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A PLS-SEM Neural Network Approach for Understanding Cryptocurrency Adoption

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ABSTRACT The majority of previous research on new technology acceptance has been conducted with single-step Structural Equation Modeling (SEM) based methods. The primary purpose of the study is to enhance the new technology acceptance based research with the Artificial Neural Network (ANN) method to enable more precise and in-depth research results as compared to the single-step SEM method. This study measures the relation between technology readiness dimension (optimism, innovativeness, discomfort, insecurity) and the technology acceptance (perceived ease of use and perceived usefulness) – and the intention to use cryptocurrency, such as bitcoin. The contribution of this study include the use of a multi-analytical approach by combining Partial Least Squares- Structural Equation Modeling (PLS-SEM) and Artificial Neural Network (ANN) analysis. First, PLS-SEM was applied to assess which factor has significant influence toward intention to use cryptocurrency. Second, an ANN was employed to rank the relative influence of the significant predictor variables attained from the PLS-SEM. The findings of the two-step PLS-SEM and ANN approach confirm that the use of ANN further verifies the results obtained by the PLS-SEM analysis. Also, ANN is capable of modelling complex linear and non-linear relationships with high predictive accuracy compared to SEM methods. Also, an Importance-Performance Map Analysis (IPMA) of the PLS-SEM results provides a more specific understanding of each factor's importance-performance.

INDEX TERMS Bitcoin, cryptocurrency, neural network, PLS-SEM, technology readiness.

I. INTRODUCTION

Cryptocurrencies such as bitcoin and Blockchain technology have gained significant attention in recent decade. It had been anticipated that cryptocurrencies would have a disruptive effect on financial systems [1]. Even though there has been an increase in not only the economic implications of cryptocurrencies and degree of interest in this, academic studies on blockchain-based cryptocurrencies have only recently surfaced [2]–[11]. The important issues concerning cryptocurrency economics and investment decision-making are related to the pricing mechanism. However, the use of cryptocurrencies is rather limited.

It was generally believed that bitcoin might eventually become a mainstream currency when there was an increase in consumer demand. Much has been written in the media about cryptocurrencies. However, there is scant scholarly research on technology readiness associated with digital money. Bitcoin reached a maximum price in December 2017 when it was valued at over USD$15,000 [12]. However, the value of bitcoin decreased since 2017, which damaged consumer enthusiasm. The questions that emerge are: *what led to this decline in the interest of individual consumers in cryptocurrency? And why didn't the consumer adoption of cryptocurrency continue?* This paper addresses the technology readiness factors which influence the acceptance of bitcoin.

Three factors that obstruct the use of bitcoin: i) inadequate infrastructure; ii) possible issues within the bitcoin network, and iii) being apprehensive of the unknown [13]. Technology can support complicated financial dealings as well as monetary transfers across borders. Previous research suggests that technology acceptance is impacted by an individual's personality and demographics [14], [15]. The technology readiness index (TRI) measures a consumer's readiness to accept

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new technology. TR is measured by evaluating the attitudes and perspectives of consumers regarding technology [15]. Such as, optimism and innovativeness have a positive impact, which are the motivators to technology adoption. Insecurity and discomfort suppress the use of new technology.

There exists many theoretical models that helps to understand individual behaviors towards using new technology [16]. However, TAM [17] is the most widely accepted model in explaining individual behavioral intention toward the technology usage [16], [18]. Furthermore, the use of personality traits factors such as TR is an important extension to TAM toward new technology acceptance [16], [18]–[20]. Therefore, this research investigates the integration of TR personality trait dimensions (discomfort, innovativeness, optimism, and insecurity) and TAM (perceived ease of use perceived usefulness) to examine their impact on intention to use cryptocurrency such as bitcoin.

Therefore, this study adopted the TRAM (TRI and TAM) model [16], [18], [19] to predict the use intention of cryptocurrency such as Bitcoin. However, majority of the previous research findings on TAM and TR has been reported using structural equation modelling (SEM) method (e.g. linear relations between constructs). So, the primary aim of this paper is therefore to enrich the new technology acceptance based research with the help of two-step approach, which is Partial Least Squares- Structural Equation Modeling (PLS-SEM) and Artificial Neural Network (ANN) analysis. ANN is capable of modelling complex linear and non-linear relationships with high predictive accuracy compared to SEM methods [21]–[23]. In addition, according to Henseler *et al.* [24] and Hair *et al.* [25], PLS-SEM performs better than covariance-based (CB) SEM in finding the true model. Therefore, the study employs a multi-analytical approach by combining Partial Least Squares- Structural Equation Modeling (PLS-SEM) and ANN analysis.

The paper is organized as follows. Section 2 presents the theoretical background of cryptocurrency and technology readiness. In section 3, we discuss hypotheses development. Following this, in section 4, we describe our research methodology. Section 5 presents the results of this study. Section 6 discusses the findings and implications of the study. Finally, this study concludes with the limitations and future directions for research.

II. RELATED STUDIES AND THEORETICAL BACKGROUND

A. BLOCKCHAIN AND CRYPTOCURRENCIES

A blockchain is a shared database that enables users to perform transactions of valuable assets within a public and pseudonymous system without depending on a mediator or central body [26], [27]. There are three generations of blockchain technology development: Blockchain 1.0, 2.0 and 3.0 named as digital currency, digital economy and digital society, respectively [28].

Cryptocurrency is the most commonly used operational blockchain mechanism. The most commonly used type of cryptocurrency is bitcoin. Bitcoin was developed in 2008 by an unknown group called Satoshi Nakamoto and was referred to as "the people's currency". Bitcoin relies on blockchain technology. Bitcoin is an electronic, peer-to-peer cash system that has been developed as an alternative payment mechanism, autonomous of central banks, governments and other aspects of the conventional monetary system. A public-private key system is used for data encryption. As with any peer-to-peer mechanism, its value shows network externality. This means that the more individuals utilizing the system, the greater the value of the system for each user [29]. Consequently, the worth of bitcoin is determined by its transaction ability which is a result of public acceptance [9]. The technology acceptance model [17], [30] states that an individual's intention to use is determined by how they view technology, and this is determined by external conditions, for example, social norms and information availability.

From the years, the researchers are focused on the technological and economic features of bitcoin, such as the verification of transactions as discussed in [9], [31], and the consumers also have concerns about privacy issues in addition to above-discussed features of bitcoin. In the light of above discussions, the researchers are now focusing their attention on user adoption. For example, Tsanidis *et al.* [32] examined Greek consumers' awareness of bitcoin, its use and their degree of trust, finding that prospective users were not familiar with the information on bitcoin, for example, its usefulness, ease of use and other potential advantages. Bohr and Bahir [33] conducted an online survey in 2013 and found that the average user is aged 32.1 years. They also found that that anonymity (approximately 8% of the sample), inadequate trust in the banking system (approximately 10% of the sample) and freedom (approximately 16% of the sample). Silinskyte [25] studied individual bitcoin usage behaviour based on the Unified Theory of Acceptance and the Use of Technology (UTAUT) model [30]. The survey found that the factors that had an impact on bitcoin usage included effort and performance expectancy, and behavioural intention [34].

B. TAM

Technology Acceptance Model (TAM) [17] is the most widely accepted model to predict technology adoption. TAM states that perceived ease of use (PEOU) and perceived usefulness (PU) have an influential effect on the acceptance and actual use of the technology.

Previous researchers have acknowledged the robustness of TAM and extended the framework with external factors significant to technology use [35]. However, the TAM was initially developed to predict technology acceptance in work environments, researchers such as [16], [18], [19], [36] extended TAM by integrating individual-specific constructs of TR.

C. TECHNOLOGY READINESS (TR)

Addressing cryptocurrency adoption concerns such as user trust and privacy issues should lead to mature user adoption.

Cryptocurrencies have not yet gained mainstream user adoption, being considered a fairly recent innovation. According to McDougall [37], cryptocurrency is still in its initial phase of adoption. As cryptocurrencies are highly innovative and technology-intensive, technology readiness theory is appropriate to investigate cryptocurrency user adoption.

Technology readiness (TR) refers to an individual's overall state of mind in terms of technology belief and attitude. The Technology Readiness Index (TRI) scale formulated by Parasuraman [15] determines the extent to which an individual is ready to adopt the technology. Previous studies on the individual use of new technologies suggest that consumers' beliefs, perceptions, feelings, and motivation can simultaneously be favorable (drivers) as well as unfavorable (inhibitors) in terms of high-tech products and services. Customers with extremely positive attitudes regarding technology show greater acceptance of technological products and services. In contrast, consumers with extremely negative attitudes towards technology are hesitant to adopt technology-related services or products.

Parasuraman and Colby [38] segregate technology adoption into four different extents: innovativeness, optimism, discomfort and insecurity. Two aspects, innovativeness and optimism have a positive impact on technology readiness, making individuals more inclined to use new technology. Other two aspects discomfort and insecurity impede in the way of technology readiness, deferring or restricting new technology endorsement. Lam *et al.* [14] assert that these four aspects of TRI have a significant impact on technology acceptance, hence each should be considered as a predictor of adopting technology-based services or products. The study carried out by Lin *et al.* [16] that concentrated on technology embracement by linking online services to the customers. There is an intuitive correlation between the factors relevant for the technology acceptance model and technology readiness [39], [40] [41]. Ratchford and Barnhart [39] argue that TRI influence various cognitive and affective constructs (for example, anxiety, fun, enjoyment, confusion and frustration) related to technology adoption.

III. HYPOTHESES DEVELOPMENT

Parasuraman and Colby [38] developed TRI 2.0, which is a robust predictor to measure actual and technology related behavioral intentions. The TRI model provides a theoretical foundation to determine the motivators and inhibitors of new technology acceptance. In this study, the effect of TR (such as optimism, innovativeness, discomfort, and insecurity) on TAM (perceived ease of use perceived usefulness) are examined. The adapted TRAM (TRI and TAM) is used to predict the use intention of cryptocurrency such as Bitcoin. The TR and TAM integration has been studied by researchers such as [16], [18], [19], [36], [42]. Figure 1 illustrates the research model.

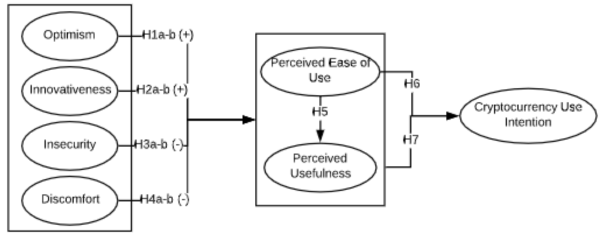

FIGURE 1. Research model.

Optimism imitates an affirmative perspective of technology that motivates and recommended the technology adoption which leads to productivity and flexibility [15]. Those with a high level of optimism perceive the use of technology is very easy, and unlike to focus on any negative consequences [19]. According to Walczuch *et al.* [19] optimists fearless about negative outcomes. Therefore, optimism has a positive effect on both the ease of use (PEOU) and perceived usefulness (PU) of a given technology [36], [42], [43]. Therefore, optimists have more positive attitudes towards technology use, so it is assumed that an optimist perceives the adoption of cryptocurrency as easy to use and useful.

H1a: Optimism is positivity related to perceived ease of use toward use intention of cryptocurrency such as bitcoin.

H1b: Optimism is positivity related to perceived usefulness toward use intention of cryptocurrency such as bitcoin.

Innovativeness reflects the tendency of the user to become a pioneer in the technological domain [15]. Innovative adopters are risk-takers and enjoy trying new things [44]. Karahanna *et al.* [45] revealed that innovative individuals beliefs about technology adoption are less arduous and more innovative individuals are the prime embracers of technology. Previous researches have also reported a positive influence of innovativeness on both PU and PEOU [19], [36], [42], [43].

H2a: Innovativeness is positively related to perceived ease of use toward use intention of cryptocurrency such as bitcoin.

H2b: Innovativeness is positivity related to perceived usefulness toward use intention of cryptocurrency such as bitcoin.

Discomfort reflects a feeling of being overwhelmed by technology and a perceived lack of control over technology [15], [38]. Individuals who experience a high degree of discomfort regarding new technologies usually find it difficult to use technology [19]. Similarly, discomfort leads to difficulties in accepting new technologies [15], [46] and indicates the apprehensions and concerns of users when using technology-related services or products. Therefore, discomfort harms PU and PEOU of a given technology [19], [36], [42], [43].

H3a: Discomfort is negatively related to perceived ease of use toward use intention of cryptocurrency such as bitcoin.

H3b: Discomfort is negatively related to perceived usefulness use intention of cryptocurrency such as bitcoin.

Insecurity in terms of technology refers to uncertainty and a lack of trust related to security and privacy [38], [46], [47]. According to Son and Han [40], insecurity is considered to be an inhibitor of technology readiness. It is likely that insecure users will be uncertain about new technology and may not be willing to make an effort to determine whether or not it is beneficial to them. Therefore, insecurity has a negative effect on PU and PEOU [19], [36], [42], [43].

H4a: Insecurity is negatively related to perceived ease of use toward use intention of cryptocurrency such as bitcoin.

H4b: Insecurity is negatively related to perceived usefulness toward use intention of cryptocurrency such as bitcoin.

Finally, Research has proposed that ease of use effects usefulness of a given technology [17]. Furthermore, extensive research has suggested the significant effect of ease of use and perceived usefulness on usage intention [18], [30], [42], [48]. Therefore, it is proposed

H5: Perceived ease of use is positively related to perceived usefulness toward use intention of cryptocurrency such as bitcoin.

H6: Perceived ease of use is positively related to use intention of cryptocurrency such as bitcoin.

H7: Perceived usefulness is positively related to use intention of cryptocurrency such as bitcoin.

IV. RESEARCH METHODOLOGY

In this study, a multi analytical methodology is employed by integrating Partial Least Squares Structural Equation Modelling (PLS-ESM) with a most significant artificial intelligence technique named as Artificial Neural Network (ANN) [49]. The analysis is performed in two phases. First phase is related to PS-SEM, which is further divided in two steps named as measurement model validation and structural model hypotheses testing. Henseler *et al.* [50] stated: "In research settings with predictive scope, weak theory, and no need for an understanding of underlying relationships, artificial neural networks (ANN) may be useful".

In the second phase, ANN is applied to examine the complement and verify the PLS-SEM analysis and measure the effectiveness of independent factors on the dependent factor. The two methods are explained in detail in section 5. Our research method is aligned with previous research such as [21], [22], [51], [52].

A data collection survey was conducted in Australia in 2019. We contacted graduate and undergraduate students and staff at the University of Technology Sydney. A Likert scale based closed-ended questionnaire is prepared to collect the responses. (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree and (5) Strongly Agree. The reliability and validity of measurement scales are ensured by modifying previously utilized instruments to ensure survey validity. Appendix A details all the items used in the study. TRI is adopted and modified from [38]. TAM (perceived ease of use and perceived usefulness) is modified from [19].

V. DATA ANALYSIS AND RESULTS

A total of 160 participants, 56% males and 44% females, completed the survey. The incomplete responses were removed out, and 140 are utilized for further analysis. All the participants are well aware of blockchain technology and cryptocurrencies. Variance based statistical analysis model called Partial Least Square (PLS) Structural Equation Model (SEM) is utilized to test the hypotheses using Smart-PLS V3.2 [53]. An effective overview of variance and covariance-based SEM (CB-SEM) is provided by [54].

In business information systems research, PLS-SEM is a preferable approach to analyse statistical data due to several reasons, i.e. small sample size, does not involve normality, able to work without distributional assumptions with nominal, ordinal and interval-scaled factors [55], [56]. Henseler et al. [24] reviewed the work of Rönkkö and Evermann [57] and showed that PLS-SEM performs better than CB-SEM in finding the true model.

Furthermore, Hair *et al.* [25] emphasized that PLS-SEM is significantly better than CB-SEM in explaining variance in the dependent factor indicators. Besides, either we are working with reflective or formative measurement model, PLS has the advantage to examine data with no bias from composite model [58]. However, according to Kock [59], Variance Inflation Factor (VIFs) are the indicators to test the biases in data. The threshold value is 3.3 for a full collinearity test. If the results are less than equal to threshold, then the model is unbiased. In our research model, all VIFs are lower than 3.3, indicating no bias in the data.

Moreover, Henseler and Sarstedt [60] showed that model fit indices such as goodness-of-fit (GoF) and the relative goodness-of-fit index are not appropriate for model validation in the PLS approach. PLS-SEM is now a well-established method in information systems research [61], [62] Therefore, variance-based SEM (also called component-based SEM) is appropriate for this study. In our research model, all factors were modelled as reflective indicators.

A. MEASUREMENT MODEL

The measurement model includes two assessments of validity and reliability, which are measured by investigating internal consistencies, convergent and discriminant validity [63]. Cronbach's reliability and internal consistencies with composite reliability for each latent factor exceed the recommended value of 0.70. Figure 2 shows that the loading of all items for each reflective construct exceeded the value of 0.7 and was significant (p-value < 0.05).

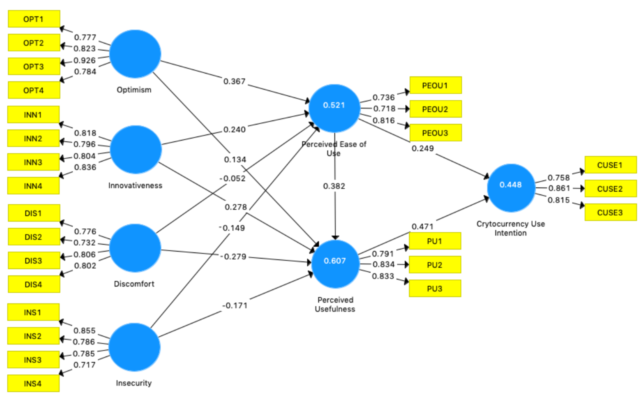

FIGURE 2. Structural model results.

TABLE 1. Reliability and validity assessment.

	AVE	CR	C-alpha
OPT	0.67	0.88	0.80
INN	0.66	0.87	0.81
DIS	0.58	0.82	0.77
INS	0.64	0.85	0.76
PEOU	0.68	0.86	0.75
PU	0.69	0.84	0.73
CUSE	0.68	0.82	0.77

Notes: Average Variance Extracted (AVE), Composite Reliability (CR), C-Alpha, Optimism (OPT), Innovativeness (INN), Discomfort (DIS), Insecurity (INS), Cryptocurrency Use Intention (CUSE)

TABLE 2. Discriminant validity- HTMT.

	OPT	INN	DIS	INS	PEOU	PU	CUSE
OPT	-						
INN	0.59	-					
DIS	0.53	0.51	-				
INS	0.52	0.59	0.63	-			
PEOU	0.75	0.68	0.72	0.61	-		
PU	0.71	0.70	0.71	0.65	0.69	-	
CUSE	0.73	0.71	0.70	0.71	0.65	0.67	-

Notes: All correlation coefficients are at level 0.05 and significant.

Table 1 and 2 show the measurement model assessment results. The AVE of all variable values exceeds the recommended value of 0.50. Hair [61] recommended that not to rely on cross-loadings for discriminant validity but instead rely on the Heterotrait-monotrait (HTMT) criteria developed by Henseler et al. [64]. HTMT achieve better discriminant validity results as compared to the cross-loading in PLS-SEM [64]. Table 2 shows all HTMT values are below the recommended value of 0.85 [64].

B. STRUCTURAL MODEL

The path coefficients significance was assessed by applying T-test which was computed using the bootstrapping technique and the significance level was 5%. Bootstrapping is a non-parametric method to test the coefficients i.e. path coefficients, outer factor weights by assessing the standard error for estimation. SmartPLS V3.2 is utilized to execute both inner and outer model to specify the t-value for significance. The threshold values for significance level 10%, 5% and 1% are 1.65, 1.96 and 2.58 respectively.

The structural model is assessed by the path coefficients significance and the R square (R^2) variance of the dependent construct. Figure 2 shows the structural model results. The results of the R^2 indicate that 52% (PU), 60% (PEOU) and 44% of the variance is the cryptocurrency use intention (CUSE). The result of the R^2 shows a satisfactory level of explanation.

Figure 2 and Table 3 shows the hypotheses testing. The findings show that optimism and innovativeness significantly and positively influence perceived ease of use and perceived usefulness. Furthermore, discomfort and insecurity negatively influence the perceived ease of use and perceived usefulness. In addition, perceived ease of use and perceived usefulness positively affect cryptocurrency use intention.

TABLE 3. Structural model testing.

	Path	Path Values	St. Dev	t-value	p-value	Findings
H1a	OPT → PEOU	0.36	0.04	5.26	0.000**	+ve and significant
H1b	OPT → PU	0.13	0.05	2.16	0.002**	+ve and significant
H2a	INN → PEOU	0.24	0.04	2.91	0.000**	+ve and significant
H2b	INN → PU	0.27	0.03	3.21	0.000**	+ve and significant
H3a	DIS → PEOU	-0.05	0.07	2.19	0.020*	-ve but significant
H3b	DIS → PU	-0.27	0.09	1.98	0.050*	-ve but significant
H4a	INS → PEOU	-0.14	0.09	1.99	0.030*	-ve but significant
H4b	INS → PU	-0.17	0.08	1.99	0.040*	-ve but significant
H5	PEOU → PU	0.38	0.03	3.56	0.000*	+ve and significant
H6	PEOU → CUSE	0.24	0.04	3.11	0.000*	+ve and significant
H7	PU → CUSE	0.47	0.04	3.96	0.000*	+ve and significant

Innovativeness (INN), Optimism (PPT), Insecurity (INS), Discomfort (DIS), Cryptocurrency Use (CUSE). **Significant at the 0.05 Level, *Significant at the 0.001 Level.

To measure the cross-validated redundancy, which assesses the predictive relevance: Q^2 Stone-Geisser criterion is investigated using blindfolding method [50]. Q^2 values (i.e. intention to use cryptocurrency = 0.308) is above the threshold value of zero, hence representing a strong predictive relevance. Furthermore, to demonstrate the predictive relevance, the PLSpredict algorithm is used to predict the PLS model's performance for the Manifest Variables (MV) and the Latent Variables (LV) [65], [66]. The PLSpredict algorithms involve cross-validated case-wise and average-case point predictions; Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The PLSpredict rests on the k-fold cross-validation principle, which is also useful for the holdout sample validation [65]. The analysis uses the ten number of folds ($k = 10$) and ten repetitions ($r = 10$) to perform the PLSpredict estimation. The prediction error is the RMSE, averaged over all k folds [67]. PLSpredict offers two naïve benchmarks 1) linear model (LM) predictions and 2) mean value Q^2 to measure the predictive quality of the PLS path model estimations. Table 4 summarises the PLSpredict performance of the latent variable (intention to use cryptocurrency) and its manifest variables (three items).

The lower values of PLS-SEM compared to the simple linear model (LM) values indicate higher predictive power. Q^2 values are also greater than zero. This shows the PLS-based prediction yields more accurate out-of-sample

TABLE 4. PLS Predict results.

	RMSE		MAE		MAPE		Q^2	
	LM	PLS-SEM	LM	PLS-SEM	LM	PLS-SEM	LM	PLS-SEM
CUSE1	1.55	1.34	1.24	1.04	45.30	35.17	0.08	0.21
CUSE2	1.67	1.55	1.43	1.32	65.44	63.91	0.09	0.18
CUSE3	1.54	1.35	1.15	1.06	43.49	41.22	0.11	0.25
Intention to use		0.572	-	0.439	-	-	-	0.308

Notes: CUSE1-3: Cryptocurrency Use indicators. PLS-SEM < Linear Model (LM); $Q^2 > 0$; Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE); See Appendix for all items.

predictions (i.e., smaller predictions errors) for all indicators. All PLS-SEM methods achieve somewhat better results than multiple linear regression (Cryptocurrency Use RMSE 0.581 for PLS). However, even better prediction could be achieved with larger samples [67].

C. ANN ANALYSIS

As discussed in the methodology section, Artificial Neural Network analysis is used in the second phase of the analysis. Significant hypothesized predictors are utilized as inputs to ANN to emphasize the relevant importance of each predictor's variable. The relationship (linear or nonlinear) between the predictor and adoption decision variables can also be examined with ANN [68], [69]. Also, ANN produces more precise predictions compared to the SEM approaches [68], [69]. SEM analysis could lead to an oversimplification of the complexities of the decision-making process [49], [68], [69]. On the other hand, the ANN method is not recommended for testing hypotheses involving causal relationships [68], [70]. However, ANN provides a higher prediction accuracy than SEM. Therefore, the use of the PLS-SEM–ANN method in this study would complement each other.

In this research, a Multilayer Perceptron (MLP) back propagation feedforward method is adopted. The MLP is the most commonly used and popular ANN method [21], [49]. The ANN analysis comprises three layers: the input layer, the hidden layer, and the output layer. In our research model, MLP- ANN is modelled using SPSS v22. The PLS-SEM model is decomposed into three ANN models with one output variable. Model 1 (Output - PEOU) and has four inputs Optimism, Innovativeness, Discomfort and Insecurity. Model 2 (Output - PU) has five inputs perceived ease of use, Optimism, Innovativeness, Discomfort and Insecurity. Model 3 (Output - Cryptocurrency Use Intention) has two inputs perceived ease of use and perceived usefulness. The ANN model-1 is shown in Figure 3. Following recommendations are given by [21], [51], [68], the hidden neurons (nodes) are automatically generated and activation function (Sigmoid Function) is utilized for both hidden and output layers. Furthermore, based on the recommendations

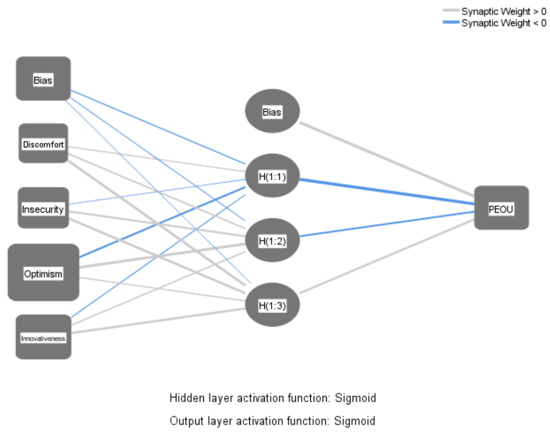

FIGURE 3. ANN model-1.

from the above authors, the prediction accuracy of the trained network is measured using ten-fold cross-validation. To avoid overfitting problem data is divided into two parts, from which 90% for training and 10% for testing [23], [49], [51].

The prediction accuracy of the ANN model was computed by the root mean square error for both the training (90%) and testing (10%) data sets (ten runs) [21]. The RMSE is calculated using equation 1 and 2 [22], where SSE is the sum of squared error, and MSE is the mean squared prediction error.

$$MSE = [1/n] \times SSE \tag{1}$$

$$RMSE = \sqrt{MSE} \tag{2}$$

As shown in Table 5 to 7, the RMSE values for the training data set and the testing data set to represent an accurate ANN model in taking the relationships between predictors and the output. According to [21], [22] lower RMSE values represent higher predictive accuracy and better data fit.

TABLE 5. RMSE values for the ANN model-1.

Input: Optimism, Innovativeness, Discomfort, Insecurity
Output: Perceived ease of use (PEOU)

Neural Network	Training (90% of data sample 140); N= 126		Testing (10% of data sample 140); N=14	
	SSE	**RMSE**	**SSE**	**RMSE**
ANN1	0.1282	0.0319	0.1100	0.0886
ANN2	0.1240	0.0314	0.1070	0.0874
ANN3	0.1274	0.0318	0.1160	0.0910
ANN4	0.1318	0.0323	0.1290	0.0960
ANN5	0.1316	0.0323	0.1180	0.0918
ANN6	0.1120	0.0298	0.1070	0.0874
ANN7	0.1125	0.0299	0.1080	0.0878
ANN8	0.1129	0.0299	0.1190	0.0922
ANN9	0.1126	0.0299	0.1150	0.0906
ANN10	0.1128	0.0299	0.1180	0.0918
	Mean	0.0309	**Mean**	0.0905

Moreover, the relative importance of each input predictor (all three ANN models) was computed in terms of normalized relative importance ranking (expressed as a %) using sensitivity analysis [21] as presented in Table 8 to

TABLE 6. RMSE values for the ANN model-2.

Input: Optimism, Innovativeness, Discomfort, Insecurity Output: Perceived usefulness (PU)				
Neural Network	Training (90% of data sample 140); N= 126		Testing (10% of data sample 140); N=14	
	SSE	**RMSE**	**SSE**	**RMSE**
ANN1	0.1172	0.0305	0.1012	0.0850
ANN2	0.1142	0.0301	0.1072	0.0292
ANN3	0.1172	0.0305	0.1051	0.0289
ANN4	0.1113	0.0297	0.0913	0.0269
ANN5	0.1014	0.0284	0.0965	0.0277
ANN6	0.1002	0.0282	0.1138	0.0301
ANN7	0.1034	0.0286	0.1186	0.0307
ANN8	0.1025	0.0285	0.1132	0.0300
ANN9	0.1045	0.0288	0.1054	0.0289
ANN10	0.1069	0.0291	0.1476	0.0342
	Mean	0.0292	**Mean**	0.0352

TABLE 7. RMSE values for the ANN model-3.

Input: Optimism, Innovativeness, Discomfort, Insecurity Output: Intention to use Cryptocurrency (CUSE).				
Neural Network	Training (90% of data sample 140); N= 126		Testing (10% of data sample 140); N=14	
	SSE	**RMSE**	**SSE**	**RMSE**
ANN1	1.986	0.1078	0.138	0.0852
ANN2	1.970	0.1073	0.137	0.0849
ANN3	1.985	0.1077	0.138	0.0852
ANN4	1.989	0.1078	0.139	0.0855
ANN5	1.956	0.1070	0.135	0.0843
ANN6	1.992	0.1079	0.140	0.0858
ANN7	1.970	0.1073	0.137	0.0849
ANN8	1.964	0.1072	0.136	0.0846
ANN9	1.988	0.1078	0.139	0.0855
ANN10	1.986	0.1078	0.138	0.0852
	Mean	0.1076	**Mean**	0.0851

TABLE 8. Normalized variable relative importance (output: PEOU).

Predictors (Output: PEOU)	**Average relative importance**	**Normalized relative importance (%)**	**Ranking**
Optimism	0.400	100	1
Innovativeness	0.285	71.3	2
Discomfort	0.100	25.1	4
Insecurity	0.214	53.3	3

10 and Figure 4, 5 and 6. Based on the normalized variable importance, optimism is the most significant predictor of intention to use cryptocurrency, followed by innovativeness, while discomfort has a weaker influence followed by insecurity.

Table 11 to 12 compares the results of ANN (all three models) and the PLS-SEM based on the strength of path coefficients (PLS-SEM) and normalized relative importance (ANN) ranking. The comparison Table 11 (Output: PEOU-Perceived Ease of Use) show that optimism and innovativeness ranked one and two respectively both in ANN and PLS-SEM analysis. However, discomfort is ranked at number four in ANN and number three in PLS-SEM in terms of predictor's influence. Similarly, insecurity is ranked three

TABLE 9. Normalized variable relative importance (Output: PU).

Predictors (Output: PU)	**Average relative importance**	**Normalized relative importance (%)**	**Ranking**
Ease of Use	0.321	100	1
Optimism	0.242	75.5	2
Innovativeness	0.191	59.6	3
Discomfort	0.083	25.8	5
Insecurity	0.163	51.0	4

TABLE 10. Normalized variable relative importance (output: CUSE).

Predictors (Output: CUSE)	**Average relative importance**	**Normalized relative importance (%)**	**Ranking**
Ease of Use	0.486	94.4	2
Usefulness	0.514	100	1

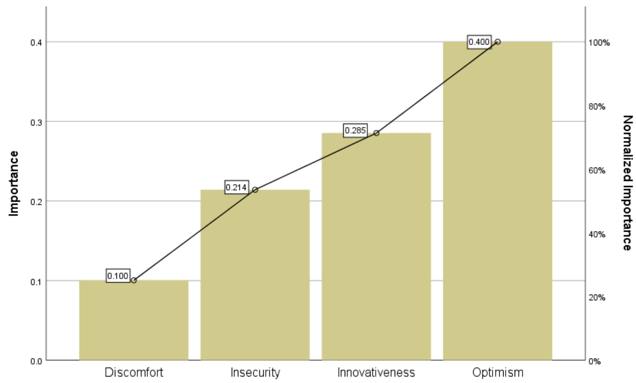

FIGURE 4. Normalized importance (Output variable: perceived ease of use).

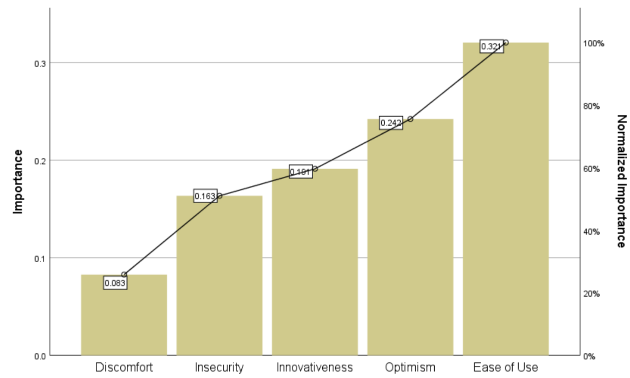

FIGURE 5. Normalized importance (Output variable: perceived usefulness).

in ANN and ranked four in PLS-SEM. The reason is that ANN measure both linear and non-linear relationship among variable with high predictive accuracy [21]–[23].

The comparison Table 12 (Output: PU-Perceived Usefulness) show that perceived ease of use, discomfort and insecurity are ranked similar both in ANN and PLS-SEM analysis. However, optimism is ranked higher than innovativeness in the ANN analysis. As discussed above, ANN measure both

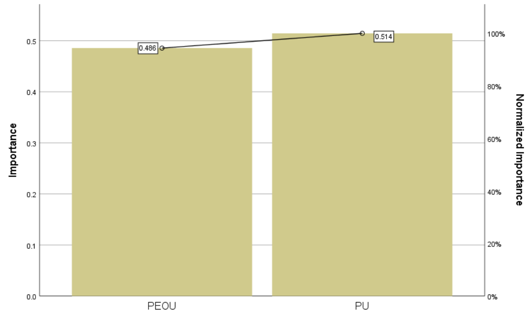

FIGURE 6. Normalized importance (Output variable: perceived usefulness).

TABLE 11. Comparison between PLS-SEM and ANN analysis (output: PEOU).

	Path mean	PLS-SEM Ranking	ANN-normalized relative importance (%)	ANN Ranking	Matched ?
OPT	0.36	1	100	1	Yes
INN	0.24	2	71.3	2	Yes
DIS	-0.05	3	25.1	4	No
INS	-0.14	4	53.3	3	No
Innovativeness (INN), Optimism (OPT), Insecurity (INS), Discomfort (DIS), Output variable PEOU: Perceived Ease of Use.					

TABLE 12. Comparison OF ANN and PLS- ANN analysis (output: PU).

	Path	PLS-SEM Ranking	ANN-normalized relative importance (%)	ANN Ranking	Matched ?
OPT	0.13	3	75.5	2	No
INN	0.27	2	59.6	3	No
DIS	-0.27	5	25.8	5	Yes
INS	-0.17	4	51.0	4	Yes
PEOU	0.38	1	100	1	Yes
Innovativeness (INN), Optimism (OPT), Insecurity (INS), Discomfort (DIS), PEOU: Perceived Ease of Use, Output variable PU: Perceived					

linear and non-linear relationship among variable with high predictive accuracy.

Finally, the comparison Table 13 (Output: CUSE-Cryptocurrency Use Intention) show that perceived usefulness and perceived ease of use are ranked one and two respectively both in ANN and PLS-SEM analysis.

VI. DISCUSSIONS – IMPLICATIONS - CONCLUSION

This papers extends the new technology acceptance-based research with ANN approach, which is traditionally based on SEM technique. The strength of each predictor input to the output (perceived ease of use, perceived usefulness and intention to cryptocurrency use) is ranked using ANN sensitivity analysis to confirm the PLS-SEM results. The findings of the ANN model generally verify the results obtained by SEM. However, there are some minimal variances, which is due to the higher prediction accuracy and non-linear nature of ANN

TABLE 13. Comparison between PLS-SEM and ANN analysis (output: CUSE).

	Path	PLS-SEM Ranking	ANN-normalized relative importance (%)	ANN Ranking	Matched ?
PEOU	0.24	2	94.4	2	Yes
PU	0.47	1	100	1	Yes
PEOU: Perceived Ease of Use, PU: Perceived Usefulness., Output variable, CUSE: Cryptocurrency Use Intention					

models. The two-step PLS-SEM and ANN method provided better in-depth results regarding the relative importance of the input factors, thus representing useful information regarding the new technology use.

The PL-SEM analysis shows that optimism has the strongest positive influence on perceived ease of use. ANN analysis confirms these findings, ranking optimism higher than innovativeness. The PLS-SEM results also show that discomfort has a negative influence perceived ease of use, followed by insecurity, but the ANN model predicts that insecurity has a higher impact than discomfort, which is by far the weakest predictor. The findings from both the PLS and ANN also showed perceived ease of use has the strongest influence on perceives usefulness. The PLS analysis shows innovativeness is ranked higher than optimism, but this is not the case in ANN. Optimism is ranked higher than innovativeness in the ANN analysis. Discomfort and insecurity are ranking are matched. Finally, both the PLS and the ANN analysis shows both perceived usefulness has a higher significant positive effect on cryptocurrency use intention than perceived ease of use.

This study has shown that technology readiness has a significant relationship with user adoption of cryptocurrency such as bitcoin. This study confirms that technology readiness has a significant relationship with technology acceptance (perceived ease of use and perceived usefulness). This shows that optimists and innovative peopl are more willing to try new things and have a more positive attitude towards new technology use such as cryptocurrency adoption and use. However, the two other dimensions of technology readiness (discomfort and insecurity) suggesting that greater complexity in using a technology-related product or service leads to uncertainties and difficulties in accepting new technologies.

Given that Parasuraman and Colby [38] demonstrated that TRI is a robust predictor of technology-related behavioural intentions as well as actual behaviours, the findings obtained in this study are consistent with the hypotheses. According to these authors, the dimensions optimism and innovativeness act as motivators,making individuals more inclined to use new technology; however, insecurity and discomfort act as inhibitors to acceptance and adoption of a given technology.

To extend the PLS-SEM analysis, we also performed Importance-Performance Map Analysis (IPMA) to report additional findings and conclusions for managerial

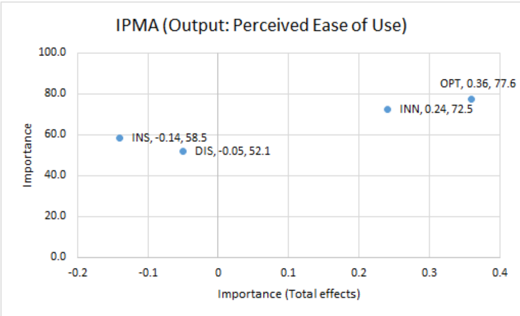

FIGURE 7. **Importance-performance map analysis (Output: PEOU).**

actions [71]. The IPMA results are drawn on two dimensions (i.e., performance and importance), which is specifically important in order to prioritize managerial actions [72], [73]. Performance is measured on a scale from 0 to 100. Undertaking an IPMA in our PLS path model includes determining a target construct, such as percieved ease of use.

Figure 7 shows optimism is highly relevant for increasing perceived ease of use due to its strong influence. However, this factor already has a high effect (importance). Hence, there is somewhat minimal potential for a further increase. The situation is similar with the performance of the innovativeness factor, although the overall effects are significantly lower than optimism. The ANN ranking normalized relative importance) also confirms optimism is the most significant predictor of perceived ease of us, followed by innovativeness. Managerial efforts should be directed at maintaining or expanding the optimism and innovativeness performance level. Similarly, Figure 7 shows that discomfort followed by insecurity is of less importance in relation to increasing perceived ease of use, as they have a relatively low influence. However, the ANN ranking placed discomfort lower than insecurity. Therefore, managerial actions should specifically consider addressing feelings of discomfort and insecurity to enhance perceived ease of use towards cryptocurrency use. Table 14 summarises the relative importance of the four predictors (optimism, innovativeness, discomfort, insecurity) of perceived ease of use.

TABLE 14. **Summary of relative importance ranking (output: PEOU).**

Output: PEOU	**OPT**	**INN**	**DIS**	**INS**
PLS-SEM	1	2	3	4
IPMA	1	2	3	4
ANN sensitivity analysis	1	2	4	3
Output variable PEOU: Perceived Ease of Use; Innovativeness (INN), Optimism (OPT), Insecurity (INS), Discomfort (DIS)				

Furthermore, in terms of perceived usefulness, Figure 8 shows perceived ease of use is highly relevant for increasing perceived usefulness due to its strong influence. However, amongst the technology readiness factors, discomfort and insecurity is of less importance in relation to increasing

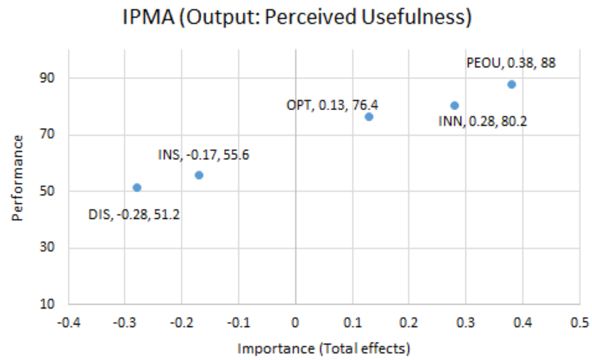

FIGURE 8. **Importance-performance map analysis (Output: PU).**

perceived usefulness, and offer major improvement in terms of the performance level.

Table 15 summarises the relative importance of the five predictors (optimism, innovativeness, discomfort, insecurity and perceived ease of use) of perceived usefulness. However, optimism is ranked higher than innovativeness in the ANN analysis.

TABLE 15. **Summary of relative importance ranking (output: PU).**

Output: PU	**OPT**	**INN**	**DIS**	**INS**	**PEOU**
PLS-SEM	3	2	5	4	1
IPMA	3	2	5	4	1
ANN sensitivity analysis	2	3	5	4	1
Innovativeness (INN), Optimism (OPT), Insecurity (INS), Discomfort (DIS), Output variable PU: Perceived Usefulness.					

Finally, regarding the direct influence on the intention to use cryptocurrency (see Figure 9 and Table 16), perceived usefulness score the highest and perceived ease of use offer potential improvement in terms of the total effects.

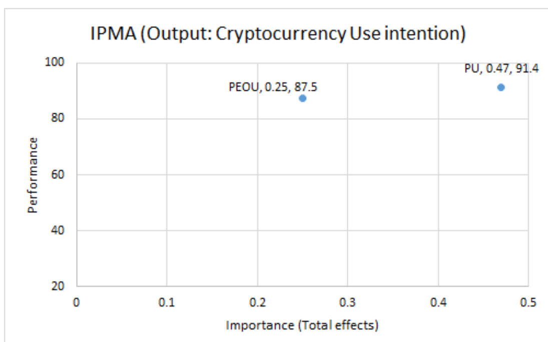

FIGURE 9. **Importance-performance map analysis (Output: CUSE).**

The IPMA results are aligned with the structural model results; this is because both the PLS and IPMA assume linear relationships [71]. However, ANN is capable of modelling complex linear and non-linear relationships and produces more precise predictions compared to SEM methods [21]. The findings of this study may be useful for future cryptocurrency adopters, investors and organisations. From a theoretical point of view, there is scant research on cryp-

TABLE 16. Summary of relative importance ranking (output: CUSE).

Output: CUSE	PEOU	PU
PLS-SEM	1	2
IPMA	1	2
ANN sensitivity analysis	1	2
PEOU: Perceived Ease of Use, PU: Perceived Usefulness., Output variable, CUSE: Cryptocurrency Use Intention		

tocurrency adoption. This study makes a significant contribution to the existing literature by investigating the effect of technology readiness on cryptocurrency adoption. The main contribution of this study is the use of two-step PLS-SEM and ANN approach provides two benefits. First, the use of ANN further verifies the results obtained by the PLS-SEM analysis. Second,ANN is capable of modelling complex linear and non-linear relationships with high predictive accuracy compared to SEM methods.

In conclusion, the two-step PLS-SEM and ANN better in-depth results compared to single-step SEM method. Also, an IPMA of the PLS-SEM findings provides a more specific understanding of each facto's importance and performance. The use of ANN enables further verification of the outcomes obtained by the PLS-SEM analysis.

A. LIMITATIONS AND FUTURE RESEARCH

This study has several limitations. First, the data were collected in one country, Australia, which may make our results less generalizable. Future research could consider carrying out a cross-country comparative study with a larger data set. Secondly, this study assumes digital currencies will be a form of payment in the future, and hence considers intention to use a digital currency, such as bitcoin. Westhuizen [74] investigated the legal status and regulation of future digital money in Australia. Thirdly, it would be interesting to include control variables such as age and gender and compare the results. Fourthly, other factors and models such as Technology Organization Environment (TOE) may be used to examine the influence of various factors on cryptocurrency adoption and use.

APPENDIX
THE MEASURES

Note: These technology readiness questions were modified from the Technology Readiness Index 2.0, which is copyrighted by A. Parasuraman and Rockbridge Associates, Inc., 2014. [38]. This scale may be duplicated only with written permission from the original authors.

[OPTIMISM]

OPT1: New digital currencies such as Bitcoin contribute to a better quality of life.

OPT2: A digital currency such as Bitcoin gives me more freedom of mobility.

OPT3: A digital currency such as Bitcoin gives people more control over their daily lives.

OPT4: A digital currency such as Bitcoin makes me more productive in my personal life.

[INNOVATIVENESS]

INN1: Other people come to me for advice on digital currency such as Bitcoin.

INN2: In general, I am among the first in my circle of friends to acquire a new digital currency when it appears.

INN3: I can usually figure out new digital currencies without help from others.

INN4: I keep up with the latest technological developments in my areas of interest, such as digital currencies.

[DISCOMFORT]

DIS1: If I get technical support from digital currency providers or exchanges, I will feel as if I am being taken advantage of by someone who knows more than I do.

DIS2: Technical support lines are not helpful because they do not explain things for digital currency use in a way that I understand.

DIS3: Sometimes, I think that digital currency, such as Bitcoin, is not designed for use by ordinary people.

DIS4: There is no such thing as a manual for digital currency such as Bitcoin that's written in plain language.

[INSECURITY]

INS1: People are too dependent on digital currency such as Bitcoin to do things for them.

INS2: Too many digital currencies distract people to the point of being harmful.

INS3: A digital currency such as Bitcoin lowers the quality of relationships by reducing personal interaction.

INS4: I do not feel confident doing business with digital currency such as Bitcoin.

[PERCEIVED EASE OF USE]

PEOU1: Learning to use the digital currency such as Bitcoin would be easy for me.

PEOU2: Usage of the digital currency such as Bitcoin is clear and understandable to me.

PEOU3: Overall, I find digital currency such as Bitcoin easy to use.

[PERCEIVED USEFULNESS]

PU1: The use of digital currency such as Bitcoin enables me to transact online more quickly.

PU2: The use of digital currency such as Bitcoin increases my productively.

PU3: The use of digital currency such as Bitcoin in my daily life is very useful.

[Intention to Use Cryptocurrency]

CUSE1: I intend to use a digital currency such as Bitcoin when it becomes widely available.

CUSE2: Whenever possible, I intend to frequently use a digital currency such as Bitcoin in my daily life.

CUSE3: I intend to use a digital currency when it is legally accepted as a form of payment in the country of my residence.

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