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Full Length Research Article

DETERMINANTS OF INTENTION TO ADOPT BLOCKCHAIN TECHNOLOGY IN NIGERIA

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ABSTRACT

The Unified Theory of Acceptance and Use of Technology (UTAUT) helps to identify the drivers of user acceptance of new information technology. Based on this concept, four categories are important to direct predictors of user behavior and acceptance. These predictors are effort expectancy, performance expectancy, social influence, and facilitators. Although various scholars have discussed the importance of emotional expectancy in user acceptance of new technologies, it is not a direct determinant in the UTAUT model. This study argues that emotional expectancy is a direct determinant of behavioral intention. Therefore, this study employed a quantitative methodology using a questionnaire distributed via email and WhatsApp to investigate the effect of emotional expectancy on behavioral intention to adopt blockchain technology among Nigerians. In doing so, we extended the UTAUT model by integrating emotional expectancy as the fifth construct of the model. The user model has not been extensively tested in developing countries; therefore, this research could guide planners to reflect on the characteristics that contribute to the successful adoption of blockchain technology for specific user groups. The results of this research could provide blockchain users with useful insights into user perceptions and behaviors toward blockchain technology, from a user perspective.

Keywords: UTAUT, Technology Acceptance Model, Emotional Expectancy, Behavioral Intention, Blockchain Technology

INTRODUCTION

The UTAUT model is a combination of the Technology Acceptance Model (TAM) and seven additional theoretical frameworks. It consists of four components: performance expectancy (PE), effort expectancy (EE), social influence (SI), and enabling factors (EF). However, the impact of these factors on intention is influenced by gender, age, experience, and usage voluntariness (Hewavitharana *et al.*, 2021). UTAUT and TAM have been widely used in biomedical informatics and Management Information Systems (MIS). Over the years, changes and adaptations have been proposed, including the addition of components from different theories and adaptations to specific applications such as telemedicine or patient acceptance of eHealth and mHealth applications. However, these theories have also been discredited (Shachak *et al.*, 2019). The current study will focus solely on extending the UTAUT model by adding human and environmental characteristics.

The Technology Acceptance Model (TAM) developed by Davis (2003), shown in Figure 1, is one of the most prominent contributions of the last three decades. TAM comprises two factors: perceived usefulness (PU) and perceived ease of use (PEOU) (Jaradat & Mashaqba, 2014). It explains the acceptance of technology and user behavior among IT users. However, as noted by Zaineldeen *et al.*, (2020), a limitation of the TAM model is that it only assesses whether the technology is useful or easy to use. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is an improvement upon UTAUT (Davis *et al.*,1989). UTAUT consists of eight theories and models that are commonly used to study the acceptance of information technology by users. These include the Social Cognitive Theory (SCT), the Personal Computer Use Model (MPCU), the Technology Acceptance Model (TAM), the Technology Acceptance Model and the Theory of Planned Behavior (C-TAM-TPB), the Motivational Model (MM), the Planned Behavior Theory (TPB), and the Theory of Reasoned Action (TRA) (Venkatesh *et al.*, 2003). UTAUT is capable of predicting around 70% of user acceptance intentions and 50% of adoption behavior when studying the application of information technology (IT) by users in the organizational environment. This is a better result than other existing technology acceptance models (Venkatesh *et al.*, 2012). UTAUT's basic components are derived from eight previously listed models and theories.

TAM, TAM2, TAM3 and UTAUT

As described by Lai (2017) in the literature, Venkatesh & Davis (2000) developed TAM2 to address the limited explanatory power (R^2) of the original TAM. TAM2 aims to maintain the original TAM structure while incorporating additional variables related to perceived usefulness and intention to use and to investigate how these determinants change over time as users gain experience with the system. TAM3 by Venkatesh & Bala (2008) integrates the features that impact the apparent ease of usage and intention to use constructs of the TAM. In contrast, TAM2 focused solely on the foundations of the perceived utility and desire to use constructs of the TAM. Therefore, TAM3 provides a comprehensive nomothetic network of factors for users' acceptance of IT. In addition, the UTAUT model integrates four key determinants: effort expectancy, performance expectancy, social influence, and facilitating conditions, alongside four important mediators: age, voluntariness, gender, and experience.

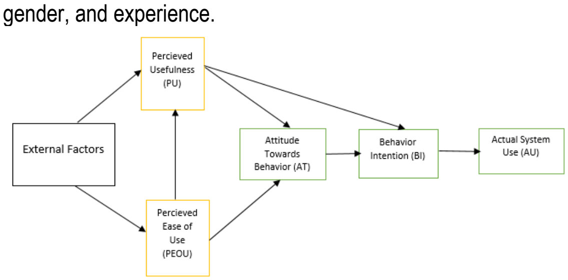

Figure 1: The Technology Acceptance Model [3]

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According to Bagozzi (2007), UTAUT has the potential to be a high-performing model due to its concise construction and strong explanatory power (R^2). However, it lacks direct empirical impact, which may have revealed novel associations and important components that were overlooked by simply incorporating them under the current categories. TAM2 and TAM3 did not explore direct impacts, which could have revealed new links, as well as several crucial study parameters. TAM2, TAM3, and UTAUT were not considered for this research on a revolutionary single-platform electronic payment method as it was intended to focus solely on market completion. To maintain objectivity, subjective standards that comprise society were excluded. Furthermore, cultural metrics have weak psychometric validity and no impact on consumers' behavioral intentions, especially for personalized IT applications like a single platform system, where individual use is optional. As UTAUT is an enhanced version of TAM2 and TAM3 that includes social influence, it is not suitable for this study. This study solely focuses on the variables and consumers' inclination to use a single platform system. Therefore, TAM2, TAM3, and UTAUT are unsuitable for researching the unique technology of a single platform system as they have excluded research on direct relationships.

Extended UTAUT

The expanded UTAUT model comprises of six constructs: effort expectation (EE), performance expectation (PE), social influence (SI), facilitating circumstances (FC), behavioral intention (BI), and usage behavior (UB). Additionally, it includes four moderators and four key decision criteria, as illustrated in Figure 2. According to the model, the four determinants of behavioral intention and usage behavior are performance expectancy, effort expectancy, social influence, and enabling factors (Chao, 2019). The original UTAUT paradigm may not be suitable for all settings as it lacks consideration and examination of the path from emotional expectancy to action intents. Therefore, this study analyses the extended model of the UTAUT, as shown in

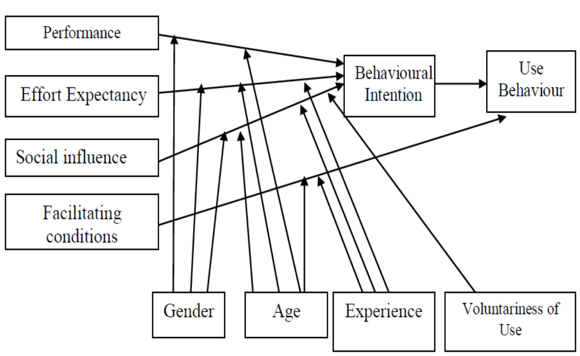

Figure 2. The original UTAUT model[7]

Figure 3. The extended model includes Performance Expectancy (PE), Effort Expectancy (EE), Social Influences (SI), Facilitators (FC), and the new factors of Emotional Expectancies (EME) (Patil *et al.*, 2020).

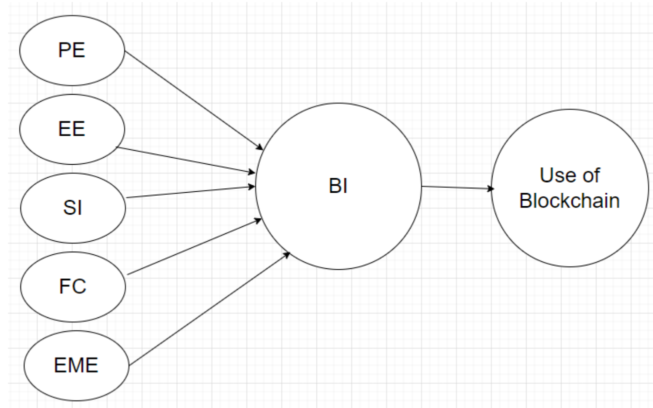

Figure 3. Our extended UTAUT model

Blockchain technology is gaining popularity due to its potential applications in various fields such as banking, cybersecurity, and healthcare (Abubakar *et. al.,* 2023; Aliyu & Liu, 2023). However, in Nigeria, there is skepticism towards embracing blockchain technology due to the prevalence of dubious pyramid schemes and fraudulent cryptocurrencies (Małgorzata, 2022). This study aims to investigate whether customers' emotions towards new technology, such as anger, anxiety, frustration, worry, and stress, affect their intention to adopt advanced technology. In addition to the ideas of Loss Emotion and Deterrence Emotion from Beaudry & Pinsonneault (2010)'s study, the UTAUT model was used to develop a theoretical framework. The framework aims to identify consumers' behavioural intentions to adopt blockchain technology. The UTAUT model can be extended by including the users' emotional perspective. This is important because the emotional perspective has been ignored in previous studies, which creates a gap in the literature. The study will investigate the impact of users' internal emotional force as a variable on the UTAUT model. The study will collect data for software that is not fully implemented in the state of the art and lacks a testing model for acceptance. Additionally, the study aims to understand the acceptability of blockchain technology in the Nigerian context. The research design consists of three stages: exploration, testing, and evaluation. During the exploratory stage, a thorough review of relevant literature is conducted to establish a foundation for the research, specifically regarding existing studies on the impact of users' behavioural and continuance intentions to use blockchain technology. The target population for this study consists of individuals in Nigeria who have used blockchain technology services, both past and present. The sample is limited to those who have voluntarily responded to the survey questionnaires and have experience using the technology.

Review of Related Literature

Several studies have identified limitations in the Technology Acceptance Model (TAM) and its variations, including TAM 1, TAM 2, UTAUT 1, and UTAUT 2, in explaining user behavior (Malatji, *et. al.,* 2020). Furthermore, these models are inadequate in predicting the adoption of information and communication technology (ICT), despite being used for this purpose (Tamilmani, *et. al.,* 2021). According to the literature, TAM is insufficient in providing a comprehensive understanding of the antecedents of mobile use, as well as the social influences and situations that enable behavior (Al-Maroof *et al.*, 2021). Similarly, a study by Yu, *et. al.,* (2023)

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argues that despite the popularity of these models, they are not satisfactory in explaining users' adoption and use of new technologies, particularly in terms of language, cultural context, and dynamic technology development.
In a recent study by Tella (2023), the Quadratic Usage Framework (QUF) was used to predict the intention of librarians in Southwest Nigerian universities to use blockchain. The study employed a survey research design and collected data from 169 librarians recruited from fifteen university libraries in Southwest Nigeria using a purely quantitative method. Recently, research by Alshurafat *et. al.,* (2022) developed a model that integrates technostress with elements of the technology acceptance model. The study involved 142 auditors from Big 4 and non-Big 4 firms who completed previously tested and validated questionnaires. The findings suggest that perceived ease of use and perceived usefulness are important determinants of attitudes toward adoption decisions, with the latter predicting behavioral intention to use blockchain technology. Similarly, Alomari & Abdullah (2023) extended the UTAUT model to investigate factors predicting the behavioral intention to use cryptocurrency among students at public universities in Saudi Arabia. The study analyzed the impact of performance expectancy, effort expectancy, facilitating conditions, social influence, security, and awareness on behavioral intention to use cryptocurrency. The authors analyzed 344 responses collected via an online survey using SmartPLS 3.2.8 software. Several other studies have also investigated the intention to use blockchain technology, employing various technology acceptance models (Patil *et. al.,* 2022; Cheng and Chong, 2022; Panjaitan, *et. al.,* 2023).

Blockchain Technology
Although there have been numerous studies evaluating items that use or potentially incorporate blockchain technology, there has been no comprehensive study of blockchain technology from the perspective of intent to use. For instance, e-shopping by Ha & Stoel, (2009), banking by Tan (2016), health technology and wearable fitness by Kirk *et al.* (2019), and application areas such as smart homes and smart farms by Aliyu *et. al.,* (2023) have all been studied in specific contexts. Although there have been studies on the behavioural intention of blockchain technology (Yusof *et al.*, 2018), no acceptance model has yet taken blockchain as a behavioral intention and usage behavior object of study. Therefore, our study presents a novel acceptance model that investigates blockchain technology in various applications and services. We use the UTAUT as the foundation for this study, supplemented with additional elements. The study examines the applications of cybersecurity, finance, and healthcare in daily life to establish segment-independent validity. It disregards factors that affect the correlation between attitudes and behavior. Instead, the study is based on various ideas about why specific elements influence behavioral intention, and it attempts to evaluate UTAUT, as well as the key determinants of behavioral intention and use behavior on products that incorporate blockchain technology, irrespective of the application area.
Several studies have been conducted on the adoption of blockchain technology in Nigeria (Akaba *et al.*, 2020; Fakunmoju *et al.,* 2022; Onyekwere, *et. al.,* 2023). Some of these have investigated the factors that influence the adoption of blockchain technology, while others have explored the challenges that Nigerian businesses encounter when attempting to implement blockchain technology. Although these and other studies make important contributions to the adoption of blockchain in Nigeria by highlighting the significance of features such as perceived usefulness, trust, and perceived ease of use in driving adoption, none of them were conducted on the basis of emotional expectancy as a direct determinant of user acceptance to adopt blockchain technology in Nigeria.
According to the expectancy framework, an individual's motivation to engage in an activity is determined by their assessment of the situation, their anticipation of the outcome, and the valence of the outcome (Tamir *et al.*, 2014). For instance, if a situation is perceived as risky, individuals are more likely to avoid it if they believe that confronting it would lead to an unfavorable outcome. However, if they believe that addressing the issue would result in a positive outcome, they are more likely to take action. The emotional expectancy framework has been used to explain a wide range of behaviors, such as risk-taking, decision-making, and stress management. It is an effective tool for comprehending how emotions impact our decisions and behaviors (Mamun *et al.*, 2020). Figure 4 displays the emotional expectancy framework.

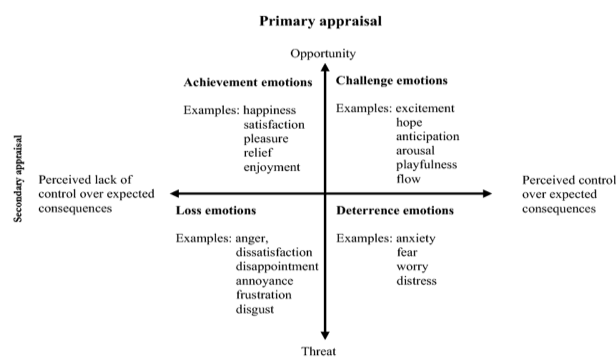

Figure 4. The emotional expectancy framework[20]

Materials and Method
During the exploration phase, a comprehensive literature review is conducted to establish a framework for the research, specifically regarding previous studies on factors that influence users' behavioural intentions and ongoing desire to use blockchain. This work critically evaluates theories and models used in information systems (IS) research, which serves as the foundation for the development of a research model used in the current study. The testing phase describes the research procedures for testing the study concepts presented in the exploration phase. During the evaluation process, quantitative methods are used to analyze the research hypotheses and model. Data is collected at this stage using an updated online questionnaire based on the prior pilot research.
The study focuses on individuals in Nigeria who have used blockchain technology-related services, both current and former users, and have voluntarily responded to the survey questionnaires. To reach a wider audience, the study employs a questionnaire distributed via email, WhatsApp, and other available media. The questionnaire was administered once, and data on exogenous variables and intent to employ Blockchain technology were collected. An advertisement for the questionnaire was posted on all social media platforms. To prevent multiple responses, participants were required to provide their identity card and mobile phone numbers. Respondents with repetitive entries were subsequently excluded from data analysis. The study excludes

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respondents who have no prior experience with blockchain technology and are not related to it, as only current users can answer questions about the six factors and emotional expectancy.
Probability sampling is a method where each member of a population has an equal and known chance of being selected. In other words, every individual in the population has a non-zero probability of being chosen, and their selection is independent of any other person (Dunn & Shultis, 2023). Non-probability sampling, on the other hand, involves selecting sampling strategies where the likelihood of each example being chosen is unknown (Tutz, 2023). The use of probability sampling, which can be applied to any available individual, is significantly more expensive and involved than non-probability sampling. However, non-probability sampling cannot generally claim that a sample is representative. In this study, non-probability sampling was employed due to its time and cost-saving benefits. This decision was motivated by two factors. Firstly, as previously stated, non-probability sampling saves time and money when compared to probability sampling. Probability sampling is difficult to carry out on a large population. In Nigeria, non-probability sampling was used to overcome the challenge of accessing the large population of interest. However, this decision may lead to issues such as uncertainty about whether the sample represents the entire population, and the inability to calculate margins of error and confidence intervals (Williams, *et. al.*, 2022). To minimize errors in the sample, this study has limited the target group to individuals in Nigeria who have prior or current experience with blockchain technology. This ensures that the sample is representative of the population with blockchain experience in Nigeria.
Determining the sample size involves deciding how many observations or repetitions to include in a statistical sample. The sample size is a crucial aspect of any empirical study that aims to deduce population inferences from a sample. Collecting data from every follower of these pages is not feasible; therefore, representative samples are selected through purposive sampling. Sample sizes are a crucial factor when studying social media platforms as they can significantly impact the accuracy of parameter estimates, model fit, and population statistical power (Ganson *et al.*, 2023).
The literature recommends examining the ratio of sample size to the most complex relationship in the research model only when determining sample size rules of thumb for PLS. The literature often refers to the '10 times' rule of thumb for deciding on the minimum sample size needed for PLS. This rule of thumb suggests that the sample size should be at least 10 times larger than the most complex relationship being studied. The most complex relationship is determined by comparing (1) the concept with the most formative indicators, if such constructs are present in the study model (also known as the largest measurement equation (LME)), and (2) the dependent latent variable (LV) with the largest number of independent LVs influencing it (also known as the largest structural equation (LSE)). The study suggests that the '10 times' rule of thumb for assessing sample size sufficiency in PLS is only valid under specific conditions, such as large effect sizes and excellent item reliability. The research model only includes reflecting variables, with the most complex relationship being the dependent LV influenced by the most independent LVs, which in our research model is ten. When using PLS to evaluate the research model, a minimum sample size of 10 (10 x 10 = 100) may be sufficient if certain conditions are met. These conditions include appropriate effect sizes, a sufficiently large number of items per construct, and highly reliable constructs. In multivariate research, it is recommended that the sample size be ten times larger than the number of variables being studied (Lund, 2021).
Furthermore, Hussey (2023) suggested using power analysis to determine the required sample size. In this study, the G*Power method was used to estimate the minimum sample size, as shown in Figure 5. A sample size of 134 is required for a structural model with twelve predictors, with a statistical power of 0.95, a moderate effect size of 0.15, and a confidence level of 0.05. A statistical power of 0.95 is employed to increase the likelihood of accurately identifying significant relationships in the research findings.

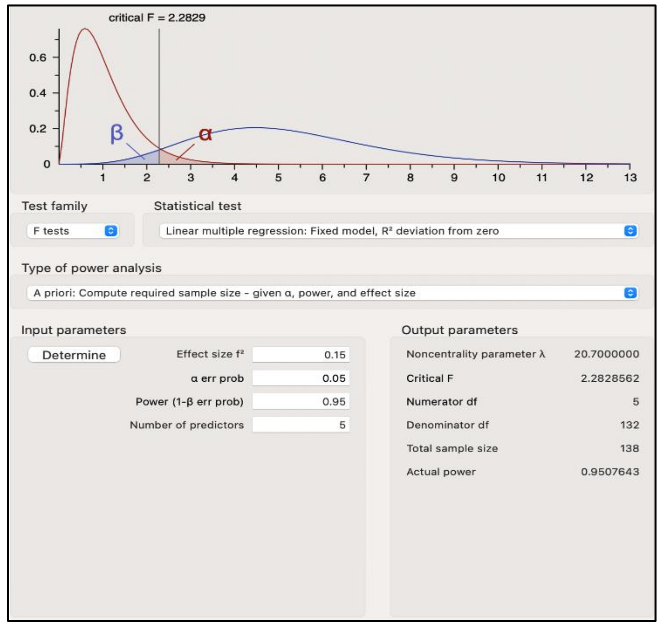

Figure 5. Sample Size G Power

All items are rated on a five-point Likert scale, with the options of 'strongly disagree' and 'strongly agree'. The questionnaire includes a list of six popular UTAUT models in Nigeria, and respondents are asked to indicate how frequently they use these models. The scale ranges from 'never' to 'many times per day'. The questionnaire was reviewed for content validity in English by a group of IT experts and academic staff. The questionnaire is administered in English, which is the official and primary language in Nigeria. It is being pilot tested with 200 users who are not included in the main questionnaire.

To evaluate the structural model and assess the hypothesized relationships, the study used partial least square structural equation modeling (PLS-SEM) with SmartPLS software. The measurement model was specified using PLS, including a method factor alongside the original latent variables. The squared factor loadings for the significant factors (i.e. original latent variables) were calculated, which explain the mean-variance. The squared factor loadings for the significant factors (i.e. original latent variables) were calculated, which explain the mean-variance. The squared factor loadings for the significant factors (i.e. original latent variables) were calculated, which explain the mean-variance. Four separate models were run to test support for the baseline UTAUT (direct effects only), and the results for predicting behavioral intention and use according to the UTAUT are reported. The study calculates Cohen's f-square to measure the magnitude of the main

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impact variables and interaction factors.

The UTAUT constructs scales, including performance, effort, social influence, facilitating conditions, and behavioral intention, are adapted from [7]. The scale for emotional expectancy is derived from Abikari (2021)'s research. Items are rated on a five-point Likert scale, with 'strongly disagree' and 'strongly agree' as the endpoints. A catalogue of six UTAUT models in Nigeria is provided, and participants are asked to indicate their frequency of use. The Five-point scale ranged from 'never' to 'many times per day.' The assessment of technology usage primarily focuses on behaviour-oriented measures, which may be subject to common method variance (CMV) to some extent, indicating that the elevated item is affected. However, the time gap between two measurements can reduce the impact of CMV, resulting in low measurement context effects (Ding, *et. al.,* 2023).

Data Analysis and Results Discussion

A total of 430 online responses were received from participants for the survey. After excluding 39 responses due to missing or incorrect data, 391 responses were used to assess the model. The first demographic variable, gender, revealed that 146 (37.3%) respondents were female and 245 (62.7%) were male. The demographic variable of age revealed that 31.5% of respondents were aged 26-32, 24.8% were aged 19-25, 24.6% were aged 33-39, and the smallest group consisted of those aged over 40, who made up 19.2% of respondents. In terms of education, the majority of respondents (49.6%) held a graduate degree. Out of the total respondents, 37.3% were post-graduates, while only 13% were high school graduates. In terms of occupation, 51.9% were employed, 23.3% were students, 16.1% were unemployed, and only 8.7% were self-employed. Finally, the income was estimated. According to the data, 45% of the total respondents had a monthly income above USD 2001. Additionally, 25.3% of the respondents had an income of USD 300 or below, 10.7% had an income between USD 301-800, 11% of the respondents had an income between USD 1401-2000, and the smallest number of respondents had an income between USD 901-1400, as shown in Table 1.

Table 1. Profile of the Respondents (391)

Variable	Category	Frequency	Percent
Gender	Female	146	37.3
	Male	245	62.7
Age	19-25	97	24.8
	26-32	123	31.5
	33-39	96	24.6
	Above 40 years	75	19.2
Education	High School	51	13
	Bachelor	194	49.6
	Postgraduate	146	37.3
Occupation	Student	91	23.3
	Employed	203	51.9
	Unemployed	63	16.1
	Self-Employed	34	8.7
Income	Below 300 USD	99	25.3
	301-800 USD	42	10.7
	901-1400 USD	31	7.9
	1401-2000 USD	43	11
	above 2001 USD	176	45

The research study's six variables were all scored on a Likert scale with five points, ranging from (1) strongly disagree to (5) strongly agree. On a five-point Likert scale, a mean value of a latent variable less than or equal to 1.99 is regarded as low, a value between 2.00 and 3.99 is considered moderate, and a value of 4.00 or more is considered high (Ekinci, 2015). However, only Actual behavior was assessed using a 7-point Likert scale with a mean of 3.5. All of the study constructs' mean values and standard deviations are shown in Table 2.

Table 2. Standard Deviation and Mean

Variable	Mean	Standard Deviation
PE	3.653	0.938
EE	3.789	0.897
SI	4.447	0.848
FC	3.804	1.018
BIU	5.573	1.438
BI	3.772	1.002

This study performed an un-rotated principal component factor analysis on all dimensional items, yielding four factors with eigenvalues greater than 1.0, accounting for 68.83% of the total variance. Factor one formed only 22.74% of the variance, showing that common method variance was not a significant issue. Table 3 below demonstrates the results of the measurement model.

Table 3. Results of the Measurement Model

Variables	Items	Loadings	Cronbach's Alpha	CR	AVE
BIU	BIU1	0.812	0.785	0.874	0.698
	BIU2	0.853			
	BIU3	0.84			
BI	BI1	0.863	0.779	0.871	0.693
	BI2	0.857			
	BI3	0.775			
EE	EE1	0.854	0.91	0.936	0.787
	EE2	0.903			
	EE3	0.913			
	EE4	0.876			
EME	EME1	0.861	0.897	0.928	0.764
	EME2	0.861			
	EME3	0.891			
	EME4	0.882			
FC	FC1	0.822	0.769	0.866	0.683
	FC2	0.86			
	FC3	0.796			
PE	PE1	0.834	0.807	0.873	0.633

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	PE2	0.723			
	PE3	0.828			
	PE4	0.792			
SI	SI1	0.849	0.828	0.897	0.744
	SI2	0.895			
	SI3	0.842			

The 0.90 criterion (HTMT.90) was employed in the study to establish the model's discriminant validity. The model's discriminant validity was demonstrated in Table 4 as all of the HTMT.90 criterion findings were less than the crucial value of 0.90. In general, the measuring model demonstrated sufficient convergent and discriminant validity.

Table 4. Discriminant Validity (HTMT.90)

Variables	BIU	BI	EE	EME	FC	PE	SI
BIU							
BI	0.625						
EE	0.57	0.376					
EME	0.627	0.664	0.526				
FC	0.875	0.494	0.43	0.538			
PE	0.416	0.726	0.321	0.467	0.336		
SI	0.513	0.657	0.404	0.615	0.406	0.633	

The output of the measurement model, as an important part of the structural equation modeling (SEM) process, is used to evaluate the quality of the latent variables and determine whether they accurately measure the constructs they are intended to measure. Figure 6 shows the output of our measurement model as Table 5 displays the Variance Inflation Factors (VIF) for Structural Model Collinearity Evaluation.

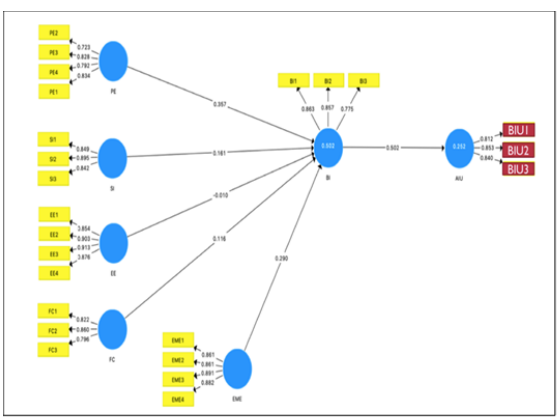

Figure 6. Output of Measurement Model

Table 5. VIFs for Structural Model Collinearity Evaluation

Variables	Blockchain Intention Use	Behavioral Intention
BI	1	
EE		1.366
EME		1.756
FC		1.324
PE		1.416
SI		1.67

The results displayed that the data gathered wasn't multivariate normal, had Mardia's multivariate skewness (β =7.41, p>0.05), and had Mardia's multivariate kurtosis (β = 79.05, p> 0.05), therefore this study used Smart PLS, a non-parametric analysis software. Figure 7 shows multivariate normality assessment using web power.

```
Sample size:  391
Number of variables:  7

Univariate skewness and kurtosis
       Skewness   SE_skew   Kurtosis  SE_kurt
BIU -0.7329755 0.1234043  0.1987767 0.246191
BI  -0.3329897 0.1234043 -0.1041976 0.246191
EE  -1.5623038 0.1234043  2.5404044 0.246191
EME -0.9119101 0.1234043  0.7823106 0.246191
FC  -0.6882144 0.1234043  0.4740834 0.246191
PE  -0.1430618 0.1234043  0.1797108 0.246191
SI  -0.4363740 0.1234043  0.2657560 0.246191

Mardia's multivariate skewness and kurtosis
                b         z p-value
Skewness  7.412245 483.03130       0
Kurtosis 79.052366  14.13879       0
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Figure 7. Multivariate Normality Assessment

The next step in the research model was to evaluate the structural model using the path coefficient. The significance of the path coefficient was established by comparing the t-values to the critical t-values indicated by Hair Jr. *et al.*, (2019) for significance levels of 0.01, 0.05, and 0.10. Additionally, the empirical t-value for the importance of the path coefficients was calculated using bootstrapping with 1000 subsamples. Table 6 presents the path coefficients obtained from the analysis to determine the statistical significance of the structural model, while Figure 8 displays the output for the structural model. The results indicate that all hypotheses were accepted, except for H2, which was rejected due to a negative path coefficient, low t-values, and high p-values.

Table 6. Structural Model Analysis Results (Direct Hypothesis)

Hyp	Path	Beta	Standard Error	T Values	P Values	5.00%	95.00%	Decision
H1	PE -> BI	0.357	0.045	7.931	0.000	0.267	0.441	Supported

H2	EE -> BI	-0.010	0.038	0.252	0.801	-0.082	0.065	Not Supported
H3	SI -> BI	0.161	0.049	3.279	0.001	0.061	0.259	Supported
H4	FC -> BI	0.116	0.042	2.739	0.006	0.029	0.201	Supported
H5	EME -> BI	0.290	0.055	5.242	0.000	0.181	0.392	Supported
H6	BI -> BIU	0.502	0.038	13.110	0.000	0.426	0.583	Supported

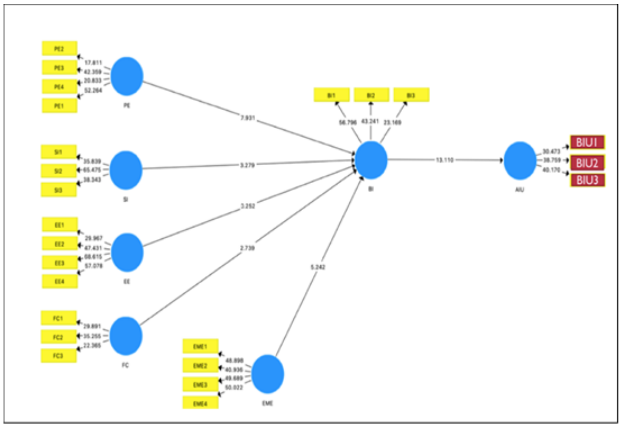

Figure 8. Output of Structural Model

The R^2 value for endogenous construct behavioral intention and use of Blockchain is given below. Table 7 presents the values of variance explained R^2 while Table 8 shows the effect size of the study variables.

Table 7. Variance Explained R^2

Variable	R^2	**Adjusted** R^2
BIU	0.252	0.25
BI	0.502	0.495

Table 8. The Study Variables' Effect Size

Effect Size		
Construct	**BIU**	**BI**
BI	0.338	
EE		0.000
EME		0.096
FC		0.021
PE		0.181
SI		0.031

Blindfolding in Smart-PLS was used to get predictive relevance **Q²**. Blindfolding was accomplished by removing every 6th data point from indicators of the endogenous construct and employing construct cross-validated redundancy. The skipped data points are then treated as missing data by Smart-PLS. The difference between the missing and projected data points was utilized to calculate the **Q²** (Fatimah *et al.*, 2018). Table 9 shows the values of Stone-Geisser's **Q²**.

Table 9. Relevance of Prediction (**Q²**)

Variables	**SSO**	**SSE**	**Q² (=1-SSE/SSO)**
BIU	1173	975.049	0.169
BI	1173	778.602	0.336
EE	1564	1564	
EME	1564	1564	
FC	1173	1173	
PE	1564	1564	
SI	1173	1173	

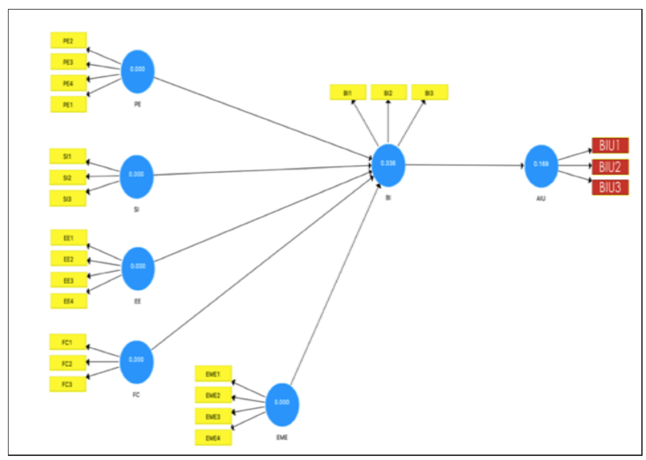

Figure 9. Predictive Relevance of the study (Blindfolding)

Predictive relevance is a measure of how well a model predicts new data. It is calculated by comparing the predicted values of the model with the actual values of the data. A model with high predictive relevance is able to accurately predict new data (Bayaga, 2022). Also, SEM uses blindfolding to evaluate the predictive relevance of a model. Blindfolding involves randomly dividing the data into two sets: a training set and a test set. The training set is used to estimate the model parameters, and the test set is used to evaluate the predictive relevance of the model as shown in figure 9.

CONCLUSION

The UTAUT theory provides the theoretical foundation for the framework proposed in this study. It includes two primary

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dependent variables: behavioural intention and usage behaviour. The independent variables examined in this study are performance expectancy, effort expectancy, social influence, facilitating factors, and emotional expectancy. Behavioural intention is also used as an explanatory variable for actual adoption. The validity of our conjecture depends on the extent to which the concept of emotional expectancy is consistent. Emotional expectancy refers to the belief that the use of blockchain technology will improve one's life and task performance. To measure this variable, we included four questions in the survey questionnaire about the quality and user satisfaction of current blockchain technology. The statistical analysis of this study indicates a favourable and significant result (β=.290, p<.05), suggesting that respondents, on average, have a positive attitude towards blockchain technology. The study considers emotional expectation as one of the strongest predictors of intention. This study indicates that current blockchain services enhance users' confidence in their productivity and have the potential to improve their lives. Therefore, individuals with positive emotional expectations are more likely to consider adopting various blockchains and their benefits. This may be because end-users believe that the implementation of blockchain will result in increased productivity and more advantageous services provided by blockchain technology.

Similar results have been reported by other researchers, albeit in varying national settings. These studies include those in developed countries such as Hariri (2014) and Rondan-Cataluña, *et. al.,* (2015), as well as in developing countries such as the study by (Alsaif, 2014). Therefore, this finding is consistent with those of (Hariri 2014; Alsaif, 2014; Rondan-Cataluña, *et. al.,* 2015). Therefore, the results support our proposal and affirm that emotional expectancy is an influencing factor in the intent to use blockchain technology. This may be due to the possibility that blockchain technology provides users with a vast scope of choices and benefits, resulting in a substantial reduction in the cost and time required to carry out these activities in the traditional way.

Our findings on the factors influencing users' perceived use and intention to use blockchain technology in the Nigerian setting are essentially consistent with results from related studies. In general, the utility of the improved UTAUT model in this type of analysis is validated. According to the findings, online trust and performance expectancy are the best determinants of intention to use blockchain technology. Similarly, a favorable environment and social influence induced behavioral intention. Effort Expectancy, on the other hand, did not. The study answered the research questions as planned, but in addition, suggests new ones that could be investigated further. These include whether attitudes toward other systems, such as Endpoint Detection and Response (EDR), Threat Intelligence, Security Information and Event Management (SIEM), and so on, can influence the likelihood of employing blockchain technology, and vice versa. Furthermore, if the study is expanded to include firms with expatriates or other developing countries, the impact of cultural computer skills and knowledge on blockchain adoption might be investigated. More research could be performed to determine why this disparity exists and how it influences the deployment of blockchain technology. This study likewise used only the quantitative technique, although a qualitative arm could provide more insights into the findings, particularly in relation to the moderating factors.

Statements and Declarations

Conflict of Interest: This research declares no conflict of interest.

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Data Availability and Ethics Statement: The necessary data used in this study are the 391 responses we received to the questionnaire, which are included in the manuscript. The software and statistical tools are also all presented and explained in the methodology and analysis sections. Links to help replicate the study are also provided in the manuscript. In addition, no special permission was required for the collection of data in the methodology, as the survey was conducted online.

Author contribution: Ahmed Abubakar Aliyu: Conceptualization, Methodology, Data curation, Writing-Original draft. Jinshuo Liu: Supervision, Visualization, Investigation, Funding Acquisition. Ezekia Gilliard: Software, Validation, Writing- Review and Editing.

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