exchange, a unit of account and a store of value. Cryptocurrencies were designed for the first function, yet the evidence suggests they perform the other two weakly. Yermack (2015) showed that Bitcoin's daily volatility was many times that of major currencies and that its exchange rates were almost uncorrelated with them, which makes it a poor unit of account. Baur et al. (2018) analyzed Bitcoin user accounts, found that about a third of coins were held by investors, and concluded that Bitcoin is used mainly as a speculative asset rather than as a currency. Volatility studies show that Bitcoin's volatility has both short-run and long-run components (Katsiampa, 2017), and asset-pricing work shows that crypto returns are driven by momentum and investor attention rather than by the fundamentals that anchor currencies (Liu & Tsyvinski, 2021). Some authors see hedging or diversification value (Bouri et al., 2017; Dyhrberg, 2016), but a hedge is not a means of payment. Baur & Dimpfl (2021) conclude that cryptocurrencies behave mainly as a speculative financial asset class.

Monetary theory has begun to model how a cryptocurrency and a central bank currency can coexist and what that coexistence implies for crypto prices and monetary policy (Schilling & Uhlig, 2019), and real-world tests have been sobering. In El Salvador, many citizens downloaded the government wallet to claim a sign-up bonus, but few continued to use Bitcoin for payments afterwards (Alvarez et al., 2023). Exchange failures such as the collapse of FTX in November 2022 also showed how much users still depend on centralized intermediaries they cannot audit (Vidal-Tomás et al., 2023). The question of substitution is therefore not technical feasibility but whether consumers believe the benefits of using crypto as money outweigh its costs.

2.2 Technology acceptance perspectives

TAM explains technology use through two beliefs: perceived usefulness, the degree to which using a system improves performance, and perceived ease of use, the degree to which using it is free of effort (Davis, 1989). In its original form these beliefs shape attitude, which in turn shapes intention (Davis et al., 1989). TAM has been extended many times (Venkatesh & Davis, 2000; Venkatesh et al., 2003, 2012), and meta-analyses confirm that usefulness is the most robust predictor while ease of use works partly through usefulness and attitude (King & He, 2006; Schepers & Wetzels, 2007).

TAM and UTAUT are now the default lenses for cryptocurrency adoption. Shahzad et al. (2018) found that usefulness, ease of use, trustworthiness and awareness predicted intention to use cryptocurrency in mainland China. Albayati et al. (2020) extended TAM with trust and external factors to explain acceptance of blockchain-based transactions. Sohaib et al. (2020) and Abbasi et al. (2021) combined PLS-SEM with neural networks to rank predictors, and Jariyapan et al. (2022) added perceived risk and financial literacy to TAM3 in emerging economies. Similar models have been tested in South Africa (Mazambani & Mutambara, 2020; Walton & Johnston, 2018), Jordan (Almajali et al., 2022), Malaysia (Ter Ji-Xi et al., 2021) and China (Nadeem et al., 2021). The consensus is that usefulness and ease of use matter, but their reported effects vary widely, which suggests that context conditions their influence.

2.3 Trust and perceived risk

Trust is the willingness to be vulnerable to another party based on positive expectations of its behavior (Mayer et al., 1995). In online settings it covers trust in the vendor, in the technology and in the surrounding institutions (McKnight et al., 2002). Cryptocurrency is often called "trustless" because consensus algorithms replace a central guarantor, yet users must still trust the protocol, the exchange, the wallet and their own ability to keep keys safe (Böhme et al., 2015; Krombholz et al., 2017). Studies consistently show that trust raises intention to use crypto (Arli et al., 2021; Mendoza-Tello et al., 2018) and that it can mediate and moderate other effects (Koroma et al., 2022).

Perceived risk is the consumer's subjective expectation of loss (Bauer, 1960). Featherman and Pavlou (2003) distinguished performance, financial, time, psychological, social, privacy and

overall risk for e-services. Pavlou (2003) and Kim et al. (2008) showed that trust lowers perceived risk and that risk in turn suppresses favorable evaluations and purchase intentions. In fintech research, perceived risk is the main barrier to adoption (Ali et al., 2021; Hu et al., 2019; Ryu, 2018). For cryptocurrency the risk set is wider: irreversible transactions, theft of keys, exchange insolvency and the absence of deposit insurance (Gao et al., 2016; Krombholz et al., 2017).

2.4 Attitude as the mechanism

In the theory of reasoned action, attitude is a person's overall evaluation of performing a behavior and is the main proximal antecedent of intention (Fishbein & Ajzen, 1975). The theory of planned behavior keeps this role (Ajzen, 1991), and comparisons of TAM and planned behavior models show that attitude carries much of the effect of beliefs on intention (Mathieson, 1991; Taylor & Todd, 1995). In fintech and cryptocurrency, attitude has been shown to predict intention strongly (Almajali et al., 2022; Kim, 2021; Lee, 2009). Nevertheless, many recent crypto models use UTAUT2, which omits attitude, so the question of whether beliefs act through attitude or directly on intention is seldom tested.

2.5 Regulatory awareness

Institutional theory holds that regulative, normative and cognitive structures make behavior legitimate and predictable (Scott, 2014). In e-commerce, institution-based trust, the belief that legal and structural safeguards are in place, encourages transactions with unfamiliar parties (McKnight et al., 2002; Pavlou & Gefen, 2004; Zucker, 1986). Regulation matters for cryptocurrency markets too. News about bans or securities treatment moves prices and volumes (Auer & Claessens, 2018), whereas clearer rules do not systematically drive traders away (Feinstein & Werbach, 2021), and regulatory quality is associated with national crypto infrastructure (Saiedi et al., 2021). Schaupp and Festa (2018) argued that regulation could be a path to mainstream adoption, and Arli et al. (2021) found that consumers trust cryptocurrencies more when transactions are regulated by government. Yet the consumer side has received little attention: what matters for behavior is not the law itself but whether the consumer knows what the rules are. This study calls that knowledge regulatory awareness. In India, where rules have changed several times since 2018, awareness is likely to vary greatly between consumers.

2.6 Volatility perception

Objective volatility is well documented (Katsiampa, 2017; Liu & Tsyvinski, 2021), but behavior responds to perceived risk rather than to statistical risk (Slovic, 1987). Volatility perception, the consumer's belief that a cryptocurrency's value may change sharply over a short period, is particularly damaging for currency use. A shopper who pays in a coin that later rises regrets the payment, and a merchant who accepts one that later falls bears a loss. Prospect theory predicts that such potential losses weigh more than equal gains (Kahneman & Tversky, 1979). Trading data show that crypto attracts risk-seeking investors (Pelster et al., 2019), which suggests that volatility may attract speculators while deterring those who want a means of payment. Stablecoins emerged largely as a response to this problem (Gorton & Zhang, 2023).

2.7 Synthesis

Table 1 summarizes representative studies and the gaps this study addresses.

Table 1. Representative studies on cryptocurrency adoption

Study	Focus	What it shows	What it leaves open
Shahzad et al. (2018)	TAM with trust and awareness, China	Usefulness, ease of use, trust and awareness raise intention	Attitude not modeled; no boundary conditions
Albayati et al. (2020)	TAM with trust and external factors	Trust is central to acceptance of blockchain transactions	Payment versus investment use not separated
Arli et al. (2021)	Consumer trust in cryptocurrency	Understanding of the technology, trust in government and transaction speed drive trust; regulated transactions are	Trust not linked to attitude or to intention to substitute currency

Study	Focus	What it shows	What it leaves open
		trusted more	
Jariyapan et al. (2022)	TAM3, perceived risk, financial literacy	Risk lowers and literacy raises intention	Volatility and regulation not modeled as moderators
Koroma et al. (2022)	Trust and ethics, Mano River Union	Trust mediates and moderates adoption	No attitude stage
Mattke et al. (2021)	Mixed methods on Bitcoin investment	Identifies the motivations behind Bitcoin investment	Currency substitution not examined
Steinmetz et al. (2021)	Population survey of ownership and uses	Ownership is mostly a long-term investment; knowledge, through trust, drives ownership	No explanatory model of intention
Schaupp and Festa (2018)	Adoption and regulation	Regulation proposed as a route to adoption	Consumer-level regulatory awareness not measured

Three conclusions follow. First, technology beliefs, trust and risk are well-established predictors but are rarely organized through attitude. Second, outcomes usually mix investing with using, so the specific question of substituting crypto for traditional currency is underdeveloped. Third, regulation and volatility are discussed as context but are almost never tested as conditions that change how attitude turns into intention.

3. Conceptual framework and hypothesis development

3.1 Conceptual framework

Figure 1 presents the research model. Four beliefs (perceived usefulness, perceived ease of use, trust and perceived risk) predict attitude towards cryptocurrency (H1 to H4). Attitude predicts behavioral intention to use cryptocurrency as a substitute for traditional currency (H5) and carries the effects of the four beliefs to intention (H6a to H6d). Regulatory awareness (H7) and volatility perception (H8) moderate the path from attitude to intention.

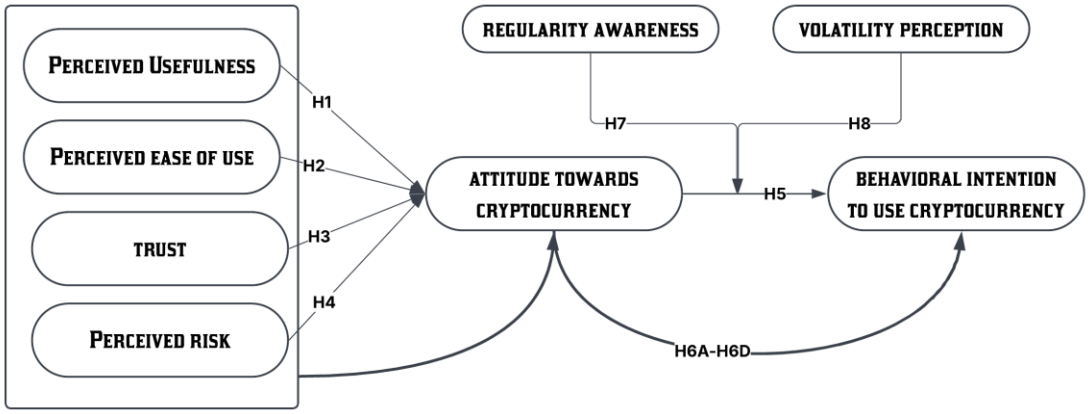


Figure 1. Conceptual framework. *Note:* the box labelled "Regularity awareness" in the original diagram refers to the construct of regulatory awareness and is named that way throughout the paper.

3.2 Theoretical foundation

The model combines three theoretical lenses.

Belief, attitude and intention chain. The theory of reasoned action holds that salient beliefs about a behavior form an attitude, and attitude forms intention (Fishbein & Ajzen, 1975). TAM applies this chain to technology, with usefulness and ease of use as the key beliefs (Davis, 1989; Davis et al., 1989). This lens explains why the four beliefs are expected to act on intention mainly through attitude.

Trust and risk framework. Transactions in uncertain digital environments depend on trust, which reduces the perceived chance of opportunistic behavior, and on perceived risk, which

captures the expected loss if things go wrong (Kim et al., 2008; Pavlou, 2003). Integrating trust and risk with TAM explains acceptance better than TAM alone (Gefen et al., 2003; Pavlou, 2003). This lens adds trust and risk as evaluative beliefs that feed attitude.

Institutional and prospect theory perspectives on conversion. Attitude does not always become intention. Ajzen (1991) noted that intention depends on whether a person believes the behavior can be carried out under existing conditions. Two conditions are specific to cryptocurrency. Institution-based trust (McKnight et al., 2002; Zucker, 1986), grounded in institutional theory (Scott, 2014), suggests that knowing the rules reduces structural uncertainty and makes it safer to act on a positive evaluation. Prospect theory (Kahneman & Tversky, 1979) suggests that the expectation of large price swings makes potential losses salient at the moment of use, which dampens the effect of a positive evaluation. Together these perspectives justify treating regulatory awareness and volatility perception as moderators of the attitude to intention link rather than as further antecedents of attitude.

3.3 Hypothesis development

Perceived usefulness and attitude. Perceived usefulness is the extent to which a consumer believes that using cryptocurrency would make payments and transfers faster, cheaper or more convenient than traditional money. Crypto transfers can settle across borders within minutes and without bank opening hours, and they can be cheaper than remittance services (Böhme et al., 2015). TAM predicts that such expected benefits produce a favorable evaluation (Davis et al., 1989), and crypto studies confirm the link (Albayati et al., 2020; Shahzad et al., 2018).

> ***H1.*** *Perceived usefulness has a positive effect on attitude towards cryptocurrency.*

Perceived ease of use and attitude. Using cryptocurrency requires learning about wallets, private keys, addresses and network fees, and errors are usually irreversible (Gao et al., 2016; Krombholz et al., 2017). When consumers believe these tasks are easy, the effort they expect to spend falls and their evaluation improves (Davis, 1989). Ease of use has been shown to shape attitude and intention in crypto and fintech settings (Hu et al., 2019; Jariyapan et al., 2022).

> ***H2.*** *Perceived ease of use has a positive effect on attitude towards cryptocurrency.*

Trust and attitude. Trust here means confidence that the cryptocurrency network, the exchanges and the wallets will work reliably and protect users' funds. Because no central authority guarantees a crypto payment, trust substitutes for institutional guarantees (Mendoza-Tello et al., 2018). Trust improves evaluations of online transactions (Gefen et al., 2003; Kim & Peterson, 2017) and of cryptocurrency in particular (Arli et al., 2021).

> ***H3.*** *Trust has a positive effect on attitude towards cryptocurrency.*

Perceived risk and attitude. Perceived risk captures expected losses from theft, fraud, exchange failure, loss of keys and lack of legal recourse. Risk lowers the attractiveness of e-services (Featherman & Pavlou, 2003) and of fintech (Ryu, 2018), and high-profile failures such as FTX make such losses vivid (Vidal-Tomás et al., 2023). Consumers who perceive more risk should therefore hold a less favorable attitude (Kim et al., 2008).

> ***H4.*** *Perceived risk has a negative effect on attitude towards cryptocurrency.*

Attitude and behavioral intention. Behavioral intention is the consumer's stated plan to use cryptocurrency for purchases, transfers or savings in place of cash or bank money. Attitude is the most proximal predictor of intention in reasoned action theories (Ajzen, 1991; Fishbein & Ajzen, 1975), and it predicts intention to use cryptocurrency strongly (Almajali et al., 2022; Kim, 2021).

> ***H5.*** *Attitude towards cryptocurrency has a positive effect on behavioral intention to use cryptocurrency.*

Mediating role of attitude. If beliefs shape attitude (H1 to H4) and attitude shapes intention (H5), attitude should transmit the effects of the beliefs to intention. This is the core logic of the belief, attitude and intention chain (Davis et al., 1989) and is consistent with evidence that attitude carries much of the influence of beliefs (Taylor & Todd, 1995). Whether the mediation is full or partial is an empirical question: usefulness and trust may also affect intention directly, as TAM2 and UTAUT assume (Venkatesh & Davis, 2000; Venkatesh et al., 2003).

> ***H6a.*** *Attitude mediates the relationship between perceived usefulness and behavioral intention.*
>
> ***H6b.*** *Attitude mediates the relationship between perceived ease of use and behavioral intention.*

> ***H6c.*** *Attitude mediates the relationship between trust and behavioral intention.*
>
> ***H6d.*** *Attitude mediates the relationship between perceived risk and behavioral intention.*

Moderating role of regulatory awareness. Regulatory awareness is the extent to which a consumer knows the legal status of cryptocurrency, the taxes that apply and the compliance duties of exchanges. A consumer who likes cryptocurrency but does not know whether using it is legal or how it is taxed faces structural uncertainty, and that uncertainty makes acting on the attitude feel unsafe. Knowing the rules provides institution-based assurance (McKnight et al., 2002; Pavlou & Gefen, 2004) and reduces the fear of unintended violations. Regulatory awareness should therefore make it easier to translate a favorable attitude into intention.

> ***H7.*** *Regulatory awareness moderates the relationship between attitude and behavioral intention, such that the relationship is stronger when regulatory awareness is high.*

Moderating role of volatility perception. Volatility perception is the belief that the value of cryptocurrency can change sharply within short periods. For money, value stability is essential: a consumer who expects a coin to lose a fifth of its value next week will hesitate to hold it as a means of payment, whatever their general attitude. Prospect theory predicts that the possibility of such losses outweighs equivalent gains (Kahneman & Tversky, 1979), and the store-of-value literature shows that volatility undermines currency functions (Baur et al., 2018; Yermack, 2015). Volatility perception should therefore make it harder to translate a favorable attitude into intention.

> ***H8.*** *Volatility perception moderates the relationship between attitude and behavioral intention, such that the relationship is weaker when volatility perception is high.*

4. Research methodology

4.1 Research design

The study follows a positivist, deductive design and tests the hypotheses with a cross-sectional survey. A survey suits the research questions because the constructs are perceptions and

intentions that are best captured through self-report, and because the aim is to test relationships across a broad consumer population rather than to manipulate conditions.

Partial least squares structural equation modeling (PLS-SEM) was chosen over covariance-based SEM for four reasons (Hair et al., 2019, 2022). First, the model is complex, with eight constructs, four mediation paths and two interaction terms. Second, the study has a predictive as well as an explanatory aim, and PLS-SEM supports out-of-sample assessment through PLSpredict (Shmueli et al., 2019). Third, PLS-SEM estimates interaction terms and conditional indirect effects without requiring multivariate normality. Fourth, the constructs are measured as composites of closely related items, for which PLS-SEM is well suited. Analysis was conducted in SmartPLS 4 (Ringle et al., 2024).

4.2 Population and sampling strategy

The target population is adult Indian consumers (18 years and above) who are aware of cryptocurrency and who already use digital payments. Awareness is required because respondents must be able to form beliefs about the technology, and digital payment use ensures that the comparison is between two digital forms of money rather than between crypto and cash alone. Both owners and non-owners of cryptocurrency were eligible, because the outcome is future intention to substitute, not past ownership.

No sampling frame exists for this population: exchanges do not share customer lists, and non-owners who are aware of crypto are not recorded anywhere. Probability sampling was therefore not feasible, and purposive (judgmental) sampling with screening questions was used (Etikan et al., 2016). Purposive sampling is appropriate when the goal is theory testing rather than estimating population parameters, because the aim is to check whether relationships hold among people to whom the theory applies (Calder et al., 1981; Hulland et al., 2018). Three screening questions confirmed that each respondent (1) was at least 18 years old, (2) had heard of cryptocurrency and could name at least one coin, and (3) had made a digital payment through the Unified Payments Interface, a card or a mobile wallet in the previous month.

To reduce the concentration that online purposive samples can show, invitations were spread across several channels: professional networking groups, fintech and investor communities on messaging platforms, and university alumni networks. Distribution was monitored weekly so that

both metro and tier 2 cities, and both owners and non-owners, were represented. The questionnaire was hosted on Qualtrics and was open for ten weeks between February and April 2026.

4.3 Sample size

Sample size was set before data collection using three criteria (Memon et al., 2020), summarized in Table 2.

Table 2. Minimum sample size criteria

Criterion	Assumptions	Minimum n
G*Power, overall model (Faul et al., 2009)	Behavioral intention with 8 predictors; $f^2 = 0.15$; $\alpha = .05$; power = .95	160
Inverse square root method (Kock & Hadaya, 2018)	Smallest expected path = 0.15; $\alpha = .05$	275
G*Power, single interaction term (Faul et al., 2009)	1 tested predictor out of 8; $f^2 = 0.02$ (small); $\alpha = .05$; power = .80	395
Final usable sample		**441**

The interaction criterion was the binding one. Interaction effects in field studies are typically small (Aguinis et al., 2005), so a sample powered only for medium effects would risk false negatives for H7 and H8. Allowing for an expected screening loss of about 15%, the target was set at 470 or more started responses.

In total, 512 responses were started. Responses were removed for failing a screening question (23), abandoning the survey before completion (17), failing an instructed-response attention check (19), and straight-lining or speeding (12; identical answers on every multi-item block, or completion in less than 40% of the median time). This left 441 usable responses (86.1% of those started), above every criterion in Table 2. Because all items after the screening page required an answer, retained cases had no missing values.

4.4 Questionnaire and measures

The questionnaire had four parts: screening, belief measures, outcome and moderator measures, and demographics. All constructs were measured with four items on seven-point Likert scales (1 = strongly disagree, 7 = strongly agree), adapted from established scales or, for the two moderators, developed from the literature and Indian regulation (Table 3). The questionnaire was in English, which is widely used for financial services among the target group.

Content validity was assessed by six experts (three marketing and finance academics, two compliance professionals from Indian crypto exchanges and one tax practitioner). Items scoring below Lawshe's (1975) critical content validity ratio of .99 for six panelists were reworded; two volatility perception items were revised at this stage. A pilot with 40 respondents, excluded from the main sample, confirmed clarity and gave Cronbach's α above .80 for all scales.

Table 3. Measurement items and sources

Construct	Code	Item	Source
Perceived usefulness (PU)	PU1	Using cryptocurrency would make my payments faster than traditional money.	Davis (1989); Shahzad et al. (2018)
	PU2	Cryptocurrency would make it cheaper for me to send money, especially across borders.	
	PU3	Using cryptocurrency would let me carry out transactions at any time of day.	

Construct	Code	Item	Source
	PU4	Overall, cryptocurrency would be useful to me as a means of payment.	
Perceived ease of use (PEOU)	PEOU1	Learning to use a crypto wallet would be easy for me.	Davis (1989); Albayati et al. (2020)
	PEOU2	Sending and receiving cryptocurrency would be clear and understandable.	
	PEOU3	It would be easy for me to become skilful at paying with cryptocurrency.	
	PEOU4	Overall, I find cryptocurrency easy to use.	
Trust (TR)	TR1	I believe cryptocurrency networks record transactions reliably.	Gefen et al. (2003); McKnight et al. (2002); Mendoza-Tello et al. (2018)
	TR2	I trust established crypto exchanges and wallets to keep my	

Construct	Code	Item	Source
		funds safe.	
	TR3	I believe cryptocurrency platforms act in the interest of their users.	
	TR4	Overall, cryptocurrency is trustworthy as a means of payment.	
Perceived risk (PR)	PR1	I could lose money through hacking, fraud or theft if I used cryptocurrency.	Featherman and Pavlou (2003); Pavlou (2003)
	PR2	Using cryptocurrency exposes me to the failure of exchanges or wallet providers.	
	PR3	If a crypto payment goes wrong, I may have no way to recover my money.	
	PR4	Overall, using cryptocurrency for payments is risky.	
Attitude towards cryptocurrency	ATT1	Using cryptocurrency instead of traditional	Ajzen (1991); Taylor and Todd (1995)

Construct	Code	Item	Source
(ATT)		currency is a good idea.	
	ATT2	Using cryptocurrency for my transactions would be wise.	
	ATT3	I like the idea of using cryptocurrency in place of cash or bank money.	
	ATT4	Using cryptocurrency for payments would be a pleasant experience.	
Behavioral intention (BI)	BI1	I intend to use cryptocurrency for some of my purchases in the future.	Venkatesh et al. (2003, 2012)
	BI2	I plan to use cryptocurrency to send or receive money instead of bank transfers.	
	BI3	I would hold part of my everyday money in cryptocurrency	

Construct	Code	Item	Source
		rather than rupees.	
	BI4	I expect to use cryptocurrency as a substitute for traditional currency within the next 12 months.	
Regulatory awareness (RA)	RA1	I know the current legal status of cryptocurrency in India.	Developed from Schaupp and Festa (2018); Government of India (2022); Ministry of Finance (2023)
	RA2	I am aware of how gains from cryptocurrency are taxed in India.	
	RA3	I know that crypto exchanges in India must follow anti-money-laundering and reporting rules.	
	RA4	I keep myself informed about government and RBI announcements on cryptocurrency.	

Construct	Code	Item	Source
Volatility perception (VP)	VP1	The value of cryptocurrency can change sharply within a single day.	Developed from Yermack (2015); Katsiampa (2017); Baur et al. (2018)
	VP2	I cannot predict what my cryptocurrency would be worth next week.	
	VP3	Cryptocurrency prices are much less stable than the value of the rupee.	
	VP4	Large price swings are a normal feature of cryptocurrency.	

Three control variables were added as predictors of intention: gender (1 = female), age in years, and prior cryptocurrency ownership (1 = currently or previously held). Each could plausibly raise or lower intention independently of the hypothesized mechanism.

4.5 Controlling common method bias

Because all constructs came from the same respondents at one point in time, procedural remedies were built into the design (Podsakoff et al., 2003, 2012). Respondents were assured of anonymity and told that there were no right or wrong answers. Predictor and criterion sections were separated by the demographic block, items were randomized within each section, and items were worded neutrally and concisely after the pilot. Statistical checks are reported in Section 5.3.

4.6 Analytical procedure

The analysis followed the two-step approach of Hair et al. (2019, 2022). The measurement model was assessed first for indicator reliability, internal consistency, convergent validity and

discriminant validity (Fornell & Larcker, 1981; Henseler et al., 2015). The structural model was then assessed for collinearity, path coefficients, explained variance, effect sizes and predictive power. The PLS algorithm used the path weighting scheme, a maximum of 3,000 iterations and a stop criterion of 10^{-7}. Significance was tested by bootstrapping with 5,000 subsamples, percentile confidence intervals and two-tailed tests at $\alpha = .05$ (Streukens & Leroi-Werelds, 2016).

Mediation was assessed with specific indirect effects and classified by also estimating the direct paths (Nitzl et al., 2016; Zhao et al., 2010). Moderation used the two-stage approach to create interaction terms, which is recommended when the aim is to test significance (Becker et al., 2018). Interactions were probed with simple slopes at ±1 SD (Aiken & West, 1991) and Johnson-Neyman floodlight analysis (Spiller et al., 2013), and conditional indirect effects were tested with the index of moderated mediation (Hayes, 2015). Predictive power was assessed with PLSpredict (Shmueli et al., 2019) and model fit with the standardized root mean square residual (SRMR; Henseler et al., 2016).

5. Data analysis

5.1 Respondent profile

Table 4 describes the 441 respondents. Most were men (61.0%) and aged 25 to 34 (56.0%; mean age = 27.87 years, SD = 6.03), and 35.4% had held cryptocurrency at some point. The younger, male-leaning profile matches population surveys of crypto awareness and ownership (Steinmetz et al., 2021). Six in ten respondents made digital payments daily, which confirms that the sample compares crypto with money that is already digital.

Table 4. Respondent profile (n = 441)

Characteristic	Category	n	%
Gender	Male	269	61.0
	Female	172	39.0
Age (years)	18 to 24	143	32.4
	25 to 34	247	56.0

Characteristic	Category	n	%
	35 to 44	40	9.1
	45 and above	11	2.5
Education	Undergraduate or below	76	17.2
	Graduate	180	40.8
	Postgraduate	162	36.7
	Doctoral or professional	23	5.2
Occupation	Salaried (private sector)	185	42.0
	Salaried (public sector)	41	9.3
	Self-employed or business	93	21.1
	Student	92	20.9
	Other	30	6.8
Monthly personal income (₹)	No independent income or below 25,000	82	18.6
	25,000 to 50,000	130	29.5
	50,001 to 1,00,000	143	32.4
	Above 1,00,000	86	19.5
City of residence	Tier 1 (Delhi NCR,	265	60.1

Characteristic	Category	n	%
	Mumbai, Bengaluru, Chennai, Hyderabad, Kolkata, Pune, Ahmedabad)		
	Tier 2 (Jaipur, Lucknow, Indore, Chandigarh, Kochi and others)	176	39.9
Cryptocurrency ownership	Currently or previously held	156	35.4
	Never held	285	64.6
Digital payment frequency	Daily	264	59.9
	Several times a week	138	31.3
	Weekly or less	39	8.8

5.2 Data screening and nonresponse bias

The retained data had no missing values. Item skewness ranged from −0.456 to 0.080 and excess kurtosis from −0.715 to 0.099, well within ±1, so there was no severe departure from normality (Hair et al., 2022). PLS-SEM does not assume normality, but this check confirms that bootstrapped intervals are not distorted by extreme distributions.

Nonresponse bias was examined by comparing the first 25% of respondents (n = 110) with the last 25% (n = 110), on the assumption that late respondents resemble nonrespondents (Armstrong & Overton, 1977). Independent-samples t-tests showed no significant difference on any of the eight constructs (largest $|t| = 1.735$ for regulatory awareness, $p = .084$; all other $p \geq .501$). Nonresponse bias is therefore unlikely.

5.3 Common method bias

Two statistical tests complemented the procedural remedies. In Harman's single-factor test, an unrotated factor analysis of all 32 items extracted seven factors with eigenvalues above 1, and the first factor explained 31.68% of the variance, well below the 50% threshold (Podsakoff et al., 2003). In the full collinearity test, every construct was regressed on all the others; all variance inflation factors (VIFs) were between 1.173 and 2.757, below the 3.3 threshold (Kock, 2015). Table 5 reports the full collinearity results. Common method bias is therefore not a concern.

Table 5. Full collinearity assessment

Construct	Full collinearity VIF
Perceived usefulness	1.506
Perceived ease of use	1.358
Trust	1.616
Perceived risk	1.482
Attitude	2.757
Behavioral intention	2.084
Regulatory awareness	1.173
Volatility perception	1.190

Note: threshold VIF < 3.3 (Kock, 2015). Harman's first factor = 31.68% of variance.

5.4 Measurement model: reliability and convergent validity

All eight constructs are reflective. Table 6 shows that every outer loading was between 0.827 and 0.897, above the 0.708 threshold, so each item shares more than half its variance with its construct (Hair et al., 2019). Indicator VIFs ranged from 1.992 to 2.826, below the conservative threshold of 3, so items within a block are not redundant.

Internal consistency was high. Cronbach's α ranged from 0.877 to 0.907, the reliability coefficient ρA from 0.886 to 0.916, and composite reliability ρC from 0.915 to 0.935. All values

lie between 0.70 and 0.95, the range recommended to avoid both unreliability and item redundancy (Dijkstra & Henseler, 2015; Hair et al., 2019). Convergent validity was established because the average variance extracted (AVE) ranged from 0.730 to 0.781, above 0.50 (Fornell & Larcker, 1981).

Table 6. Reliability and convergent validity

Construct	Item	Loading	VIF	α	ρA	ρC	AVE
Perceived usefulness	PU1	0.872	2.480	0.899	0.901	0.930	0.768
	PU2	0.888	2.640				
	PU3	0.860	2.318				
	PU4	0.885	2.652				
Perceived ease of use	PEOU1	0.871	2.374	0.889	0.894	0.923	0.750
	PEOU2	0.871	2.405				
	PEOU3	0.881	2.477				
	PEOU4	0.841	2.209				
Trust	TR1	0.877	2.571	0.901	0.902	0.931	0.771
	TR2	0.882	2.706				
	TR3	0.886	2.614				
	TR4	0.868	2.369				
Perceived risk	PR1	0.855	2.362	0.892	0.897	0.925	0.755

Construct	Item	Loading	VIF	α	ρA	ρC	AVE
	PR2	0.890	2.613				
	PR3	0.888	2.645				
	PR4	0.842	2.081				
Attitude	ATT1	0.892	2.826	0.903	0.904	0.932	0.775
	ATT2	0.888	2.675				
	ATT3	0.874	2.479				
	ATT4	0.868	2.435				
Behavioral intention	BI1	0.883	2.634	0.907	0.907	0.935	0.781
	BI2	0.892	2.769				
	BI3	0.883	2.640				
	BI4	0.878	2.602				
Regulatory awareness	RA1	0.847	2.154	0.877	0.886	0.915	0.730
	RA2	0.884	2.347				
	RA3	0.859	2.283				
	RA4	0.827	1.992				
Volatility perception	VP1	0.868	2.421	0.888	0.916	0.922	0.748

Construct	Item	Loading	VIF	α	ρA	ρC	AVE
	VP2	0.897	2.459				
	VP3	0.846	2.364				
	VP4	0.847	2.149				

Note: thresholds: loading > 0.708; VIF < 3; α, ρA and ρC between 0.70 and 0.95; AVE > 0.50.

5.5 Discriminant validity

Discriminant validity was assessed with both the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT).

Fornell-Larcker criterion. The square root of each construct's AVE (diagonal of Table 7, 0.854 to 0.884) was greater than its correlation with every other construct. The largest correlation, between attitude and intention, was 0.663, still well below the smaller of the two square roots (0.880). Table 7 also reports construct means: respondents saw cryptocurrency as useful (M = 5.16) and volatile (M = 5.19), but their trust in it was the lowest of all constructs (M = 4.31).

Table 7. Descriptive statistics and Fornell-Larcker criterion

Construct	Mean	SD	PU	PEOU	TR	PR	ATT	BI	RA	VP
PU	5.16	1.07	**0.876**							
PEOU	4.89	1.12	0.399	**0.866**						
TR	4.31	1.15	0.340	0.245	**0.878**					
PR	4.69	1.12	−0.211	−0.174	−0.379	**0.869**				
ATT	4.78	1.10	0.527	0.478	0.564	−0.487	**0.880**			
BI	4.48	1.13	0.459	0.340	0.499	−0.36	0.663	**0.884**		

Construct	Mean	SD	PU	PEOU	TR	PR	ATT	BI	RA	VP
						4				
RA	4.41	1.10	0.160	0.111	0.297	−0.137	0.233	0.353	**0.854**	
VP	5.19	1.08	−0.014	−0.065	−0.211	0.344	−0.146	−0.231	−0.101	**0.865**

Note: bold diagonal values are the square roots of AVE; off-diagonal values are construct correlations. Means and SDs are on the 1 to 7 scale.

HTMT ratio. Because the Fornell-Larcker criterion can miss discriminant validity problems when loadings are high and similar (Henseler et al., 2015), the HTMT ratio was also computed. Table 8 shows that the highest value was 0.731 (attitude and intention), below the conservative threshold of 0.85 (Henseler et al., 2015; Kline, 2016). The upper bounds of the bootstrapped 95% confidence intervals (5,000 subsamples) were all below 0.85, the highest being 0.784, which confirms that every HTMT value is significantly lower than the threshold (Franke & Sarstedt, 2019). Discriminant validity is therefore established by both criteria.

Table 8. Heterotrait-monotrait ratio (HTMT)

Construct	PU	PEOU	TR	PR	ATT	BI	RA
PEOU	0.445 [0.526]						
TR	0.377 [0.466]	0.271 [0.364]					
PR	0.234 [0.334]	0.192 [0.299]	0.421 [0.507]				
ATT	0.584 [0.649]	0.531 [0.608]	0.624 [0.688]	0.540 [0.616]			

Construct	PU	PEOU	TR	PR	ATT	BI	RA
BI	0.508 [0.583]	0.377 [0.466]	0.552 [0.622]	0.403 [0.491]	0.731 [0.784]		
RA	0.178 [0.278]	0.125 [0.231]	0.333 [0.420]	0.151 [0.251]	0.259 [0.354]	0.393 [0.484]	
VP	0.053 [0.127]	0.077 [0.172]	0.228 [0.325]	0.391 [0.479]	0.155 [0.257]	0.250 [0.357]	0.106 [0.202]

Note: values in brackets are the upper bounds of the bootstrapped 95% confidence intervals (97.5th percentile, 5,000 subsamples). Threshold HTMT < 0.85.

5.6 Structural model assessment

Collinearity. Inner VIF values ranged from 1.009 to 1.290 (Table 9), far below 3, so collinearity among predictors does not bias the path coefficients (Hair et al., 2019).

Explanatory power. The four beliefs explained 56.5% of the variance in attitude ($R^2 = 0.565$; adjusted $R^2 = 0.561$), and the full set of predictors explained 53.5% of the variance in behavioral intention ($R^2 = 0.535$; adjusted $R^2 = 0.526$). Both values exceed the 0.50 benchmark for moderate explanatory power in consumer research (Hair et al., 2019).

Effect sizes. Following Cohen (1988), f^2 values of 0.02, 0.15 and 0.35 indicate small, medium and large effects. Attitude had a large effect on intention ($f^2 = 0.713$). Trust had a medium effect on attitude (0.172), and usefulness (0.125), risk (0.142) and ease of use (0.118) had small to medium effects. Interaction terms are judged against Kenny's (2018) thresholds of 0.005, 0.01 and 0.025: the regulatory awareness interaction was large (0.045) and the volatility perception interaction medium (0.022).

Model fit. The SRMR was 0.030 for the saturated model and 0.037 for the estimated model, both below 0.08 (Henseler et al., 2016; Hu & Bentler, 1999). Because fit indices in PLS-SEM are still debated, SRMR is reported as supplementary evidence only (Hair et al., 2019).

Table 9. Collinearity, explanatory power and effect sizes

Path	Inner VIF	f^2	Effect size
Perceived usefulness → Attitude	1.290	0.125	Small to medium
Perceived ease of use → Attitude	1.213	0.118	Small to medium
Trust → Attitude	1.285	0.172	Medium
Perceived risk → Attitude	1.183	0.142	Small to medium
Attitude → Behavioral intention	1.091	0.713	Large
Regulatory awareness → Behavioral intention	1.074	0.068	Small
Volatility perception → Behavioral intention	1.035	0.028	Small
Attitude × Regulatory awareness → Behavioral intention	1.025	0.045	Large (Kenny, 2018)
Attitude × Volatility perception → Behavioral intention	1.024	0.022	Medium (Kenny, 2018)
Gender → Behavioral intention	1.016	0.001	None
Age → Behavioral intention	1.010	0.004	None

Path	Inner VIF	f^2	Effect size
Prior ownership → Behavioral intention	1.009	0.003	None
R^2 (adjusted R^2)	Attitude: 0.565 (0.561)	Behavioral intention: 0.535 (0.526)	Moderate
SRMR	Saturated: 0.030	Estimated: 0.037	Below 0.08

5.7 Hypothesis testing: direct and moderating effects

Table 10 and Figure 2 report the bootstrapped path coefficients. All four beliefs significantly affected attitude in the hypothesized direction. Perceived usefulness ($\beta = 0.265$, $t = 7.421$, $p < .001$), perceived ease of use ($\beta = 0.250$, $t = 6.571$, $p < .001$) and trust ($\beta = 0.310$, $t = 8.623$, $p < .001$) had positive effects, supporting H1, H2 and H3. Perceived risk had a negative effect ($\beta = -0.270$, $t = 7.445$, $p < .001$), supporting H4. Trust was the strongest determinant of attitude and risk the second strongest in absolute size.

Attitude had a strong positive effect on behavioral intention ($\beta = 0.602$, $t = 20.063$, $p < .001$), supporting H5. Both interaction terms were significant. The interaction of attitude and regulatory awareness was positive ($\beta = 0.146$, $t = 4.529$, $p < .001$), supporting H7, and the interaction of attitude and volatility perception was negative ($\beta = -0.102$, $t = 2.915$, $p = .004$), supporting H8. None of the 95% confidence intervals for H1 to H8 included zero. Of the non-hypothesized paths, regulatory awareness had a positive main effect on intention ($\beta = 0.184$, $p < .001$) and volatility perception a negative one ($\beta = -0.116$, $p < .001$), while gender, age and prior ownership were not significant (all $p \geq .204$).

Table 10. Structural model results: direct and moderating effects

Hypothesis	Path	β	M	SD	t	p	95% CI	Decision
H1	Perceived usefulne	0.265	0.264	0.036	7.421	< .001	[0.194, 0.334]	Supported

Hypothesis	Path	β	M	SD	t	p	95% CI	Decision
	ss → Attitude							
H2	Perceived ease of use → Attitude	0.250	0.250	0.038	6.571	< .001	[0.176, 0.324]	Supported
H3	Trust → Attitude	0.310	0.310	0.036	8.623	< .001	[0.239, 0.381]	Supported
H4	Perceived risk → Attitude	−0.270	−0.272	0.036	7.445	< .001	[−0.343, −0.201]	Supported
H5	Attitude → Behavioral intention	0.602	0.599	0.030	20.063	< .001	[0.538, 0.656]	Supported
H7	Attitude × Regulatory awareness → Behavio	0.146	0.144	0.032	4.529	< .001	[0.080, 0.207]	Supported

Hypothesis	Path	β	M	SD	t	p	95% CI	Decision
	ral intention							
H8	Attitude × Volatility perception → Behavioral intention	−0.102	−0.101	0.035	2.915	.004	[−0.170, −0.032]	Supported
	Regulatory awareness → Behavioral intention	0.184	0.187	0.035	5.227	< .001	[0.117, 0.256]	Main effect
	Volatility perception → Behavioral	−0.116	−0.118	0.033	3.489	< .001	[−0.184, −0.054]	Main effect

Hypothesis	Path	β	M	SD	t	p	95% CI	Decision
	intention							
	Gender → Behavioral intention	0.026	0.025	0.033	0.776	.437	[−0.040, 0.089]	Control, ns
	Age → Behavioral intention	−0.043	−0.043	0.034	1.270	.204	[−0.107, 0.024]	Control, ns
	Prior ownership → Behavioral intention	0.039	0.040	0.033	1.191	.234	[−0.025, 0.106]	Control, ns

Note: β = path coefficient; M = bootstrap mean; SD = bootstrap standard deviation; CI = bias-uncorrected percentile confidence interval; 5,000 subsamples; two-tailed tests; ns = not significant.

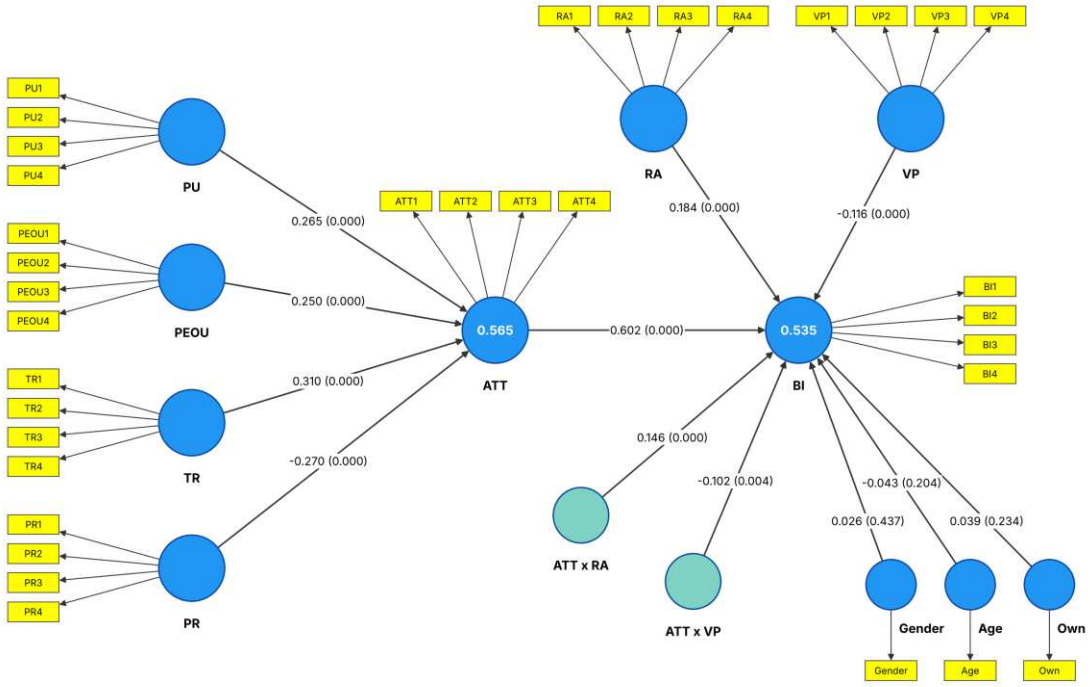


Figure 2. Structural model results (bootstrapping, 5,000 subsamples). Inner paths show path coefficients with p-values in parentheses; values inside ATT and BI are R^2. ATT x RA and ATT x VP are the two-stage interaction terms.

5.8 Mediation analysis

H6a to H6d were tested with the specific indirect effects of each belief on intention through attitude, following Zhao et al. (2010) and Nitzl et al. (2016). All four indirect effects were significant and their 95% confidence intervals excluded zero (Table 11), so attitude mediates the effect of every belief on intention, supporting H6a to H6d.

To classify the type of mediation, the model was re-estimated with direct paths from each belief to intention. Perceived usefulness ($\beta = 0.147$, $p < .001$) and trust ($\beta = 0.125$, $p = .001$) retained significant direct effects with the same sign as their indirect effects, which indicates complementary partial mediation. The direct effects of perceived ease of use ($\beta = 0.006$, $p = .866$) and perceived risk ($\beta = -0.016$, $p = .668$) were not significant, which indicates full (indirect-only) mediation. The variance accounted for (VAF), the share of the total effect that runs through attitude, agrees with this classification: 44.5% for usefulness and 52.5% for trust

(partial, between 20% and 80%) and 94.7% for ease of use and 88.1% for risk (full, above 80%; Hair et al., 2022).

Table 11. Mediation analysis

Hypothesis	Indirect path	Indirect β	SD	t	p	95% CI	Direct β (p)	VAF	Type of mediation	Decision
H6a	PU → ATT → BI	0.159	0.023	6.798	< .001	[0.113, 0.205]	0.147 (< .001)	44.5%	Complementary partial	Supported
H6b	PEOU → ATT → BI	0.150	0.024	6.221	< .001	[0.103, 0.197]	0.006 (.866)	94.7%	Full (indirect-only)	Supported
H6c	TR → ATT → BI	0.187	0.024	7.708	< .001	[0.140, 0.234]	0.125 (.001)	52.5%	Complementary partial	Supported
H6d	PR → ATT → BI	−0.163	0.022	7.263	< .001	[−0.207, −0.119]	−0.016 (.668)	88.1%	Full (indirect-only)	Supported

Note: indirect effects are from the hypothesized model. Direct effects and VAF are from the model re-estimated with direct paths, in which the indirect effects were 0.118 (PU), 0.112 (PEOU), 0.139 (TR) and −0.121 (PR), all $p < .001$, and the total effects were 0.266, 0.118, 0.264 and −0.137. VAF = indirect effect / total effect.

5.9 Moderation analysis

Simple slopes. To interpret H7 and H8, the effect of attitude on intention was estimated at one standard deviation below and above the mean of each moderator (Table 12; Figure 3). When regulatory awareness was low, the effect of attitude was 0.456; when it was high, the effect rose to 0.747, a 64% increase. When volatility perception was low, the effect of attitude was 0.704; when it was high, it fell to 0.499, a 29% decrease. The effect of attitude stayed positive and significant at every level, so the moderators change the strength of the attitude to intention link but do not switch it off.

Table 12. Simple slope analysis: effect of attitude on behavioral intention

Moderator	Level	β	SD	t	p	95% CI
Regulatory awareness	Low (−1 SD)	0.456	0.045	10.248	< .001	[0.366, 0.542]
	Mean	0.602	0.030	20.063	< .001	[0.538, 0.656]
	High (+1 SD)	0.747	0.044	17.189	< .001	[0.656, 0.827]
Volatility perception	Low (−1 SD)	0.704	0.048	14.707	< .001	[0.603, 0.789]
	Mean	0.602	0.030	20.063	< .001	[0.538, 0.656]
	High (+1 SD)	0.499	0.044	11.269	< .001	[0.408, 0.583]

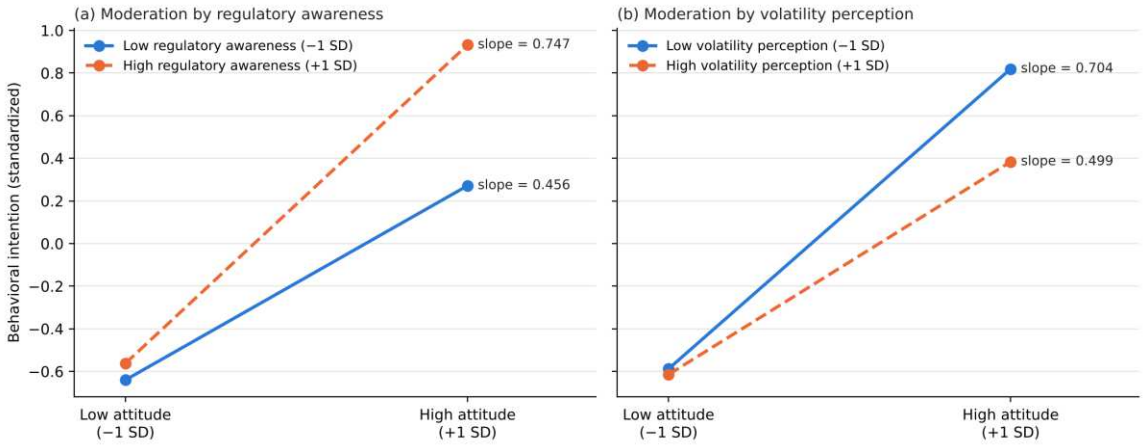


Figure 3. Simple slope plots for (a) regulatory awareness and (b) volatility perception. Predicted intention is in standardized units.

Johnson-Neyman floodlight analysis. Simple slopes test only two arbitrary points, so the conditional effect of attitude was also estimated across the whole range of each moderator (Spiller et al., 2013). For regulatory awareness, the 95% confidence interval excluded zero for all values above −2.83 SD. Because the lowest observed score was −2.68 SD, attitude affected intention significantly for every respondent in the sample. For volatility perception, the interval excluded zero across the entire range examined (−3 to +3 SD). Figure 4 shows both floodlight plots.

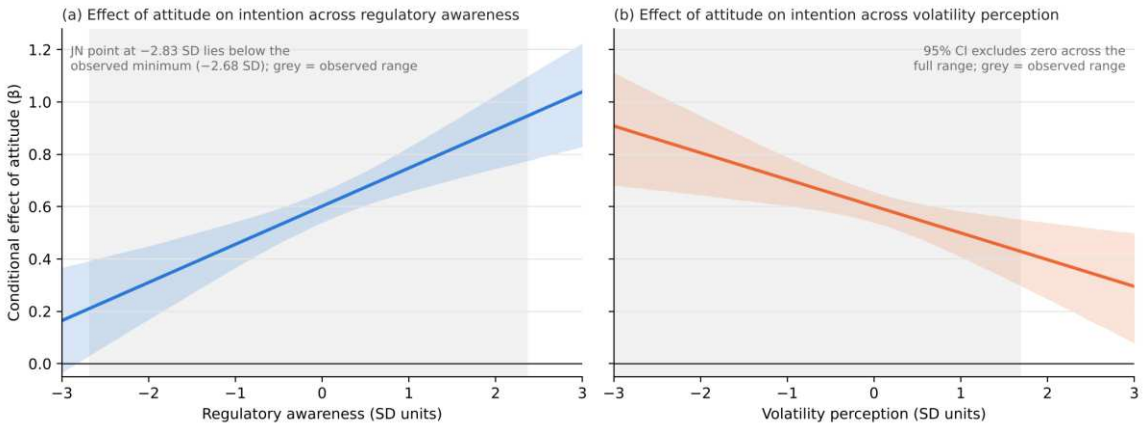


Figure 4. Johnson-Neyman floodlight plots. The line is the conditional effect of attitude on intention, the band is its bootstrapped 95% confidence interval, and the grey area marks the observed range of the moderator.

Moderated mediation. Because both moderators act on the second stage of the mediation chain, they also change the indirect effects tested in H6a to H6d (Hayes, 2015). Table 13 shows that every indirect effect was larger when regulatory awareness was high and smaller when volatility perception was high. All eight indices of moderated mediation were significant, with confidence intervals that excluded zero. For example, the indirect effect of trust rose from 0.141 at low regulatory awareness to 0.232 at high awareness (index = 0.045), and fell from 0.218 at low volatility perception to 0.155 at high volatility perception (index = −0.032).

Table 13. Conditional indirect effects and index of moderated mediation

Indirect path	Moderator	Low (−1 SD)	Mean	High (+1 SD)	Index of moderated mediation [95% CI]
PU → ATT → BI	Regulatory awareness	0.121	0.159	0.198	0.038 [0.020, 0.059]
	Volatility perception	0.186	0.159	0.132	−0.027 [−0.049, −0.008]
PEOU → ATT → BI	Regulatory awareness	0.114	0.150	0.186	0.036 [0.018, 0.057]
	Volatility perception	0.176	0.150	0.125	−0.025 [−0.044, −0.008]
TR → ATT → BI	Regulatory awareness	0.141	0.187	0.232	0.045 [0.024, 0.068]
	Volatility perception	0.218	0.187	0.155	−0.032 [−0.054, −0.010]

Indirect path	Moderator	Low (−1 SD)	Mean	High (+1 SD)	Index of moderated mediation [95% CI]
PR → ATT → BI	Regulatory awareness	−0.123	−0.163	−0.202	−0.039 [−0.059, −0.021]
	Volatility perception	−0.190	−0.163	−0.135	0.028 [0.009, 0.048]

Note: all conditional indirect effects were significant ($p < .001$; every 95% CI excluded zero). For perceived risk, a negative index under regulatory awareness means the negative indirect effect becomes stronger as awareness rises; a positive index under volatility perception means it becomes weaker as volatility perception rises.

5.10 Predictive power

Predictive relevance was assessed with PLSpredict, using 10 folds and 10 repetitions on the main-effects specification of the model (Shmueli et al., 2019). Every indicator of attitude and intention had a Q^2predict above zero (0.299 to 0.468), so the model predicts better than the indicator means. PLS-SEM also produced lower prediction errors than the linear regression benchmark for all eight indicators. RMSE was used as the primary metric, and MAE gave the same result. According to Shmueli et al. (2019), lower errors for all indicators indicate high predictive power. The indicator-level predictive results are presented in Table 14.

Table 14. PLSpredict results

Indicator	Q^2predict	PLS-SEM RMSE	LM RMSE	PLS-SEM MAE	LM MAE
ATT1	0.418	0.963	0.980	0.783	0.793
ATT2	0.468	0.900	0.911	0.710	0.719

Indicator	Q^2predict	PLS-SEM RMSE	LM RMSE	PLS-SEM MAE	LM MAE
ATT3	0.405	0.976	0.995	0.789	0.801
ATT4	0.425	0.954	0.971	0.757	0.772
BI1	0.299	1.105	1.129	0.906	0.921
BI2	0.335	1.029	1.056	0.822	0.829
BI3	0.323	1.047	1.071	0.847	0.860
BI4	0.318	1.056	1.066	0.850	0.855

Note: LM = linear regression benchmark; RMSE = root mean squared error; MAE = mean absolute error.

5.11 Robustness checks

Two additional checks were run (Sarstedt et al., 2020). First, a quadratic term for attitude was added to the equation for intention to test for nonlinearity. Its effect was not significant (β = 0.048, p = .226, 95% CI [−0.030, 0.123]), so the linear specification is appropriate. Second, the model with direct paths from the four beliefs to intention (Section 5.8) raised the R^2 of intention only slightly, to 0.562. In that model attitude still predicted intention (β = 0.447, p < .001), and both interactions remained significant (regulatory awareness β = 0.143, p < .001; volatility perception β = −0.101, p = .004). The substantive conclusions therefore do not depend on the model specification.

5.12 Summary of hypothesis testing

Table 15 summarizes the results of the hypothesis tests, including the direct effects, mediation effects, and moderation effects.

Table 15. Summary of hypotheses

Hypothesis	Statement	Key statistic	p	Decision
H1	Perceived	β = 0.265	< .001	Supported

Hypothesis	Statement	Key statistic	p	Decision
	usefulness → Attitude (+)			
H2	Perceived ease of use → Attitude (+)	β = 0.250	< .001	Supported
H3	Trust → Attitude (+)	β = 0.310	< .001	Supported
H4	Perceived risk → Attitude (−)	β = −0.270	< .001	Supported
H5	Attitude → Behavioral intention (+)	β = 0.602	< .001	Supported
H6a	Attitude mediates PU → BI	Indirect = 0.159	< .001	Supported (partial)
H6b	Attitude mediates PEOU → BI	Indirect = 0.150	< .001	Supported (full)
H6c	Attitude mediates TR → BI	Indirect = 0.187	< .001	Supported (partial)
H6d	Attitude mediates PR → BI	Indirect = −0.163	< .001	Supported (full)
H7	Regulatory awareness	Interaction β =	< .001	Supported

Hypothesis	Statement	Key statistic	p	Decision
	strengthens ATT → BI	0.146		
H8	Volatility perception weakens ATT → BI	Interaction β = −0.102	.004	Supported

6. Results and discussion

The results support all eleven hypotheses. Consumers' intention to use cryptocurrency in place of traditional currency rests on an evaluative attitude, which is formed by four beliefs and turned into intention more or less readily depending on what consumers know about regulation and how volatile they believe crypto to be. The model explained 56.5% of the variance in attitude and 53.5% in intention and showed high out-of-sample predictive power.

6.1 Beliefs that shape attitude

Trust was the strongest driver of attitude (β = 0.310). This agrees with work showing that trust is the gatekeeper of crypto adoption (Arli et al., 2021; Mendoza-Tello et al., 2018) and of online transactions in general (Gefen et al., 2003; Kim & Peterson, 2017). It also matters that trust had the lowest mean of all constructs (4.31 on a seven-point scale). The belief that matters most is the one consumers hold most weakly, which makes trust the main lever for change.

Perceived usefulness (β = 0.265) and perceived ease of use (β = 0.250) had effects of similar size. The usefulness result confirms the central place of expected benefits in TAM (Davis, 1989; King & He, 2006) and in crypto studies (Shahzad et al., 2018). The ease of use result is stronger than meta-analyses of TAM usually report, where ease of use often works only through usefulness (Schepers & Wetzels, 2007). A likely reason is that cryptocurrency is still technically demanding: private keys, wallet addresses and irreversible transfers make effort and the fear of mistakes salient (Gao et al., 2016; Krombholz et al., 2017).

Perceived risk lowered attitude ($\beta = -0.270$), and its effect was larger in absolute size than that of usefulness. This is consistent with the trust and risk framework (Kim et al., 2008; Pavlou, 2003) and with crypto studies that identify risk as a key barrier (Jariyapan et al., 2022). For currency use, the risks of theft, exchange failure and lack of recourse appear to weigh as heavily as the benefits of speed and low cost.

6.2 Attitude as the mechanism

Attitude was by far the strongest predictor of intention ($\beta = 0.602$, $f^2 = 0.713$), and it mediated the effect of every belief. This supports the original belief, attitude and intention chain of TAM and the theory of reasoned action (Davis et al., 1989; Fishbein & Ajzen, 1975) and questions the common practice of dropping attitude from crypto adoption models.

The pattern of mediation is informative. Ease of use and risk acted fully through attitude: they change how consumers feel about cryptocurrency, and that feeling, not the belief itself, drives intention. Usefulness and trust acted partly through attitude and partly directly. This fits TAM2 and UTAUT, which allow usefulness to affect intention directly as an instrumental judgment (Venkatesh & Davis, 2000; Venkatesh et al., 2003), and it suggests that trust works both as a basis for evaluation and as a direct enabling condition: consumers who trust the system are willing to plan its use even before they have formed a strongly positive view.

6.3 Regulatory awareness as an enabling condition

Regulatory awareness strengthened the attitude to intention link (interaction $\beta = 0.146$). At high awareness, the effect of attitude was 64% larger than at low awareness. This supports the view that knowledge of rules acts as institution-based assurance (McKnight et al., 2002; Pavlou & Gefen, 2004): a favorable attitude is acted upon more readily when consumers know what is legal, how they will be taxed and what obligations exchanges must meet. The result is notable in India, where the rules include a 30% tax on gains and a 1% tax deducted at source (Government of India, 2022). One might expect that knowing about such a demanding tax regime would discourage use. Instead, knowledge of the rules seems to reduce uncertainty more than it raises perceived cost, in line with evidence that clear regulation does not drive users away from crypto markets (Feinstein & Werbach, 2021). Regulatory awareness also had a positive main effect on intention ($\beta = 0.184$).

6.4 Volatility perception as a constraining condition

Volatility perception weakened the attitude to intention link (interaction $\beta = -0.102$). At high volatility perception, the effect of attitude was 29% smaller than at low volatility perception. This supports the prospect theory argument that the salience of possible losses dampens action (Kahneman & Tversky, 1979) and the monetary argument that volatility undermines the store-of-value and unit-of-account functions of money (Baur et al., 2018; Yermack, 2015). The floodlight analysis adds an important nuance: the effect of attitude remained positive and significant across the full range of volatility perception. Volatility slows the conversion of liking into intention but does not prevent it, which is consistent with the rise of stablecoins, private tokens designed to hold a fixed value so that they can serve as a means of payment (Gorton & Zhang, 2023).

6.5 Context shapes the value of every belief

Because both moderators act on the second stage of the chain, they change the indirect effect of every belief. The indirect effect of trust, for instance, was 0.232 at high regulatory awareness and 0.141 at low awareness. In practical terms, efforts to build trust, improve usability or highlight usefulness pay off much more among consumers who understand the rules and much less among those who fear price swings. This moderated mediation pattern (Hayes, 2015) shows that the beliefs and the context are not independent explanations but parts of one process.

6.6 Control variables

Gender, age and prior ownership did not affect intention once the model's constructs were included. The null effect of ownership is especially telling: having held crypto as an investment does not by itself make consumers more willing to use it as money. This supports the decision to separate currency substitution from speculative ownership (Baur et al., 2018; Mattke et al., 2021).

7. Implications

7.1 Theoretical implications

Reframing the outcome. Most crypto adoption studies predict intention to "use" or "adopt" without separating payment from investment. By defining the outcome as intention to use cryptocurrency as a substitute for traditional currency, and by showing that prior ownership does

not predict it, this study shows that currency substitution is a distinct behavior that deserves its own models. Future work that mixes the two risks attributing speculative motives to payment adoption.

Restoring attitude. The study supports the original structure of TAM and the theory of reasoned action, in which beliefs act through attitude (Davis et al., 1989; Fishbein & Ajzen, 1975). The full versus partial mediation pattern also refines theory. Ease of use and risk are evaluative beliefs that change intention only by changing attitude, while usefulness and trust are also instrumental beliefs that affect intention directly. Models that drop attitude, as UTAUT2-based crypto studies often do, therefore misattribute the effects of ease of use and risk.

Integrating institutional and prospect theory into technology acceptance. The study shows that two contextual beliefs, regulatory awareness and volatility perception, act as opposing boundary conditions on the attitude to intention link. This extends Ajzen's (1991) idea that intention depends on the perceived feasibility of acting by naming two conditions specific to digital currencies. Regulatory awareness draws on institution-based trust (McKnight et al., 2002) and works as an enabler; volatility perception draws on prospect theory (Kahneman & Tversky, 1979) and works as a constraint. Treating them as moderators, rather than adding them as further antecedents, explains why favorable attitudes do not always become use.

Contingent mediation. The significant indices of moderated mediation show that the indirect effects of all four beliefs depend on context (Hayes, 2015). Theories of crypto adoption should therefore be stated conditionally: the value of building trust or usability depends on whether consumers understand the rules and how they perceive price stability.

Evidence from a leading but ambiguous market. India combines very high crypto activity with a regulatory regime that taxes and monitors crypto without recognizing it as money. The study offers evidence from this setting and shows that the model works in a market where regulation is present but contested.

7.2 Managerial and policy implications

Exchanges and wallet providers. Trust is the strongest driver of attitude and the weakest belief in the sample, so it should be the first priority. Practical steps include publishing proof-of-reserves reports, keeping most customer funds in cold storage, commissioning independent

security audits and offering clear dispute resolution. Ease of use comes next: interfaces modeled on familiar payment apps, simple key recovery and confirmation screens that prevent irreversible errors would lower the effort that consumers expect. Usefulness messages should focus on situations where crypto has a real advantage, such as cross-border transfers, rather than on returns.

Regulatory communication as a product feature. Because regulatory awareness makes favorable attitudes more likely to become intention, platforms should treat compliance information as part of the customer experience. In-app tax calculators that show the 30% tax and 1% tax deducted at source, clear statements of registration with the Financial Intelligence Unit, and short explainers on what the law allows can turn uncertainty into confidence. The analysis suggests that informing consumers about demanding rules does not reduce intention; it helps them act on a positive view.

Managing volatility. Volatility perception reduces the payoff of every other effort. For payment use cases, providers and merchants can offer instant conversion to rupees at the point of sale, short price-lock windows and clear displays of the rupee value at the time of payment, wherever such features are permitted. Communication should avoid celebrating price surges, which strengthen the perception of instability among the very consumers who might use crypto as money.

Targeting. The moderated mediation results suggest a segmentation logic. Consumers with high regulatory awareness and low volatility perception will respond most to trust and usability messages, so they are the natural early segment for payment features. Consumers with low awareness should first receive regulatory education, and those with high volatility perception need stability features before other messages will work.

Policymakers and regulators. The results show that clarity matters for behavior. A consistent and well-communicated framework, whatever its content, would let consumers act on informed judgments rather than on rumor. Regulators concerned with consumer protection can use the same findings: because trust and risk drive attitude, standards on custody, disclosure and recourse would protect consumers and reduce the risks that make attitudes unfavorable. Finally, the findings are relevant to the Reserve Bank of India's digital rupee (Reserve Bank of India, 2022). A central bank digital currency can offer the usefulness and ease of a digital token with

the stability and legal certainty that crypto lacks; the model suggests that these are exactly the conditions under which favorable attitudes become use.

8. Limitations and future scope

The study has limitations that open directions for future research.

1. **Cross-sectional design.** All constructs were measured at one point in time, so causal direction is inferred from theory rather than observed. Attitudes towards crypto may also shift quickly with market cycles. Longitudinal panels, ideally spanning a boom and a downturn, would show whether the relationships hold as prices and sentiment change.
2. **Intention rather than behavior.** The outcome is stated intention, and the gap between intention and behavior is well documented (Sheeran, 2002). Future studies could link survey responses to actual payment or transfer behavior, with consent, or follow up respondents after six to twelve months.
3. **Sampling and generalizability.** The purposive online sample was young, urban, English-speaking and digitally active. This suits theory testing but limits generalization to rural, older or less digitally connected consumers. Probability samples or quota designs matched to national data, and translated instruments, would broaden the evidence.
4. **Single country.** India's regulatory mix of taxation without legal tender status is distinctive. Comparative studies in countries that ban crypto, recognize it as legal tender or regulate it comprehensively (such as the European Union) would test whether regulatory awareness works the same way under different regimes.
5. **Measures of the moderators.** Regulatory awareness and volatility perception were measured with newly developed scales. Although they showed strong reliability and validity, further validation is needed, including tests of whether objective regulatory knowledge (a quiz) behaves like self-rated awareness, and whether perceived volatility tracks actual market volatility at the time of response.
6. **Omitted variables.** The model focused on beliefs and two contextual conditions. Social influence, financial literacy, fear of missing out, privacy concerns and trust in government could add explanatory power. Multigroup analysis by ownership, age or city tier, importance-performance map analysis (Ringle & Sarstedt, 2016) and necessary condition analysis (Richter et al., 2020) would add further insight.

7. **Alternative digital money.** Consumers may compare crypto not only with cash and bank money but also with the digital rupee and stablecoins. Future work could model the choice among these options, for example through discrete choice experiments.

9. Conclusion

This study asked why consumers would, or would not, use cryptocurrency as a substitute for traditional currency. Using a survey of 441 cryptocurrency-aware Indian consumers and PLS-SEM, it found that the answer runs through attitude. Trust, perceived usefulness and perceived ease of use make consumers' attitude more favorable, perceived risk makes it less favorable, and attitude is the strongest predictor of intention. Attitude fully carries the effects of ease of use and risk and partly carries those of usefulness and trust.

Whether a favorable attitude becomes intention depends on context. Knowing the regulatory rules makes the conversion stronger, while perceiving crypto as volatile makes it weaker, and these conditions raise or lower the indirect effect of every belief. All eleven hypotheses were supported, the measurement model met every reliability and validity criterion, and the structural model showed moderate explanatory power and high predictive power.

The central message is that liking cryptocurrency is not enough for it to become money. Consumers act on a favorable view when they understand the rules and believe the value will hold. For providers and policymakers, building trust and usability is necessary, but making regulation clear and value stable is what allows those efforts to pay off.

Ethics statement

The study was exempt from ethics committee review under the *National Ethical Guidelines for Biomedical and Health Research Involving Human Participants* of the Indian Council of Medical Research (ICMR, 2017).[1] These guidelines apply to "biomedical, social and behavioural science research for health" and allow exemption for "proposals with less than minimal risk where there are no linked identifiers." The study qualified on both counts. It was a non-

[1] Indian Council of Medical Research (2017), Scope (p. 2) and Table 4.2 (p. 37): https://ethics.ncdirindia.org/asset/pdf/ICMR_National_Ethical_Guidelines.pdf

interventional consumer survey on cryptocurrency and payments, not research for health, and it collected no health data or biological material. The risk was less than minimal because respondents only gave their opinions, with no intervention, deception or sensitive personal questions, and no identifiers were linked because the anonymous Qualtrics link recorded no name, contact details, IP address or location. In addition, only adults took part, participation was voluntary and unpaid, respondents could stop at any time, and the data were analysed only in aggregate.

Accordance and informed consent. All research was performed in accordance with relevant guidelines and regulations, namely the Declaration of Helsinki (World Medical Association, 2025)[2] and the ICMR (2017) guidelines. Informed consent was obtained from all participants and/or their legal guardians. All participants were adults, and only those who selected "I agree" on the first page of the questionnaire could continue (Supplementary file S1).

Data Availability Statement

The anonymised raw survey export, processed analysis dataset, exclusion log, survey instrument and data collection protocol, variable codebook, and supporting statistical results are provided as supplementary materials accompanying this manuscript. Additional documentation on variable coding, data processing and analytical procedures is included where applicable. The shared files have been reviewed to protect respondent confidentiality.

[2] World Medical Association Declaration of Helsinki, 2024 revision adopted at the 75th WMA General Assembly, Helsinki, October 2024: https://doi.org/10.1001/jama.2024.21972

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