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Factors Influencing Cryptocurrency Addiction Among Young Adults in Nigeria: An Exploratory Study

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Abstract

Purpose – This study tested an integrated behavioral model to identify psychosocial predictors of cryptocurrency addiction among young adults in Nigeria, focusing on the paradoxical role of self-efficacy. *Methodology* – Using a quantitative, cross-sectional design, data were collected from 181 young traders. A model integrating the Theory of Planned Behavior, Social Learning Theory, and Behavioral Addiction Theory was analyzed via PLS-SEM. *Findings* – personality (β = .238), social norms (β = .173), and attitude (β = .156) were significant positive predictors of addiction. Critically, self-efficacy was the strongest positive predictor (β = .261). perceived utility and technology facilitation were not significant. the model demonstrated substantial explanatory power (r^2 = .787). *Practical implications* – Findings support educational interventions focused on behavioral biases like overconfidence and emotional regulation. For platforms, we recommend responsible design tools such as user-set trading limits, automated 'cooling-off' periods, and in-app addiction resources. *Originality/value* – The study's primary contribution is empirically validating the 'self-efficacy paradox' in crypto trading. It provides evidence that high self-efficacy can function as a significant risk factor by fostering overconfidence, thereby refining behavioral addiction theory for high-risk financial domains.

Keywords: *Cryptocurrency Addiction, Behavioral Addiction, Overconfidence, Theory of Planned Behavior, Social Learning Theory, Nigeria.*

Introduction

The last decade has witnessed the explosive growth of cryptocurrencies, which have evolved from a niche technological curiosity into a significant, albeit volatile, component of the global financial landscape (Maishanu, 2024). These digital assets hold a particular allure for younger, digitally native generations, who are often drawn to the promise of high returns and the pursuit of quick money that characterizes the decentralized ethos of Web3 technologies (Joseph, 2025). This rapid adoption, however, is fraught with considerable risks. The 24/7 nature of the market and its extreme price volatility create a high-stakes environment where the potential for substantial financial loss is ever-present.

Beyond financial risk, there is a growing concern regarding the behavioral and psychological impacts of cryptocurrency trading. Recent systematic reviews confirm a strong connection between problematic trading and addictive behaviors, identifying shared psychological risk factors and pathways to compulsion that mirror established disorders (Loscalzo, *et al.*, 2025). This form of behavioral addiction is characterized by compulsive engagement and loss of control despite negative consequences, with many researchers framing crypto speculation as a new frontier for gambling and addiction (Nemlioglu *et al.*, 2024; Xu *et al.*, 2025). The potential for cryptocurrency trading to foster these compulsive behaviors represents a significant and emergent public health issue.

While the problem is increasingly recognized, few studies have proposed and tested comprehensive behavioral models, especially within the context of an emerging economy like Nigeria. In this environment, high adoption rates often coexist with unique socio-economic pressures and a desire for rapid wealth accumulation that can heighten risks (Joseph, 2025). To address this gap, this study proposes an integrated model that draws from the theory of planned behavior (TPB) to understand attitudinal drivers (Ajzen, 2020), social learning theory (SLT) to account for the powerful influence of peer and online communities (Bandura, 2006), and Behavioral Addiction Theory to frame the resulting compulsive behaviors (Griffiths, 2005).

A central component of this investigation involves a nuanced examination of self-efficacy. While traditionally viewed as a protective factor, its role in high-risk financial contexts can be paradoxical. Recent research directly supports this complexity, demonstrating that high financial self-efficacy among novice traders can inflate overconfidence, which in turn acts as a key mediator leading to problematic and compulsive cryptocurrency trading (Tjondro *et al.*, 2024). This study, therefore, challenges the assumption that self-efficacy is purely protective and instead explores its potential as a critical risk factor in the pathway to addiction.

Therefore, this study aims to test an integrated behavioral model to identify the significant psychological and social predictors of cryptocurrency addiction among young adults in Nigeria. Specifically, we examine the influence of perceived utility, social norms, technology facilitation, personality factors, attitude, and the dual-edged role of self-efficacy in driving compulsive engagement with cryptocurrency applications.

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Literature Review and Theoretical Framework

The Cryptocurrency Phenomenon: A High-Risk, High-Reward Landscape

The emergence of cryptocurrency has been a defining feature of the 21st-century financial revolution, representing a paradigm shift in how value is perceived, stored, and exchanged (Maishanu, 2024). This digital asset class has attracted widespread interest, particularly from younger demographics intrigued by its potential for high returns and its alignment with a culture of pursuing quick money (Joseph, 2025). Despite known risks, many investors continue to engage with cryptocurrencies, driven by a complex mix of technological optimism and speculative desire (Alsmadi *et al.*, 2024). However, this high-return potential is inextricably linked to extreme market volatility, creating a high-stakes environment where participants can experience significant psychological and behavioral consequences, including profound harm and financial loss (Johnson *et al.*, 2023; Mosbey *et al.*, 2024).

Problematic Trading as a Behavioral Addiction

Recent academic inquiry has increasingly framed problematic cryptocurrency engagement through the lens of behavioral addiction. Scholars now identify a clear nexus between cryptocurrency speculation and gambling, noting that both activities can foster compulsive behaviors driven by similar psychological mechanisms and cognitive distortions (Nemlioglu *et al.*, 2024; Xu *et al.*, 2025). This perspective is supported by systematic reviews which conclude that problematic trading constitutes a significant public health concern, sharing core features with other well-documented addictions and having a measurable impact on mental health (Jain *et al.*, 2025; Loscalzo, *et al.*, 2025).

The addictive potential is exacerbated by the design of trading platforms, which often employ "dark patterns" and "sludge" to encourage continuous engagement, blurring the lines between investing and gambling (Newall, 2025). The harmful consequences of such speculation are becoming increasingly evident, highlighting the urgent need to understand the individual and contextual factors that contribute to this modern form of addiction (Grubbs & Kraus, 2024).

The Duality of Self-Efficacy in High-Risk Financial Behavior

A critical construct within this framework is self-efficacy—an individual's belief in their ability to succeed. In many contexts, high self-efficacy is a positive trait, but in the volatile domain of cryptocurrency trading, its role is paradoxical. Behavioral finance literature suggests that among novice investors, high self-efficacy can become distorted into overconfidence, a cognitive bias where individuals overestimate their knowledge, underestimate risks, and make speculative investment decisions based on flawed personal judgment (Sharma *et al.*, 2024; Tanveer *et al.*, 2025).

Recent research provides direct evidence for this pathway, demonstrating that overconfidence acts as a crucial mediator linking traits like financial naivety and personality to a higher intention of continued, often problematic, cryptocurrency engagement (Tjondro *et al.*, 2024). When individuals feel overly confident in their trading abilities—a feeling bolstered by high self-efficacy and amplified by social phenomena like *fear of missing out* (FOMO) (Anaza *et al.*, 2024)—they may engage in more frequent, riskier trades. This increased engagement, driven by a misplaced sense of control, makes them more susceptible to developing the compulsive and addictive behaviors this study seeks to model, challenging the traditional view of self-efficacy as a purely protective factor.

An Integrated Theoretical Framework for Understanding Crypto Addiction

To understand the factors contributing to cryptocurrency addiction, a single theoretical lens is insufficient. This study, therefore, adopts an integrated framework that synergizes three key theories. While the TPB provides the core internal drivers—explaining how an individual's personal attitudes and intentions are formed (Ajzen, 2020)—it does not fully account for the powerful external factors at play. This is where SLT becomes essential, offering a lens to understand *how* these norms and behaviors are transmitted and reinforced within influential online communities (Bandura, 2006), such as Reddit, where novice traders model the actions of others (Bouma-Sims *et al.,* 2024). Finally, BAT provides the critical pathological framework, explaining why the behavior can become compulsive and persist even in the face of significant negative consequences (Griffiths, 2005), thus moving beyond rational choice into the realm of addiction (Grubbs & Kraus, 2024). These theories collectively provide and underpin the variables investigated in this study, culminating in the conceptual framework depicted in Figure 1. This holistic approach allows for a more holistic analysis of the phenomenon by integrating factors from all three theoretical perspectives.

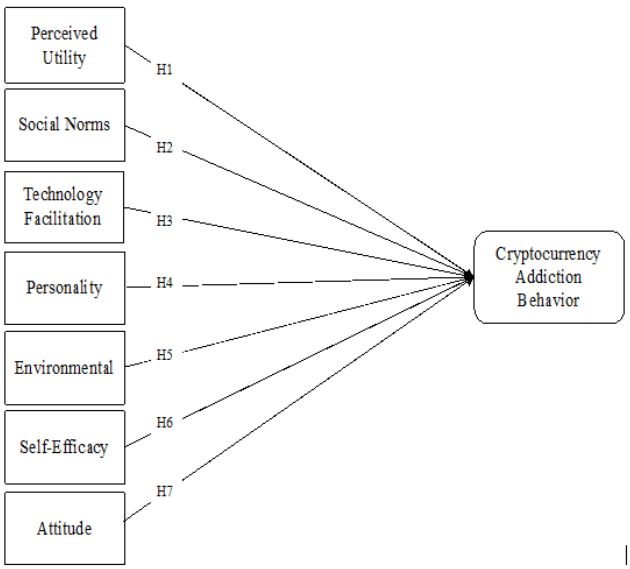

Figure 1. Conceptual Framework

Hypotheses Development

Perceived Utility (PU)

Perceived utility refers to the benefits individuals believe they will gain from engaging in a behavior. In the context of cryptocurrency, this extends beyond simple financial gains to include factors like excitement, convenience, and the perceived technological advantage of decentralized finance (Maishanu, 2024). When users perceive high utility—whether through profit, entertainment, or efficiency—their intention to continue using the technology is strengthened, creating more opportunities for habitual and potentially addictive engagement (Al Omoush *et al.*, 2024).

H_1: *Perceived utility will positively influence addiction behavior among young people using cryptocurrency applications.*

Social Norms (SN)

Social norms, the unwritten rules of behavior within a group, are powerful drivers of action, as posited by SLT (Bandura, 2006). In the cryptocurrency space, where online communities and social media are central, norms are rapidly formed and transmitted (Bouma-Sims *et al.*, 2024). The *fear of missing out* (FOMO) is a significant social motivator, where the perception of peer engagement and success creates pressure to participate actively, often leading to impulsive and herd-like consumption patterns (Anaza *et al.*, 2024).

H_2: *Subjective norms will positively influence addiction behavior among young people using cryptocurrency applications.*

Technology Facilitation (TF)

Technology facilitation is the degree to which technology is perceived as easy to use and accessible. Modern trading platforms are designed for seamless navigation and constant engagement, lowering barriers to entry (Kim, 2024). However, this facilitation can be deceptive. Many platforms incorporate "dark patterns" and "sludge" in their design, features intended to nudge users toward more frequent and potentially compulsive trading, blurring the line between user-friendliness and user-exploitation (Newall, 2025).

H_3: *Technology facilitation will positively influence addiction behavior among young people using cryptocurrency applications.*

Personality (PE)

Certain personality traits are established predictors of addictive behaviors and risk-taking (Grubbs & Kraus, 2024). Factors such as impulsivity, sensation-seeking, and low self-control can make individuals more susceptible to the allure of volatile markets and the intermittent rewards of trading (Anaza *et al.*, 2024). These dispositional factors can moderate how an individual interacts with trading platforms, with certain traits increasing the likelihood of developing problematic usage patterns (Changchit *et al.*, 2024).

H_4: *Personality factors will positively influence addiction behavior among young people using cryptocurrency applications.*

Environmental Factors (EN)

The broader trading environment, including market volatility and regulatory uncertainty, profoundly shapes trader behavior (Minhat *et al.*, 2024). In a socio-economic context like Nigeria, environmental factors can also include the pervasive "culture of quick money," which creates immense pressure on youth to engage in high-risk ventures like cryptocurrency trading and Ponzi schemes as a means of rapid wealth accumulation (Joseph, 2025; Okosun, 2025).

H_5: *Environmental factors will positively influence addiction behavior among young people using cryptocurrency applications.*

Self-Efficacy (SE)

As discussed in the literature review, the role of self-efficacy in this context is complex. Rather than acting as a protective factor, high self-efficacy in novice traders can manifest as overconfidence, leading to speculative decisions and an underestimation of risk (Sharma *et al.*, 2024). Based on evidence that this overconfidence is a key mediator in the pathway toward problematic engagement (Tjondro *et al.*, 2024), we hypothesize a positive relationship between self-efficacy and addiction.

H_6: *Based on literature suggesting high self-efficacy in novice traders can manifest as overconfidence, it is hypothesized that self-efficacy will have a significant positive relationship with cryptocurrency addiction behavior.*

Attitude (AT)

According to the TPB, an individual's overall positive or negative evaluation of a behavior is a strong predictor of their intention to perform it (Ajzen, 2020). A favorable attitude toward cryptocurrency—viewing it as a legitimate and exciting investment vehicle despite its acknowledged dangers—is expected to lead to greater and more persistent engagement, even when faced with market risks (Alsmadi *et al.*, 2024).

H_7: *Attitude will positively influence addiction behavior among young people using cryptocurrency applications.*

Methodology

Research Design and Philosophical Stance

This study adopted a positivist philosophical stance, emphasizing that phenomena can be understood through objective, systematic observation and measurement. Aligned with this perspective, a quantitative, cross-sectional research design was employed to investigate the predictive relationships between several psychosocial and technological factors and cryptocurrency addiction behavior. This design is well-suited for testing a theoretical model by analyzing data collected from a sample at a single point in time to identify significant associations between variables.

Sampling and Data Collection

The study utilized a non-probability convenience sampling method. This approach was chosen for its efficiency in reaching a niche demographic of young, digitally-active individuals with experience in cryptocurrency trading. The target population consisted of young adults residing in Nigeria.

An electronic questionnaire was created using Google Forms and distributed via online channels, including university-affiliated WhatsApp groups, email, and social media platforms. The data collection period lasted four weeks. An initial 300 questionnaires were distributed, from which 198 were completed and returned. After a thorough data screening process, 17 responses were discarded due to significant missing information or inconsistent response patterns, resulting in a final, valid sample of $n = 181$ for analysis.

Ethical procedures were paramount throughout the research process. Prior to participation, individuals were presented with an informed consent form on the first page of the survey, outlining the study's purpose, the voluntary nature of their participation, and their right to withdraw at any time. The anonymity and confidentiality of all responses were guaranteed. No personally identifiable information was collected. The study protocol received ethical approval from the institutional review board of the authors' affiliated university.

Measurement Instrument

The survey instrument was developed based on established literature and previously validated scales to ensure content and construct validity. The development of a robust measurement tool is a critical step in addiction research (Senocak *et al.*, 2024). The survey instrument was structured in two parts. Section A collected standard demographic information (gender, age, education) to profile the sample of young adult traders. The core of the instrument, Section B, comprised 32 measurement items designed to assess the study's theoretical constructs, with all items rated on a five-point Likert scale (1 = *Strongly Disagree* to 5 = *Strongly Agree*). The dependent variable, addiction behavior, was operationalized using items adapted from recent literature on developing and

identifying problematic trading patterns (Senocak *et al.*, 2024). The independent variables were selected to provide a holistic model, encompassing technological factors like perceived utility and technology facilitation (Al Omoush *et al.*, 2024; Kim, 2024); social dynamics such as social norms and environmental pressures (Joseph, 2025); and crucial psychological traits including personality, attitude, and self-efficacy, which are established as significant predictors of investment decisions and compulsive consumption in cryptocurrency contexts (Anaza *et al.*, 2024; Tjondro *et al.*, 2024). The complete list of measurement items is detailed in Appendix A.

To ensure the quality of the measurement instrument, content validity was established prior to data collection. The initial pool of 32 items was submitted to a panel of three academic experts with research experience in cryptocurrency, behavioral finance, and technology adoption. Based on their feedback regarding item clarity, relevance, and wording, minor revisions were made to enhance the instrument's face and content validity. Construct validity and reliability were subsequently assessed during the data analysis phase.

Data Analysis Procedure

The data analysis was conducted using a two-stage process that involved both IBM SPSS Statistics (Version 23) for preliminary analysis and SmartPLS (Version 4) for the primary analysis of the structural model. Initially, the dataset of 181 valid responses was imported into SPSS for data screening and preparation. This essential first step involved examining the data for normality, identifying and handling any missing values, and screening for outliers that could unduly influence the results. Following this cleaning process, descriptive statistics, including frequencies, percentages, means, and standard deviations, were calculated to summarize the demographic characteristics of the sample and provide an initial overview of the responses to the core constructs of the study.

The primary analytical technique employed was Partial Least Squares Structural Equation Modeling (PLS-SEM). This method was selected for several reasons that align with the study's objectives and data characteristics. PLS-SEM is particularly well-suited for testing complex, multi-variable predictive models and is considered a robust technique when dealing with non-normal data or smaller sample sizes, which are common in behavioral research (Sharma *et al.*, 2024). Its focus on maximizing the explained variance of the dependent variable (Addiction Behavior) makes it an ideal choice for this study's exploratory and predictive nature.

Following established best practices, the PLS-SEM analysis was executed in two sequential stages. The first stage involved a rigorous assessment of the measurement model to ensure its reliability and validity. This was accomplished by evaluating: (a) the reliability of individual indicators through their outer loadings; (b) the internal consistency of each construct using both Cronbach's Alpha and composite reliability scores; (c) the convergent validity, confirmed by ensuring the average variance extracted (AVE) for each construct was 0.50 or higher; and (d) discriminant validity, which was established using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio of correlations (HTMT). This stage is critical for verifying that the survey items reliably and accurately measure their intended latent constructs (Anaza *et al.*, 2024).

Once the measurement model was deemed satisfactory, the second stage commenced: the assessment of the structural model. This stage directly addressed the research hypotheses by examining the path coefficients (β-values), which indicate the strength and direction of the relationships between the independent variables and the dependent variable. The statistical significance of these paths was determined through a bootstrapping procedure (5,000 resamples) to generate p-values. Finally, the model's overall predictive power was evaluated by examining the coefficient of determination (R^2) for the endogenous construct, Addiction Behavior, providing a clear indication of the extent to which the model explains the variance in cryptocurrency addiction (Tjondro *et al.*, 2024).

Results

Demographic Profile

The final sample consisted of 181 young adults in Nigeria active in the cryptocurrency market. As detailed in Table 1, the respondents were predominantly male (n = 127, 70.2%), a significant gender skew that aligns with broader participation trends in high-risk financial markets and suggests that the drivers of addiction may be particularly pronounced in this demographic (Blue *et al.*, 2025). The age distribution confirms the study's focus on youth, with the largest cohort being 25–34 years old (n = 97, 53.6%), followed by those aged 18–24 (n = 52, 28.7%). Combined, these young adults constitute over 82% of the sample, representing a demographic often characterized by increasing financial independence coupled with a higher propensity for risk-taking, particularly within a socio-economic environment that may promote the pursuit of quick money (Joseph, 2025).

Table 1. Demographic Information

SN	Variables	Scale	Frequency	Percentage
1	Gender	Male	127	70.20
		Female	54	29.80
2	Age	18-24	52	28.70
		25-34	97	53.60
		35-44	28	15.50
		More than 45	4	2.20
3	Education	High School	18	9.90
		Collage	34	18.80
		University	129	71.30

A particularly revealing characteristic of the sample is its high level of formal education. A significant majority of respondents held a university degree (n = 129, 71.3%), with an additional 18.8% (n = 34) having attended college. This indicates that over 90% of the sample has post-secondary education. The critical implication of this finding is that higher education and the cognitive skills needed to engage with complex financial technology do not appear to confer immunity to the behavioral biases underlying addiction. On the contrary, this high level of education may even contribute to the development of overconfidence or the kind of inflated self-efficacy that this study identifies as a significant positive predictor of addiction behavior, a paradoxical relationship that has been noted in recent literature on the topic (Tjondro *et al.*, 2024).

Measurement Model Assessment

Prior to testing the structural model, the measurement model was rigorously evaluated to ensure its reliability and validity. Internal consistency was the first criterion assessed, using both Cronbach's Alpha (*CA*) and composite reliability (*CR*) as

indicators. As shown in Table 2, all constructs demonstrated excellent internal consistency. Composite Reliability values ranged from .822 to .939, and Cronbach's Alpha values ranged from .708 to .938. Both sets of values comfortably exceed the widely accepted threshold of .70, which is considered indicative of strong reliability in exploratory research (Sharma *et al.*, 2024). The high scores across all constructs confirm that the sets of items used to measure each latent variable—from Perceived Utility to Addictive Behavior—are homogenous and consistently capture their intended underlying concept.

Table 2. Construct Reliability and Validity

Constructs	Items	Loadings	AVE	CR	CA
Perceived Utility	PU1	0.824	0.814	0.926	0.924
	PU 2	0.794			
	PU 3	0.821			
Social Norms	SN1	0.868	0.764	0.939	0.938
	SN2	0.780			
	SN3	0.679			
	SN4	0.836			
Technology Facilitation	TF1	0.882	0.915	0.916	0.800
	TF2	0.895			
	TF3	0.655			
	TF4	0.749			
	TF5	0.852			
Personality	PE1	0.971	0.876	0.888	0.732
	PE2	0.965			
	PE3	0.929			
	PE4	0.772			
Environmental	EN1	0.934	0.914	0.823	0.708
	EN2	0.978			
	EN3	0.951			
	EN4	0.961			
Self-Efficacy	SE1	0.928	0.767	0.902	0.898
	SE2	0.908			
	SE3	0.855			
	SE4	0.909			
Attitude	AT1	0.915	0.790	0.915	0.910
	AT2	0.793			
	AT3	0.827			
	AT4	0.879			
Addictive Behavior	AB1	0.923	0.627	0.822	0.803
	AB2	0.915			
	AB3	0.924			
	AB4	0.904			
	AB5	0.866			

The validity of the constructs was then examined. Convergent validity, which assesses the degree to which items truly measure their intended construct, was strongly supported. The AVE for all constructs ranged from .627 to .915 (see Table 3), surpassing the recommended .50 threshold (Tjondro *et al.*, 2024). This indicates that, on average, more than half of the variance in the items was explained by their respective latent construct, confirming that the measures are indeed converging appropriately. At the indicator level, nearly all item loadings were well above the ideal value of .70. While a few items, such as SN3 (loading = .679) and TF3 (loading = .655), were slightly below this mark, they were retained because the overall reliability and convergent validity of their respective constructs remained exceptionally high (Anaza *et al.*, 2024).

Discriminant validity was assessed to ensure each construct is empirically distinct from others in the model, using the method proposed by Fornell and Larcker (1981). According to this criterion, the AVE for each latent variable should be greater than its correlation with any other construct, demonstrating that a construct shares more variance with its own indicators than with other constructs. As presented in Table 3, this condition was met for all latent variables. For example, the square root of the AVE for addiction behavior (AB), shown in bold on the diagonal at .907, is demonstrably higher than its correlation with any other construct, including Attitude (AT; r = .804) and Self-Efficacy (SE; r = .827). A thorough inspection of the matrix confirms this pattern holds across the model, thus establishing that discriminant validity was adequately demonstrated and confirming that the constructs are distinct and well-defined.

Table 3. Discriminant Validity using Fornell-Larcker Criterion

Construct	1	2	3	4	5	6	7	8
1. AB	**0.907**							
2. AT	0.804	**0.836**						
3. EN	0.792	0.829	**0.824**					
4. PE	0.819	0.808	0.796	**0.900**				
5. PU	0.657	0.602	0.589	0.652	**0.813**			
6. SE	0.827	0.795	0.811	0.794	0.610	**0.877**		
7. SN	0.763	0.714	0.729	0.700	0.608	0.747	**0.794**	
8. TF	0.547	0.551	0.544	0.565	0.484	0.548	0.508	**0.845**

Note: AB = Addictive Behavior, AT = Attitude, EN = Environmental, PE = Personality, PU = Perceived Utility, SE = Self-Efficacy, SN = Social Norms, TF = Technology Facilitation

Structural Model and Test of Hypotheses

The analysis of the structural model, presented in Table 4, revealed that four of the seven proposed hypotheses were statistically significant, confirming the influence of key psychological and social factors on cryptocurrency addiction. The most powerful predictor was self-efficacy (β = .261, p = .003), which, contrary to traditional views but in line with our revised hypothesis, positively influenced addiction. This suggests that for novice traders, high self-efficacy may manifest as the cognitive bias of overconfidence, leading to more speculative and compulsive behaviors (Sharma *et al.*, 2024; Tjondro *et al.*, 2024). Personality also emerged as a robust predictor (β = .238, p = .011), supporting the view that dispositional traits like risk-taking and impulsivity are central to addictive consumption in the crypto space (Anaza *et al.*, 2024). Furthermore, social norms (β = .173, p = .018) and a positive attitude (β = .156, p = .021) were significant drivers, highlighting that peer influence and favorable personal beliefs motivate continued engagement, even when risks are acknowledged (Alsmadi *et al.*, 2024).

Table 4. Results of Hypothesis Tests

Hypothesis	Path	β	*SD*	*t*	*p*	Decisions
H_1	PU → AB	0.096	0.073	1.310	0.190	Not Supported
H_2	SN → AB	0.173	0.073	2.364	0.018	Supported
H_3	TF → AB	0.008	0.043	0.183	0.855	Not Supported
H_4	PE → AB	0.238	0.094	2.541	0.011	Supported
H_5	EN → AB	0.075	0.088	0.857	0.392	Not Supported
H_6	SE → AB	0.261	0.087	2.981	0.003	Supported
H_7	AT → AB	0.156	0.068	2.307	0.021	Supported

Conversely, three hypotheses were not supported, providing equally valuable insights into the nature of cryptocurrency addiction. The non-significant paths from perceived utility (β = .096, p = .190), technology facilitation (β = .008, p = .855), and environmental factors (β = .075, p = .392) suggest that the drivers of this behavior may be less rational and technical than commonly assumed. The lack of influence from perceived utility indicates that the addictive cycle may transcend a simple cost-benefit analysis, aligning with literature that frames problematic trading as a behavioral addiction akin to gambling (Nemlioglu *et al.*, 2024; Loscalzo, *et al.*, 2025). Similarly, the non-significance of technology facilitation suggests that for a digitally native population, ease-of-use may be a baseline expectation rather than a driving factor for addiction itself. These null findings help to refine the behavioral model, indicating that for this cohort, internal psychological dispositions and immediate social pressures are more powerful predictors of compulsive crypto engagement than external or purely rational considerations.

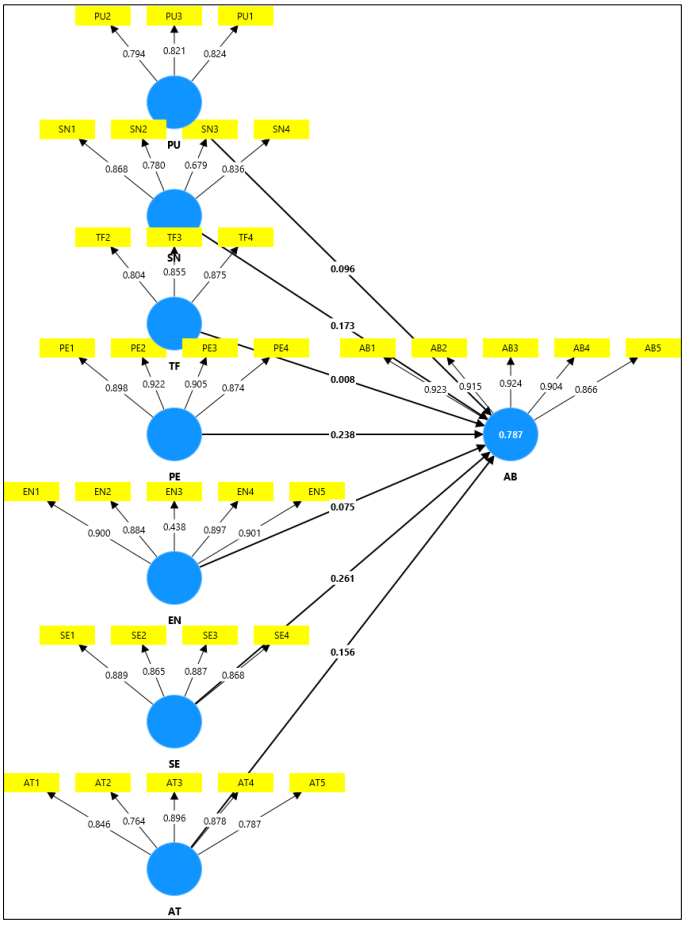

Figure 2. Structural Model

Coefficient of Determination

The overall explanatory power of the structural model was assessed by examining the coefficient of determination (R^2) for the endogenous construct, Addiction Behavior. The model achieved an R^2 value of .787, indicating that the combination of the seven predictor variables collectively explains a substantial 78.7% of the variance in Addiction Behavior among the sample of young cryptocurrency users. According to established guidelines for interpreting R^2 values in the context of behavioral studies using PLS-SEM, a value of .75 is typically considered to represent 'substantial' explanatory power (Sharma, Khan, Singh, & Birari, 2024). The finding of R^2 = .787 therefore confirms that the integrated theoretical framework and the selected predictor variables are highly effective and relevant in explaining the factors that contribute to cryptocurrency addiction in this specific context, giving strong credence to the model's overall validity.

Predictive Relevance

In addition to assessing the model's in-sample explanatory power, its out-of-sample predictive relevance was evaluated using a $PLS_{predict}$ procedure. As shown in Table 5, the model achieved a $Q^2_{predict}$ value of .766 for the primary endogenous construct, Addictive Behavior. According to established guidelines for PLS-SEM, a $Q^2_{predict}$ value greater than zero indicates that the model has predictive power for new cases outside of the original sample (Sharma *et al.*, 2024). The high value obtained in this study suggests that the model possesses a very strong degree of predictive relevance. The accompanying prediction error metrics, the root mean square error (RMSE = .493) and mean absolute error (MAE = .329), further quantify the model's predictive performance. Overall, these statistics confirm that the structural model is not only effective at explaining the variance within the sample but is also robust in its ability to predict addiction behavior in this context.

Table 5 Predictive Relevance

Construct	$Q^2_{predict}$	RMSE	MAE
Addictive Behavior	0.766	0.493	0.329

Discussion of Findings

The Paradox of Self-Efficacy: Overconfidence as a Key Driver of Crypto Addiction

The most striking finding of this study is the strong, positive relationship between self-efficacy and addiction behavior (H6: β = .261, p = .003). This result contradicts the conventional view of self-efficacy as a purely protective psychological asset and serves as the paper's lead insight. In the high-risk, high-uncertainty context of cryptocurrency trading, high self-efficacy does not

appear to foster control; instead, it manifests as overconfidence, a cognitive bias that has been shown to be a critical mediating factor linking financial naivety and other traits to problematic, compulsive engagement with cryptocurrency (Tjondro *et al.*, 2024). Individuals who are highly confident in their abilities may underestimate risks, engage in more speculative trading, and develop an "illusion of control" over market outcomes—all of which are established pathways to addiction (Sharma *et al.*, 2024).

This finding provides critical empirical weight to the argument that in volatile financial domains, self-efficacy can be a dual-edged sword, functioning more as a vulnerability than a strength (Blue *et al.*, 2025). The results suggest that what is being measured as self-efficacy may in fact be a financially-focused self-concept that, when confronted with the intermittent reinforcement of trading, encourages gambling-like behavior rather than disciplined investing (Louderback *et al.*, 2025). This paradox underscores the harmful consequences that can arise when confidence is not matched by expertise, a dynamic central to understanding modern behavioral addictions.

The Power of Social Influence and Personal Conviction

The results strongly confirm the significant influence of social and internal psychological factors on cryptocurrency addiction. The support for H2 (social norms), H4 (personality), and H7 (attitude) paints a clear picture of a behavior driven by conviction and community. The significance of social norms ($\beta = .173$) highlights the power of peer networks and online communities, such as those on Reddit, in shaping trading habits and normalizing high-risk behaviors (Bouma-Sims *et al.*, 2024). This is often amplified by a socially contagious "fear of missing out" (FOMO) that drives impulsive consumption (Anaza *et al.*, 2024).

Personality ($\beta = .238$) emerged as a very strong predictor, confirming that dispositional traits like risk-taking and impulsivity are central to developing addictive patterns (Grubbs & Kraus, 2024). Indeed, certain personality traits can moderate an individual's psychological response to technology, making some more susceptible to compulsive use (Changchit *et al.*, 2024). Finally, a positive attitude ($\beta = .156$) toward crypto trading—viewing it as a beneficial and exciting activity—was also a significant driver. This shows that once a favorable personal belief is formed, it can fuel continued engagement even when faced with acknowledged market risks and volatility (Alsmadi *et al.*, 2024).

Re-evaluating Assumed Drivers: The Non-Significance of Utility and Technology

Equally revealing are the factors that did not emerge as significant predictors of addiction. The non-significant effects of perceived utility (H1), technology facilitation (H3), and environmental factors (H5) challenge common assumptions about technology adoption. The lack of influence from technology facilitation suggests that for this digitally native demographic, a seamless user interface is no longer a novel driver but a "hygiene factor"—a baseline expectation that does not, in itself, push users toward addiction. In fact, research suggests the addictive potential may lie less in facilitation and more in the deliberate use of "dark patterns" and deceptive design features that sludge or nudge users toward compulsive behavior (Newall, 2025).

Similarly, the non-significance of perceived utility implies that addictive behavior in this context is less about a rational calculation of financial gain and more about the emotional and social rewards of trading. The drivers appear to be more aligned with gambling motivations and the desire to escape negative feelings than with a cold assessment of utility (Xu *et al.*, 2025). This distinction is a hallmark that separates compulsive behavior from rational investment and aligns with systematic reviews framing problematic trading as a behavioral addiction (Loscalzo, *et al.*, 2025).

Implications for the Integrated Behavioral Model

Synthesizing these findings provides a more nuanced understanding of the proposed behavioral model. For young adults in Nigeria, cryptocurrency addiction appears to be driven primarily by a potent socio-psychological engine rather than rational or purely technical considerations. The integrated theoretical framework is thus validated but also significantly refined. SLT is powerfully supported by the role of social norms. The TPB is only partially supported; while Attitude and Social Norms were significant, its rational-choice assumptions are fundamentally challenged by the non-significance of utility and the paradoxical, risk-driving role of self-efficacy.

It is here that BAT provides the most critical insight, serving as the necessary lens to interpret these contradictions. The key drivers identified—personality, social norms, and overconfidence-as-self-efficacy—are precisely those that best explain a departure from calculated decisions toward compulsive, emotionally-driven engagement (Griffiths, 2005). The model suggests that the pathway to addiction for young crypto users is paved more by who they are (personality), who they know (social norms), and how confident they feel (self-efficacy) than by what they stand to gain (utility) or how easy the tools are to use (technology).

Recommendations

Practical Recommendations

Based on these findings, targeted interventions are recommended for key stakeholders.

For Educators and Policymakers: To mitigate the identified risks, educational and policy interventions should move beyond traditional financial advice. Financial literacy programs ought to be developed with a specific focus on behavioral biases, such as the overconfidence and illusion of control identified in this study. Curricula should incorporate modules on emotional regulation and risk perception to equip young adults with the psychological tools to manage the pressures of volatile markets.

For Cryptocurrency Platforms: The organizations that provide trading services have a crucial role to play in fostering a safer trading environment. They should be encouraged to integrate responsible gaming tools, such as allowing users to voluntarily set limits on daily trades or deposits. Secondly, platforms could implement automated 'cooling-off' periods that are triggered after significant losses or exceptionally high trading frequency. Finally, providing prominent in-app links to addiction awareness resources and professional support services could offer a vital lifeline to users experiencing harm.

Future Research Directions

To build upon this exploratory study, three specific avenues for future research are recommended:

1. A longitudinal study is needed to track a cohort of young traders over time. This would allow researchers to observe how high self-efficacy evolves into overconfidence and to identify the tipping point where engagement becomes compulsive and clinically significant.
2. A cross-cultural comparative study would provide valuable insights into the influence of market structure. Comparing the prevalence and drivers of addiction among youth in highly

regulated markets (e.g., in the EU or UK) versus less regulated markets like Nigeria could illuminate the impact of policy and consumer protections on user behavior.

3. A mixed-methods study is required to explore the subjective experience behind the self-efficacy paradox. By combining quantitative survey data with in-depth qualitative interviews, researchers could uncover the personal narratives, motivations, and rationalizations of traders who exhibit high confidence alongside harmful behavior.

Conclusion

This study investigated the psychosocial drivers of cryptocurrency addiction among young adults in Nigeria, revealing a complex interplay of internal and social factors. The study's principal contribution to the literature is its elucidation of the paradoxical role of self-efficacy as a significant positive predictor of addictive behavior. This finding challenges the conventional view of self-efficacy as a protective asset. Instead, it suggests that in the volatile and uncertain context of cryptocurrency trading, high self-efficacy may manifest as a detrimental overconfidence, leading individuals to underestimate risk and engage more readily in compulsive trading.

Beyond this central finding, the research confirmed that internal dispositions (personality) and external social pressures (social norms) are powerful drivers of addiction. Conversely, the non-significance of factors like perceived utility and technology facilitation suggests that for this demographic, the pathway to addiction is paved less by rational calculation or technological ease-of-use and more by a potent combination of personality, social influence, and a misplaced sense of personal competence. The integrated behavioral model is thus refined, pointing towards a socio-psychological, rather than a techno-rational, explanation for this modern form of behavioral addiction.

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