:: IJEBD::
(International Journal of Entrepreneurship and Business Development)
Volume 08 Number 02 March 2025

ISSN: 2597-4785 (ONLINE)
ISSN: 2597-4750 (PRINTED)

The Adoption Puzzle: Investigating the Supply Side Determinants of Blockchain Technology Adoption for Entrepreneurial Financing

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ABSTRACT

Purpose: Access to financing is vital for the growth of entrepreneurial firms in emerging economies like South Africa. Technological innovations such as blockchain can reduce transaction costs and disrupt traditional models, offering benefits like reliability, trust, security, and efficiency. However, adoption barriers persist, including infrastructure limitations and the emerging nature of the technology.

Methodology: This study employs a quantitative approach to investigate factors affecting the adoption of blockchain technology among employees of entrepreneurial financing firms through an online survey. Using Partial Least Squares Structural Equation Modelling and Artificial Neural Network Analysis (PLS-SEM ANN).

Findings: the findings indicate that facilitating conditions, social influence, anxiety, and attitude significantly impact the behavioral intention to adopt blockchain, while effort expectancy, performance expectancy, and self-efficacy do not. The study recommends creating supportive environments, leveraging social networks, addressing anxiety, and fostering positive attitudes toward blockchain. It suggests investing in infrastructure, increasing awareness of blockchain benefits, improving communication to alleviate anxieties, and showcasing success stories to enhance adoption.

Originality/value: This paper is original

Paper type: a Research Paper

Keyword: *ANN, Blockchain Technology, Entrepreneurial Financing, PLS-SEM*

Received: November 13th

Revised: February 18th

Published: March 31th

I. INTRODUCTION

Blockchain and other technological developments can transform transaction costs in organisations and markets, challenging traditional coordination models (Bogusz, Laurell, & Sandström, 2020). Blockchain is described as digital information, or a 'block', that is maintained in a public or private database known as the 'chain' (Li, Cai, Deng, Yao, & Wang, 2019). In a blockchain, transactions are organised into blocks that join to form a chain. These blocks are authenticated and recorded by a platform-wide consensus mechanism known as 'distributed consensus' (Chen, 2018; Angelis & Da Silva, 2019). The blockchain goes beyond the role of a simple safe database; it is a technique for documenting transactions in a form that users perceive as an accurate picture of those transactions, promoting trust among the parties involved.

The distributed nature of blockchain technology alters how economic operations are conducted and how economic agents interact (Weeks, 2018). This has led to changes in the nexus between enterprises and markets, as well as how they are coordinated or managed (An, Duan, Hou, & Xu, 2019; Block, Groh, Hornuf, Vanacker, & Vismara, 2020). Blockchain, in particular, disrupts the coordination mechanisms of entrepreneurial financing firms and markets due to its qualities that allow for speedier trust-building, which may result in changes to the financial infrastructure (Chang, Baudier, Zhang, Xu, Zhang, and Arami, 2020).

ISSN: 2597-4785 (ONLINE)
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Coordination and governance issues have resulted in a funding gap, particularly for entrepreneurial firms, necessitating the use of technologies such as blockchain to close it (Ahluwalia, Mahtob & Guerrero, 2020; Robyn, Mac a Bhaird, Hussain & Botelhi, 2019; Chalmers, Matthews & Hyslop, 2019). Some authors (Cai, 2018; Catalini & Gans, 2018; Fisch, 2019) predicted that blockchain might help close the entrepreneurial finance gap by addressing constraints such as asymmetric knowledge and collateral scarcity, as well as making transactions more efficient. Similarly, Chen (2018) suggested that blockchain democratises investment opportunities by allowing investors to invest in early-stage enterprises without jurisdictional boundaries. Ante, Sandner, and Fiedler (2018) emphasised the role of blockchain in addressing the signalling issues that entrepreneurial enterprises confront.

Despite this, Kher, Terjesen, and Liu (2020) claimed that blockchain is an emergent phenomenon that has gotten little attention from management and entrepreneurship researchers, particularly in terms of transaction cost reduction and as a financing tool for entrepreneurial enterprises. Similarly, in a systemic review of blockchain literature, Frizzo-Barker, Chow-White, Adams, Mentanko, Ha, and Green (2020) and Kulkarni and Patil (2020) concluded that blockchain research is still in its early and exploratory stages, resulting in a scarcity of empirically driven studies on blockchain adoption, particularly in non-western economic contexts. Furthermore, Schuetz and Venkatesh (2020) argued that the implementation of blockchain-based solutions presents unique contextual issues in emerging economies such as South Africa.

The present investigation was thus partially motivated by these observations. This study seeks to examine the factors influencing the adoption of blockchain technology by entrepreneurial financiers within the framework of entrepreneurial financing in South Africa. This study advances the literature by augmenting the unified theory of acceptance and usage of technology (UTAUT) model with variables from Social Cognitive Theory (SCT), including attitude, anxiety, and self-efficacy, in contrast to previous research. This also addresses the appeal made by Venkatesh et al. (2016) to amalgamate UTAUT with additional theories.

The study is organised as follows; the introduction is followed by theoretical perspective, research method and hypothesis development, material and methods, findings, discussion of findings. The study continues with a discussion of theoretical contributions, limitations, areas for further investigation, and study conclusions.

A. Theoretical Perspectives

Understanding people's behaviours and attitudes is crucial for predicting technology adoption, and various theories explain technology adoption by organizations or individuals. These include the Technology Acceptance Model (TAM) (Davis et al., 1989), Theory of Planned Behaviour (TPB) (Ajzen, 1985), Diffusion of Innovation (DOI) theory (Rogers, 2004), Theory of Reasoned Action (TRA) (Fishbein & Azjen, 1975), Technology, Organisation and Environment (TOE) framework (Tornatsky & Fleischer, 1990), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Many studies use one of these models or combine multiple models to conduct their research (Taherdoost, 2017, 2022).

The UTAUT model, which explains over 70% of technology acceptance behaviour, is a stronger explanatory model than other models, according to a comparison of theoretical models (Waehama, McGrath, Korthaus & Fong, 2014). Its strength lies in its building on four dominant theoretical models: TRA, TAM, TPB, and DOI (Ikumoro and Jawad 2019). Williams et al. (2015) emphasized the need for further research on the application of UTAUT in various contexts and countries. Therefore, the study adapted UTAUT as the theoretical framework governing the study.

The UTAUT model, developed by Venkatesh et al. (2003) identifies four constructs: performance expectancy, effort expectancy, social influence, and facilitating condition, as direct determinants of behavioural intention and actual behaviour. It is used in technology adoption studies because it is integrative and incorporates various explanatory variables from other theoretical models (Attuquayefio & Addo 2014).

Venkatesh et al. (2016) suggested that the UTAUT can be expanded by introducing new constructs, using different moderating variables, investigating moderation effects on new relationships, and examining different outcomes. Subsequently, the study expanded the UTAUT theory by incorporating additional elements from social cognitive theory, specifically attitude, anxiety, and self-efficacy.

II. METHODS

A. Sampling and Data Collection

The research employed a purposive non-probability sampling method to determine the study sample, partly due to the lack of a full sampling frame for employees in entrepreneurial financing organisations in South Africa. The study aimed to investigate the factors influencing the adoption of blockchain technology by employees of entrepreneurial financing firms in South Africa, targeting 1000 respondents. Of the 1000 intended respondents, only 844 provided responses, and among them, only 505 were complete. A structured online questionnaire was

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ISSN: 2597-4750 (PRINTED)

utilised as the data gathering instrument. Nayak and Narayan (2019) asserted that online surveys provide several benefits, such as cost efficiency, time savings, and access to a wider demography. Data was gathered with Qualtrics, an online survey platform provided by the University of Pretoria.

B. Measurement Scales

The measurement scales employed to operationalise the constructs in this study were sourced from instruments that have been extensively utilised and are well-established in the literature on technology acceptance (e.g., Wong *et al.,* 2020; Nuryyev *et al.,* 2020; Palau Saumell *et al.,* 2019; Lee *et al.,* 2019). In the present investigation, the five-item scale established by Venkatesh et al. (2003) was adapted to investigate FC, PE, EE, SI, ATT, and ANX. Additionally, SE was assessed using the five-item scale developed by Tan and Teo (2000). A five-item scale created by Venkatesh et al. (2003) was modified to assess the BI.

C. Data Analysis

The study utilized a two-staged Partial Least Squares Structural Equation Modelling (PLS-SEM) and Artificial Neural Network (ANN) technique. In the first stage, the study used PLS-SEM to examine hypothesised relationships using SmartPLS 4.2. In the second phase, the study performed an ANN analysis to rank the normalised significance of the key predictors derived from the PLS-SEM analysis, owing to the existence of non-linear interactions between the independent and dependent variables (Zaidan et al., 2023).

D. Ethical Considerations

Participants were presented with an informed consent letter outlining the study's purpose and participation criteria. They were guaranteed that their responses would be kept confidential and anonymous, as individual identification from the obtained data was unfeasible. No incentives were offered to promote participation. This procedure guaranteed the meticulous adherence to ethical research requirements. Furthermore, ethical approval for the study was obtained from the authors' associated university.

The research model, presented in Figure 1, based on various scholarly positions, suggests that variables like social influence, performance expectancy, anxiety, attitude, self-efficacy, and behavioural intention play distinct roles in the adoption of blockchain technology, highlighting the importance of understanding these factors in the context of technology adoption.

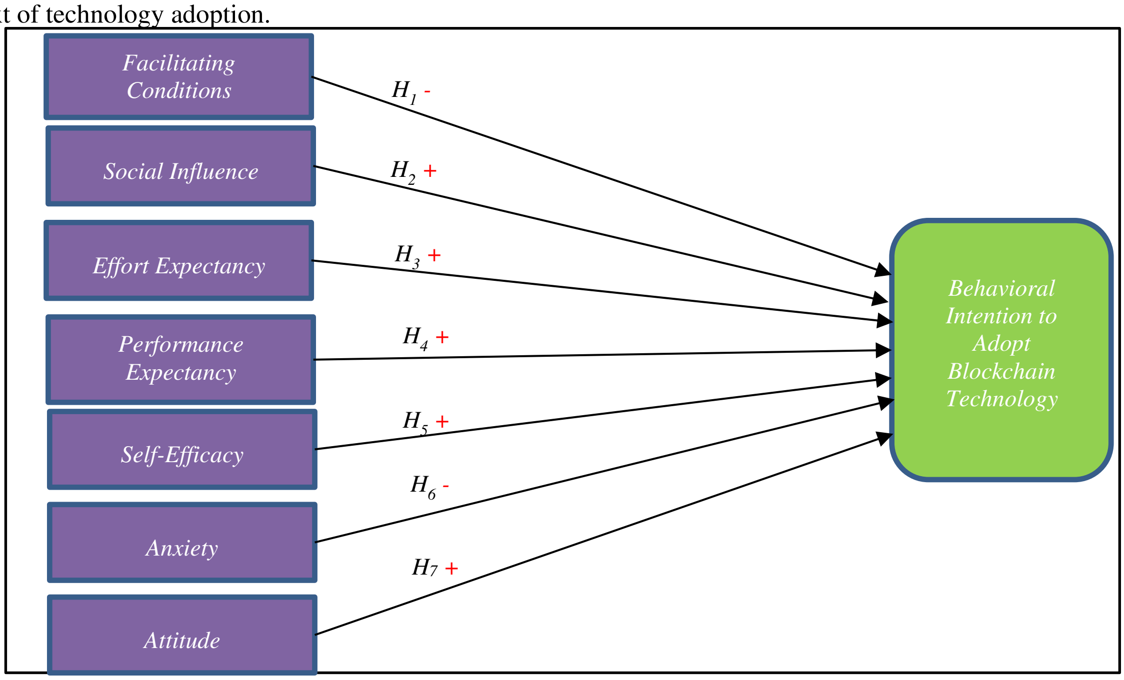

Figure 1: Research Model for Blockchain Technology Adoption

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III. RESULTS AND DISCUSSION

1. Common Method Bias

The study investigated common method bias (CMB) by conducting the Harman single factor test, following Abbasi et al.'s (2021) precedence, as the predictor and outcome variables were collected using a single data instrument. Harman's single factor test requires a variance percentage of less than 50% associated with the first factor (Kock, 2021). The Harmans single factor test of CMB revealed that a single factor accounted for 26.1% of the overall variance in BI, indicating that the issue of CMB does not exist.

2. Multivariate Statistical Assumptions

Multivariate assumptions including linearity, collinearity, and normality (Ooi, Lee, Tan, Hew, & Hew, 2018) were assessed. A one-sample Kolmogorov-Smirnov test was performed to assess the normal distribution of the data, with results shown in Table 1 reflecting non-normal data distribution, as the p-values are below 0.05.

Table 1: One Sample Kolmogorov-Smirnov Normality Test Results

	ATT	ANX	PE	BI	SE	FC	EE	SI
K-S stat	3.226	3.088	4.269	2.300	2.661	2.062	4.139	2.718
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Variance inflation factor (VIF) was utilised to evaluate collinearity. VIF values exceeding 5 suggest potential collinearity problems among predictor constructs, although collinearity may also arise at lower VIF values ranging from 3 to 5 (Becker et al., 2015). Table 2 delineates the results of multicollinearity.

Table 2: Variance Inflation Factor Collinearity Assessment Results

Constructs	Tolerance	VIF	Decision
ATT -> BI	0.649	1.541	No multicollinearity problem
ANX -> BI	0.828	1.208	No multicollinearity problem
PE -> BI	0.640	1.562	No multicollinearity problem
SE -> BI	0.592	1.690	No multicollinearity problem
FC -> BI	0.512	1.955	No multicollinearity problem
EE -> BI	0.864	1.158	No multicollinearity problem
SI -> BI	0.449	2.226	No multicollinearity problem

As shown in Table 2, and consistent with Hew and Kadir (2016) given VIFs remaining below the normal threshold of 3, and tolerances range from 0.449 to 0.864, the multicollinearity condition was met.

The results presented in Table 3 indicate that the p-values for both linearity and deviation from linearity were below 0.05, based on Analysis of Variance (ANOVA) test, as suggested by Abbasi et al. (2021), demonstrating that the model encompasses both linear and non-linear interactions between the target dependent and independent variables.

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ISSN: 2597-4750 (PRINTED)

Table 3: Linearity of Relationships (ANOVA Test) Results

	Relationship	Sum of Squares	df	Mean Square	F-stat	P-value
ATT * BI	(Combined)	152.445	19	8.023	13.497	0.000
	Linearity	119.231	1	119.231	200.565	0.000
	Deviation from Linearity	33.214	18	1.845	3.104	0.000
ANX * BI	(Combined)	92.304	15	6.154	8.635	0.000
	Linearity	38.843	1	38.843	54.509	0.000
	Deviation from Linearity	53.461	14	3.819	5.359	0.000
PE * BI	(Combined)	118.083	11	10.735	16.401	0.000
	Linearity	103.354	1	103.354	157.906	0.000
	Deviation from Linearity	14.729	10	1.473	2.250	0.014
SE * BI	(Combined)	154.899	19	8.153	13.832	0.000
	Linearity	108.653	1	108.653	184.339	0.000
	Deviation from Linearity	46.246	18	2.569	4.359	0.000
FC * BI	(Combined)	246.166	20	12.308	30.613	0.000
	Linearity	216.336	1	216.336	538.063	0.000
	Deviation from Linearity	29.830	19	1.570	3.905	0.000
EE * BI	(Combined)	36.019	13	2.771	3.361	0.000
	Linearity	2.264	1	2.264	2.747	0.000
	Deviation from Linearity	33.755	12	2.813	3.412	0.000
SI * BI	(Combined)	260.824	18	14.490	39.136	0.000
	Linearity	220.206	1	220.206	594.751	0.000
	Deviation from Linearity	40.617	17	2.389	6.453	0.000

Source: Authors own compilation

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ISSN: 2597-4750 (PRINTED)

3. Assessment of Measurement Model

Table 4 displays the reliability and convergent validity outcomes for the study constructs.

Table 4: Reliability and Convergent Validity Results

Construct and Items	*Loading*	*Communality*	*α*	*Rho_c*	*AVE*
Attitude (ATT)			*0.939*	*0.954*	*0.805*
ATT1	*0.876*	*0.767*			
ATT2	*0.925*	*0.856*			
ATT3	*0.887*	*0.787*			
ATT4	*0.922*	*0.85*			
ATT5	*0.875*	*0.766*			
Anxiety (ANX)			*0.794*	*0.863*	*0.612*
ANX1	*0.482*	*0.232*		*dropped*	
ANX2	*0.749*	*0.561*			
ANX3	*0.822*	*0.676*			
ANX4	*0.798*	*0.637*			
ANX5	*0.758*	*0.575*			
Self-Efficacy (SE)			*0.858*	*0.897*	*0.636*
SE1	*0.738*	*0.545*			
SE2	*0.856*	*0.733*			
SE3	*0.872*	*0.76*			
SE4	*0.774*	*0.599*			
SE5	*0.739*	*0.546*			
Performance Expectancy (PE)			*0.876*	*0.925*	*0.804*
PE1	*0.539*	*0.291*		*dropped*	
PE2	*0.377*	*0.142*		*dropped*	

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ISSN: 2597-4750 (PRINTED)

PE3	*0.810*	*0.656*			
PE4	*0.939*	*0.882*			
PE5	*0.935*	*0.874*			
Effort Expectancy (EE)			*0.901*	*0.903*	*0.702*
EE1	*0.447*	*0.200*		*dropped*	
EE2	*0.728*	*0.530*			
EE3	*0.810*	*0.656*			
EE4	*0.828*	*0.686*			
EE5	*0.968*	*0.937*			
Facilitating Conditions (FC)			*0.846*	*0.891*	*0.621*
FC1	*0.761*	*0.579*			
FC2	*0.883*	*0.780*			
FC3	*0.737*	*0.543*			
FC4	*0.792*	*0.627*			
FC5	*0.758*	*0.575*			
Social Influence (SI)			*0.889*	*0.918*	*0.692*
SI1	*0.831*	*0.691*			
SI2	*0.832*	*0.692*			
SI3	*0.864*	*0.746*			
SI4	*0.828*	*0.686*			
SI5	*0.803*	*0.645*			
Behavioural Intention to use blockchain (BI)			*0.887*	*0.922*	*0.748*
BI1	*0.892*	*0.796*			

ISSN: 2597-4785 (ONLINE)
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BI2	*0.878*	*0.771*	
BI3	*0.900*	*0.810*	
BI4	*0.785*	*0.616*	
BI5	*-0.017*	*0.000*	*dropped*

The current analysis established a recommended threshold of 0.708, confirming the reliability of the indicator (Hair et al., 2021). Item loadings below the 0.708 threshold were dropped, whereas the retained measurement items exhibited factor loadings ranging from 0.728 to 0.968, affirming the indicator reliability of the measurement items employed in the study.

Further, the results shown in Table 4 demonstrate that the α and rho_c values for all constructs exceeded the recommended threshold of 0.700, indicating that the study satisfied the criteria for internal consistency reliability. Table 5 presents the findings of the discriminant validity. The results indicate that the correlations among each variable set did not exceed the square root of their AVE. Secondly, the heterotrait-monotrait correlation ratio (HTMT) values for all components are below 0.850, indicating that discriminant validity is not a concern. The results indicate that the examined variables had strong discriminant validity.

Table 5: Discriminant Validity Results

	HTMT							
ANX								
ATT	*0.199*							
BI	*0.351*	*0.575*						
EE	*0.259*	*0.076*	*0.088*					
FC	*0.337*	*0.34*	*0.804*	*0.302*				
IEF	*0.285*	*0.561*	*0.536*	*0.381*	*0.498*			
PE	*0.358*	*0.392*	*0.550*	*0.190*	*0.509*	*0.507*		
SE	*0.435*	*0.399*	*0.571*	*0.201*	*0.603*	*0.334*	*0.569*	
SI	*0.235*	*0.629*	*0.799*	*0.086*	*0.672*	*0.577*	*0.533*	*0.511*

4. Structural Model and Hypothesis Testing

The research employed PLS-SEM with a bootstrapping resampling method utilising 10,000 subsamples following recommendation by Streukens and Leroi-Werelds (2016). The concept of model fit from CB-SEM is not applicable to PLS-SEM, as it aims to maximize explained variance instead of minimizing divergence between covariance matrices (Hair, Sarstedt, & Ringle 2019). The structural model assessment evaluates the model's explanatory and predictive power using criteria like path coefficient significance, R^2, effect size (f^2), and predictive relevance (Q^2) (Hair et al, 2021).

ISSN: 2597-4785 (ONLINE)
ISSN: 2597-4750 (PRINTED)

The present study investigated the direct relationship among ATT, ANX, PE, EE, SE, FC, SI, and BI utilising a PLS-SEM path analysis model, as illustrated in Figure 2. Figure 2 illustrates the path coefficients and t-statistics for the relationships: EE (β = -0.024, t = 0.581); PE (β = 0.061, t = 1.476); ATT (β = 0.181, t = 5.124); ANX (β = -0.072, t = 2.307); SE (β = 0.035, t = 0.913); FC (β = 0.397, t = 8.523); SI (β = 0.315, t = 7.721) and BI. Furthermore, Figure 2 reveals an R^2 of 0.667, suggesting that ATT, ANX, PE, EE, SE, FC, and SI account for 66.7% of the variance in BI, indicating that the structural model possesses significant predictive power.

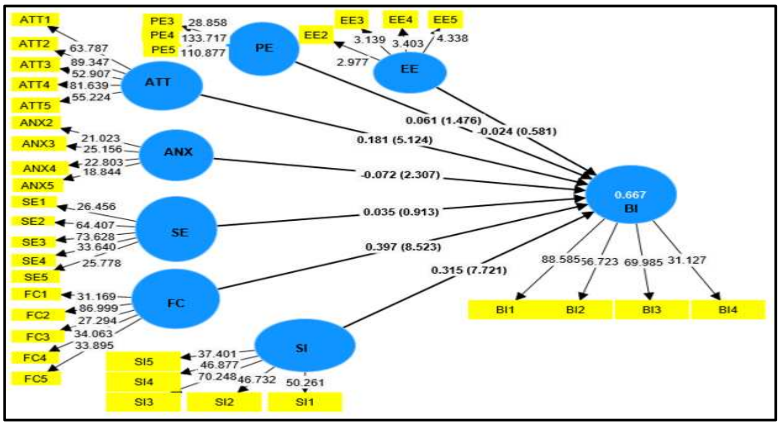

Figure 2: PLS-SEM direct relationship path analysis structural model results

Table 6 presents the findings of the path analysis, including p-values, f^2, 95% confidence intervals, and statistical conclusions related to the hypotheses. The findings indicated that the model exhibited a Q^2 of 0.653, demonstrating that FC, SI, SE, EE, PE, ANX, and ATT possess significant predictive value regarding the adoption of blockchain technology by entrepreneurial financing firms.

Table 6: PLS-SEM Hypothesis Test Results

Hypothesis	*Structural Path*	*β*	*t-stat*	*p-value*	*f^2*	*95% CI*		*Decision*
						LL	*UL*	
H_1	*FC -> BI*	*0.397*	*8.523*	*0.000*	*0.239*	*0.314*	*0.469*	*Supported*
H_2	*SI -> BI*	*0.315*	*7.721*	*0.000*	*0.139*	*0.249*	*0.382*	*Supported*
H_3	*EE -> BI*	*-0.024*	*0.581*	*0.280*	*0.005*	*-0.081*	*0.053*	*Not Supported*
H_4	*PE -> BI*	*0.061*	*1.476*	*0.070*	*0.010*	*-0.009*	*0.127*	*Not Supported*
H_5	*SE -> BI*	*0.035*	*0.913*	*0.181*	*0.005*	*-0.028*	*0.098*	*Not Supported*
H_6	*ANX -> BI*	*-0.072*	*2.307*	*0.011*	*0.017*	*-0.125*	*-0.022*	*Supported*
H_7	*ATT -> BI*	*0.181*	*5.124*	*0.000*	*0.067*	*0.123*	*0.239*	*Supported*
R^2 for explanatory power		*0.667*						
Q^2 for predictive power		*0.653*						

Source: Authors own compilation

The PLS-SEM structural model path analysis results revealed that FC, SI, ANX, and ATT are statistically significant drivers of blockchain technology adoption among entrepreneurial financiers in South Africa. In contrast, PE, EE, and SE were identified as statistically insignificant factors influencing the adoption of blockchain technology by entrepreneurial financiers in South Africa.

5. Artificial Neural Network Analysis

Following Liebana-Cabanillas *et al*., (2018) a two-staged approach utilising ANN as a secondary analysis tool is adopted to enhance the PLS-SEM model. This approach addresses the limitations of traditional linear frameworks in capturing complex human decision-making (Faasolo & Sumarliah, 2022). Further, integrating ANN with PLS-SEM addresses multicollinearity, nonlinearity, homoscedasticity, nonnormality of distribution, and noise (Hew *et al*., 2018).

An ANN is a machine learning model with hierarchical levels, including an input, hidden, and output layer (Yan, Siddik,Yong, Dong, Zheng & Rahman, 2022). In this study, the input layer included four independent variables (namely; FC, SI, ANX, and ATT), while the output layer contained only one outcome variable (namely; BI), resulting in a single ANN model as depicted in Figure 3. The system predicts analytical results using a feed-forward-backward-propagation (FFBP) algorithm, with inputs fed forward and estimated errors moving backward (Taneja & Arora, 2019).

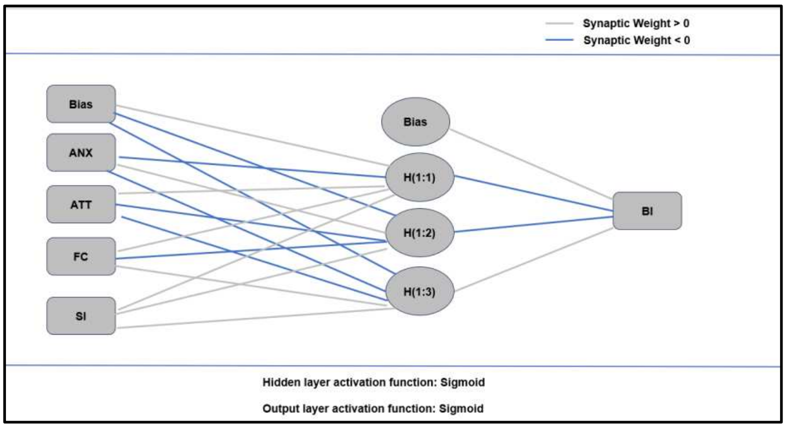

Figure 3: Artificial Neural Network Diagram

A 10-fold cross-validation technique was employed to mitigate overfitting, leading to the computation of the squared sum of errors (SSE) and the root mean square error (RMSE) (Ooi & Tan, 2016). Hyndman and Koehler (2006) proposed that reliability may be assessed by RMSE, a scale-dependent measure of predictive accuracy that evaluates particular datasets to quantify errors. The minimum value for RMSE is zero, but there is no specified maximum value for the statistic. Faasolo and Sumarliah (2022) assert that a reduced RMSE value signifies a more precise model. The RMSE results for the ANN analysis conducted in this study are presented in Table 7.

Table 7: Root Mean Square of Errors (RMSE) Results

Neural Network	*TRAINING*			*TESTING*			*Total n*
	n	*SSE*	*RMSE*	*n*	*SSE*	*RMSE*	
NN1	*453*	*4.107*	*0.095*	*52*	*0.380*	*0.085*	*505*
NN2	*456*	*4.432*	*0.099*	*49*	*0.384*	*0.089*	*505*
NN3	*445*	*4.012*	*0.095*	*60*	*0.571*	*0.098*	*505*
NN4	*453*	*4.340*	*0.098*	*52*	*0.419*	*0.090*	*505*

NN5	*447*	*4.027*	*0.095*	*58*	*0.689*	*0.109*	*505*
NN6	*463*	*5.369*	*0.108*	*42*	*0.273*	*0.081*	*505*
NN7	*455*	*4.122*	*0.095*	*50*	*0.412*	*0.091*	*505*
NN8	*447*	*4.424*	*0.099*	*58*	*0.386*	*0.082*	*505*
NN9	*461*	*4.256*	*0.096*	*44*	*0.276*	*0.079*	*505*
NN10	*446*	*4.315*	*0.098*	*59*	*0.573*	*0.099*	*505*
Mean		*4.340*	*0.098*		*0.436*	*0.090*	
Std Dev		*0.373*	*0.004*		*0.127*	*0.009*	

Table 7 reveals minimal RMSE values for training and testing methods, indicating acceptable model fitness and accurate linear and nonlinear relationship identification. Sensitivity analysis was conducted to measure the predictive power of each input neuron, highlighting the importance of each independent variable, while the significance of each independent variable indicated how much the value projected by the network structure differed, with different independent variable values (Leong *et al.,* 2020). Table 8 presents the sensitivity analysis findings.

Table 8: Sensitivity Analysis Results

Neural Network	*ANX*	*ATT*	*SI*	*FC*
Neural Network 1 (NN1)	*0.230*	*0.527*	*0.546*	*1.000*
Neural Network 2 (NN2)	*0.308*	*0.488*	*0.789*	*1.000*
Neural Network 3 (NN3)	*0.267*	*0.542*	*0.887*	*1.000*
Neural Network 4 (NN4)	*0.281*	*0.558*	*0.675*	*1.000*
Neural Network 5 (NN5)	*0.254*	*0.444*	*0.655*	*1.000*
Neural Network 6 (NN6)	*0.077*	*0.682*	*1.000*	*0.999*
Neural Network 7 (NN7)	*0.285*	*0.371*	*0.593*	*1.000*
Neural Network 8 (NN8)	*0.275*	*0.497*	*0.836*	*1.000*
Neural Network 9 (NN9)	*0.366*	*0.408*	*0.749*	*1.000*
Neural Network 10 (NN10)	*0.321*	*0.370*	*1.000*	*0.975*
Average Importance	*0.266*	*0.489*	*0.773*	*0.997*

Normalised Importance (%)	*27%*	*49%*	*78%*	*100%*

The results outlined in Table 8, show that FC (with normalised importance of 100%) is the most important predictor of behavioural intention to adopt blockchain technology among the cohort of entrepreneurial financiers. This is followed by SI (78%), ATT (49%) and lastly, ANX (27%), implying that amongst the cohort of entrepreneurial financiers ANX is the least important determinant of blockchain adoption.

Conclusively, the results from the ANN align with those of the PLS-SEM analysis based on the f2 values outlined in Table 6. This finding reinforces the notion that in the context of blockchain technology adoption for entrepreneurial financing in South Africa, the key determinant is facilitating conditions, followed by social influence, attitude of entrepreneurial financing firms employees, and technological anxiety is the least aspect to consider.

A. Discussion of Results

The study found that facilitating conditions, social influence, anxiety, and attitude are the main factors driving blockchain adoption for entrepreneurial financing, while variables like effort expectancy, performance expectancy, and self-efficacy have no significant relationship. The study reveals a positive correlation between FC and BI, suggesting that facilitating conditions enhance the adoption of blockchain technology by entrepreneurial financiers. This aligns with previous research by Yusof et al. (2018), Wong et al. (2020), and Teo et al. (2015), which emphasizes the importance of sufficient organizational and technical infrastructure. Employees of entrepreneurial financing firms are more likely to adopt blockchain technology when they perceive robust support structures, including sufficient infrastructure and technical assistance. These conditions reduce adoption obstacles by providing essential resources and assistance. The study reveals that SI positively influences the decision-making process for blockchain technology adoption in entrepreneurial financing firms. This is consistent with Walrave et al. (2020) findings that influential individuals, such as friends, family, and colleagues, positively affect individuals' technology adoption decisions. Employees of entrepreneurial financing firms are more likely to embrace blockchain technology if they believe their peers, mentors, or influential individuals support and actively use it. This highlights the importance of social networks and community support in promoting technology acceptance, with endorsements and positive reviews from influential individuals potentially influencing blockchain adoption.

The study found a negative and statistically insignificant relationship between EE and BI among the sampled entrepreneurial financing firms. It suggests that the perceived ease or complexity of using blockchain technology does not influence its adoption. The study suggests that entrepreneurial financing firms may prioritize rewards or external influences over the effort required to execute blockchain technology. This contradicts previous studies by Fitrianie et al. (2021) and Zhu et al. (2022), which found a positive correlation between effort expectancy and technology adoption.

The study reveals a positive relationship between PE and BI, suggesting that while employees of entrepreneurial financing firms may have optimistic expectations about blockchain technology's advantages, these expectations alone do not significantly influence the adoption of blockchain technology. This contradicts previous research by Martins et al. (2014) and Kabra et al. (2017), which found that PE positively influences the intention to adopt a technology. The study suggests that context is crucial in entrepreneurial financing studies, as the results may not be significant enough to persuade firms to adopt blockchain technology. The study found a positive and statistically insignificant relationship between SE and BI among entrepreneurial financiers in South Africa. This suggests that while SE in using blockchain technology can be beneficial, it may not be the determining factor in adopting the technology. This contradicts San-Martín et al.'s (2020) findings, which found that SE positively affects cognitive and affective aspects of technology acceptance.

The study found a negative relationship between ANX and BI, suggesting an inverse relationship between anxiety and adoption of blockchain technology for entrepreneurial financing. Employees of entrepreneurial financing firms who are concerned about the complexity, safety, or potential drawbacks of blockchain are less likely to adopt it. This highlights the need to address and reduce concerns about blockchain technology to promote its wider acceptance in the entrepreneurial financing domain. This aligns with Faqih (2022) study, which found that anxiety negatively impacts the intention to adopt new technology.

The study found a positive correlation between ATT and BI, suggesting that employees of entrepreneurial financing firms with a positive attitude towards blockchain are more likely to use it for financing, emphasizing the importance of positive perception in technology adoption.

ISSN: 2597-4785 (ONLINE)
ISSN: 2597-4750 (PRINTED)

B. Contribution of the Study

The study's significant theoretical contribution is the acknowledgement that facilitating conditions and social influence are essential factors of blockchain technology adoption. The study's findings underscore the significance of external support systems and social networks in the adoption process, suggesting that adequate resources and a supportive social environment can influence entrepreneurial decisions regarding the utilisation of blockchain technology for financing ventures. The study offers valuable insights for entrepreneurs considering blockchain technology for financing. It suggests prioritizing the development of robust support systems and infrastructure, including specialized training, reliable technology assets, and a supportive network of peers. To fully utilize social influence, firms should actively participate in industry communities and networks to promote a positive view of blockchain technology, facilitating its adoption and seamless integration into business operations. The study emphasizes the importance of addressing psychological and perceptual barriers to blockchain adoption in entrepreneurial financing firms. It suggests that firms should organize educational workshops, provide practical training, and provide clear information about the benefits and drawbacks of blockchain technology. This approach can increase the adoption rate by fostering a positive attitude and reducing resistance, ultimately boosting users' confidence and proficiency, thereby facilitating the seamless integration of blockchain technology into entrepreneurial financing practices.

C. Limitations and Areas for Future Research

This research is limited as it was conducted in a Southern African nation, rendering the findings unsuitable for generalisation and application to other countries, such as those in the West. Consequently, future studies may adopt a cross-national or cross-cultural approach to broaden the scope of the present study. Secondly, the study employed a cross-sectional methodology that recorded respondents' answers at a single moment in time. Consequently, future research may consider employing a longitudinal strategy to investigate the proposed interactions. This study focused on the developing South African economy, hence restricting the applicability of the findings to other economies. We propose that future research should conduct a comparative study on the determinants of blockchain technology adoption for entrepreneurial financing across developed and developing economies to enhance understanding of the impact of national development status on financial technology.

IV. CONCLUSION

The study concluded that four factors, facilitating conditions, social influence, anxiety, and attitude—are the principal variables that promote the adoption of blockchain technology for entrepreneurial finance. These characteristics underscore the importance of a supportive environment, peer influence, and emotions in influencing the decisions of employees in entrepreneurial finance organisations concerning the adoption of blockchain technology for entrepreneurial financing. The study also revealed no statistically significant correlation between the independent variables of effort expectancy, performance expectancy, and self-efficacy, and the dependent variable of blockchain technology adoption. The significance of contextual and social factors surpasses that of elements such as perceived ease of use, expected benefits, and personal confidence in utilising the technology. These findings urge governments and stakeholders to concentrate on enhancing conditions, social influence, fear, and attitudes to promote the broader adoption of blockchain technology in entrepreneurial finance.

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