IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received January 11, 2021, accepted January 27, 2021, date of publication February 1, 2021, date of current version February 8, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3055785

Technology Readiness and Cryptocurrency Adoption: PLS-SEM and Deep Learning Neural Network Analysis

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This work was supported by the Taif University researchers supporting project, Taif University, Saudi Arabia, under Grant TURSP -2020/231.

ABSTRACT Today's world is increasingly dependent on technology directly or indirectly. The rapid technological advancement has impacted people to adopt the technology. As cryptocurrency recently commenced, few studies have attempted to investigate this use of technology. In this study, the technology readiness aspects- Optimism, Innovativeness, Discomfort, and Insecurity are used to understand the people's adoption of cryptocurrency. A multi-approach of Partial Least Squares- Structural Equation Modeling (PLS-SEM) and Deep learning Artificial Neural Network (ANN) analysis was performed. Deep learning Artificial Neural Network (ANN) analysis was performed to complement PLS-SEM findings and predict higher accuracy. This study shows that technology readiness dimensions - Optimism, Innovativeness, Discomfort, and Insecurity have meaningful relationships with cryptocurrency adoption.

INDEX TERMS Cryptocurrency, PLS, SEM, neural network, technology readiness.

I. INTRODUCTION

The advancement in technology has made our lives easier in many ways. Such as online trading increasingly influences today's highly competitive world. The evolving technology has created its new product called cryptocurrency, a digital currency that has recently impacted the world economy. Cryptocurrency is a peer-to-peer virtual cash model that allows users to pay the other party directly without any financial institution. For instance, Bitcoin is a popular Cryptocurrency developed in 2008 by Satoshi Nakamoto. However, the Cryptocurrency market and adoption are exceptionally complicated [1].

According to Tapscott [2], cryptocurrencies have disruptive effects on financial systems. Prior research implies that technology adoption is affected by an individual's demographics and personality [3], [4]. The technology readiness (TR) developed by Parasuraman [4] trials an individual's readiness to accept or reject new technology. Optimism and innovativeness are the motivators, while Insecurity and Discomfort are the new technology adoption inhibitors. This study aims to assess the relationship between technology readiness (Optimism, Innovativeness, Discomfort, and Insecurity dimensions) and Cryptocurrency adoption.

Blockchain technology includes a communal databank that facilitates consumers to complete transactions without being liable on a central body [5], [6]. Cryptocurrency, such as bitcoin, is the most common form of blockchain technology. Previous researchers investigated the technological and economic aspects of cryptocurrency [7], [8]. TAM [9] is the most widely used research study describing an individual's technology usage [9], [10]. Such as Tsanidis *et al.* [11] investigated bitcoin usefulness and ease of use. Silinskyte [12] examined Cryptocurrency usage behavior centered on the Unified Theory of Acceptance model [13]. Previous studies also adopted a combination of TR and TAM models [9], [10], [14] predicting new technology acceptance.

The technology awareness and understanding benefits complicated financial solutions such as cryptocurrency. However, technology readiness is influenced by people's personalities and demographics [4]. For example, optimism and innovativeness positively affect new technology adoption. On the other hand, Insecurity and discomfort negatively affect new technology adoption [3], [4]. However, an individual

The associate editor coordinating the review of this manuscript and approving it for publication was Emanuele Bellini.

adoption of new technology adoption such as Cryptocurrencies is limited and need further research [1], [2]. Thus, a deep understanding of technology readiness which can motivate the adoption of cryptocurrencies is essential.

Prior studies on new technology acceptance findings [9]–[14] are reported using linear relations such as Structural Equation Modeling (SEM) approach between the study variables. SEM statistical technique is a general approach for predictive modelling research. One of the critical shortcomings of conventional SEM techniques (i.e., linear relationships) is that it oversimplifies the human decision-making process, which is a complex process [15].

Therefore, the benefits of applying neural network analysis include the modelling of complex non-linear and linear associations with high-pitched predictive correctness compared to the SEM approach [15], [16]. The ANN recommendations are followed in previous studies, such as [15]–[18]. However, these ANN analyses follow a shallow approach [19]. The shallow approach means ANN consists of a single hidden layer in modeling the neural network.

Therefore, to fill this gap in technology-based research, this study extends the previous research [16] by following a deep learning-based ANN model using two or more hidden layers to improve predictive accuracy [19], [20]. The study aims to enhance the research related to new technology adoption using a multi-step approach, such as first the Partial Least Squares- Structural Equation Modeling (PLS-SEM) and deep learning-based Artificial Neural Network (ANN) analysis. To further elaborate the findings for managerial implications, Importance-Performance Map Analysis (IPMA) was also performed to complement the results of PLS-SEM.

The paper is structured as follows: Section two presents the theoretical background and hypotheses development. Then section three is the methodology, followed by the discussion in Section four. Finally, the study concludes.

II. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

As mentioned in the Introduction section, previous researches have investigated technology acceptance /adoption using various theoretical models [8]–[13]. The technology acceptance theory [13] describes that human feelings also determine an individual's usage intention. Prior studies indicated that individual perceptions of new technology acceptance could be positive (motivators) and negative (inhibitors)—users with a very positive attitude towards technology express more significant endorsement of technology-related services. On the other hand, users with a very negative attitude regarding technology are hesitant to adopt technological services. Cryptocurrencies adoption is considered the latest innovation. Cryptocurrency is in its early stage of user adoption [16], [21]. Technology readiness theory [4], [22] is appropriate for investigating cryptocurrency adoption because cryptocurrencies are highly innovative and technology intensive. Cryptocurrencies, also known as the digital currencies, is the most generally operational blockchain 3.0 technology [5], [6], [16]. Blockchain technology consists of a shared databank that enables consumers to complete trades without being liable on a central body, such as financial banks [6]. Users utilizing the cryptocurrency technology generates more excellent value for each user such that the number of transactions determines the currency ability, which is an effect of public acceptance [8].

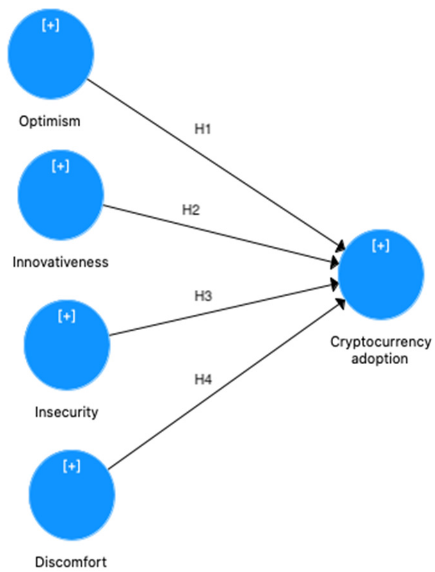

FIGURE 1. Research model.

Prior researchers have focused on cryptocurrency's technological and economic aspects, for example, transactions verification [7], [8]. However, there is also a need to investigate user adoption [11], [16]. The Technology Readiness Index (TRI) developed by Parasuraman [4], [22] governs the technology's adoption. Optimism and Innovativeness positively influence technology readiness, while the other two dimensions, Discomfort and Insecurity, describe the negative effect on new technology adoption. Figure 1 shows the research model. Lam *et al.* [3] state that each TRI dimension is a predictor of new technology adoption.

- Optimism: This means a positive view of technology and believes that it improves the control, flexibility, and efficiency of everyday life due to technical reasons.
- Innovativeness: Innovators are the first among people to use new technology.
- Insecure: This is about not trusting the technology for privacy and security purposes.
- Discomfort: This is related to an individual lack of control or discomfort feeling over technology.

Optimism is about people positive attitude and tends to experience effective results in their lives [22], [23]. Optimists are more likely to accept the current situation. High optimists feel the use of technology is straightforward and are unlikely to focus on adverse events [24]. Vigna and Casey [25] believe that cryptocurrency is the electronic money to allow people out of any financial institution and government control. Therefore, optimists would adopt cryptocurrency in their everyday life and would be worried about the adverse outcomes. Therefore, *Optimism has a positive effect on Cryptocurrency adoption.*

Innovativeness is an individual tendency to become an innovator in the technological domain [21], [22], [26]. Innovators are invariants which are not affected by the environment or internal factors [27]. Early adopters of technology value innovation, despite when their implied benefits are not apparent. Vigna and Casey [25] stated that cryptocurrency is well-made innovation with high values. Therefore, *Innovativeness has a positive effect on Cryptocurrency adoption.*

Insecurity regarding technology is the uncertainty related to security and privacy or a lack of trust in the technology [22]. The doubt in unstable payment solutions will decrease the virtual currency value [24]. Individuals tend to avoid using technology because of the fear and distrust of unknown circumstances [28]. Individuals may feel insecure about cryptocurrencies when the use and legal requirements are incomplete [29]. Chen *et al.* [30] established that some obvious technology acceptance obstacles were security and privacy concerns. Therefore, *Insecurity has a negative effect on Cryptocurrency adoption.*

Discomfort is related to an individual's lack of control or discomfort over technology [4], [22]. People may feel significant fluctuations in cryptocurrency transactions—however, information feedback may improve technology's ease of use [30]. But individuals with high levels of discomfort sense technology as more complicated and thus less likely to adopt. *Therefore, discomfort has a negative effect on cryptocurrency adoption*.

III. RESEARCH METHODOLOGY

This study used a convenience sampling method to collect data. Students and staff from the Faculty of Engineering and IT, University of Technology Sydney, were invited to participate in the survey in Dec 2019. The researcher chose the non-random sampling (convenience sampling) because participants ease access and willingness to participate. Also, Internet usage in students is comparatively higher. The criterion for selecting participants was to have a fundamental understanding and awareness of cryptocurrencies. A survey (closed-ended questionnaire) in English using a Likert five-point scale was used to collect the data. The measurement items are adopted to ensure the items' validity and reliability to represent the study constructs accurately. The TRI questionnaire is adopted and modified from [16], [22]. Participation in the survey was voluntary, and ethics approval was obtained from the University.

A total of 180 responses were collected, and after removing the 20 missing or incomplete responses, 160 usable responses are used for the data analysis. 58% of the participants were males, and 42% were females. All participants had Internet experience of 7 years or above and well aware of digital money. 45% of participants were enrolled in the Bachelor of Science in Information Technology. 30% were enrolled in Master of Information Technology. 15% of participants were PhD students, and 10% were staff members at the Faculty of IT.

TABLE 1. Reliability and validity assessment.

	AVE	CR	C-alpha
OPTI	0.68	0.87	0.81
INNO	0.67	0.85	0.80
DISC	0.59	0.81	0.77
INSE	0.61	0.83	0.75
CA	0.67	0.83	0.76

Notes: Average Variance Extracted (AVE), Composite Reliability (CR), C-Alpha, Optimism (OPTI), Innovativeness (INNO), Discomfort (DISC), Insecurity (INSE), Cryptocurrency Acceptance (CA)

For analyzing the data, a multi-step approach of PLS-SEM and deep learning neural network analysis was performed. he benefits of using neural network analysis include modeling complex non-linear and linear relationships with high predictive correctness compared to the SEM approach [15], [16]. PLS-SEM is a preferred analysis method in technology adoption research [16]. ANN is very useful in research content when there is a weak theory or a limited understanding of the underlying relationships [16].

In the first step, Partial Least Squares- Structural Equation Modeling (PLS-SEM) was applied. Hair *et al.* [31], [32] recommend that PLS-SEM, because it performs better in small sample sizes, does not comprise normality, and without distributional assumptions. Furthermore, according to Henseler *et al.* [33], PLS-SEM analysis is an effective approach than CB-SEM in a result of a true model. A detailed comparison of PLS-SEM and CB-SEM is provided by Reinartz *et al.* [34]. In the study [19], TR is modelled as a second-order formatively construct with TR dimensions as formative indicators. In contrast, this study research model is modelled as reflective (TR dimensions as separate reflective constructs).

In the second step, deep learning-based Artificial Neural Network (ANN) analysis was performed to complement PLS-SEM findings. Deep learning ANN analysis was performed using two hidden layers in modeling the ANN model, which is considered a more accurate approach than a single hidden layer approach [19], [20]. The details of PLS-SEM and ANN deep learning is presented in the following section.

IV. RESULTS

The following sections show analysis of PLS-SEM followed by deep-learning ANN.

V. PLS-SEM

The research model was first statistically examined using Partial Least Squares (PLS) using SmartPLS v3 software. PLS-SEM was conducted in two steps: measurement model validation and structural model testing. Table 1 to 3 shows the measurement model assessment results. The measurement model contains validity and reliability assessments using internal consistencies, convergent and discriminant validity [35]. For each factor, Cronbach's reliability and

TABLE 2. Items loadings.

Items	Loadings
OPTI1: I believe cryptocurrency (i.e. Bitcoin) can improve quality of life.	0.831
OPTI2: I believe cryptocurrency (i.e. Bitcoin) offers freedom of economic mobility.	0.829
OPTI3: I believe cryptocurrency (i.e. Bitcoin) will give me more control over my financial decisions in my everyday life.	0.839
OPTI4: I believe cryptocurrency (i.e. Bitcoin) will make me more productive in my everyday life.	0.701
INNO1: I usually keep up with the latest technological developments in my areas of interest.	0.843
INNO2: People often asks me for advice on cryptocurrency (i.e. Bitcoin)	0.647
INNO3: I can typically figure out new cryptocurrencies (i.e. Bitcoin) without any help from others.	0.673
INNO4: I believe I am among the first in my circle of friends to acquire a Cryptocurrency (i.e. Bitcoin).	0.731
INSE1: People will be overly dependent on cryptocurrency (i.e. Bitcoin).	0.847
INSE2: Various type of Cryptocurrencies diverts me to the point of being unsafe.	0.841
INSE3: A Cryptocurrency (i.e. Bitcoin) decreases the relationships by diminishing personal communication.	0.764
INSE4: I am not confidently doing business with cryptocurrency (i.e. Bitcoin).	0.710
DISC1: Getting technical support from Cryptocurrency (i.e. Bitcoin) providers feels like someone has taken advantage of me who knows more than I do.	0.771
DISC2: I believe, technical support services regarding cryptocurrency (i.e. Bitcoin) are not effective because they won't clarify things for the use of currency in a way that I understand.	0.729
DISC3: I believe cryptocurrency (i.e. Bitcoin) is not devised for use by ordinary people.	0.786
DISC4: I believe there is no manual for cryptocurrency (i.e. Bitcoin) written in plain language.	0.721
CA1: I intend to adopt a Cryptocurrency (i.e. Bitcoin) when it becomes broadly available.	0.904
CA2: I intend to frequently use/adopt a Cryptocurrency (i.e. Bitcoin) in my everyday life whenever possible.	0.949
CA3: I intend to use a Cryptocurrency (i.e. Bitcoin) when t's legally accepted as a payment form in the country I reside.	0.823
Note: These TR questions were modified from the Technology Readiness Index 2.0, which is copyrighted by A. Parasuraman and Rockbridge Associates, Inc., 2014. [22]. This scale may be duplicated only with written permission from the original authors.	

internal consistencies (composite reliability) surpass the threshold value of 0.70. According to Hair *et al.* [36], Item loading lower than 0.4 must be removed. Figure 2 and Table 2 show all items loadings are well above 0.6 and significant (p-value < 0.05). The AVE also exceeded the threshold value of 0.50. For discriminant validity, Henseler *et al.* [37] developed the Heterotrait-monotrait (HTMT) criteria in assessing discriminant validity results which is considered a better approach than the cross-loading in PLS. All HTMT values are below the threshold value of 0.85 [37], as shown in Table 3. Henseler *et al.* [37] also suggested HTMT confidence intervals using a bootstrapping procedure. Table 4 shows the value are within the confidence interval range, which means the constructs are empirically dissimilar.

TABLE 3. Discriminant validity- HTMT.

	OPTI	INNO	DISC	INSE	CA
OPTI	-				
INNO	0.59	-			
DISC	0.53	0.51	-		
INSE	0.52	0.59	0.63	-	
CA	0.75	0.68	0.72	0.61	-
Notes: All correlation coefficients are at level 0.05 and significant.					

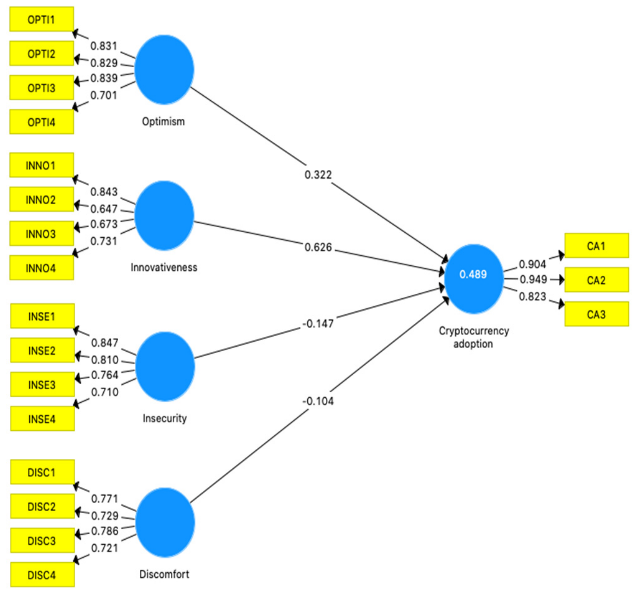

FIGURE 2. Path modelling.

TABLE 4. Discriminant validity- HTMT Confidence interval.

Path	Bias Corrected 95% confidence interval.
OPTI → CA	[0.659, 0.731]
INNO → CA	[0.839, 0.901]
INSE → CA	[0.645, 0.735]
DISC → CA	[0.632, 0.711]

The path modelling (Figure 2) significance was measured using the bootstrapping technique [31], [32] with a p-value of 0.05 and the R^2 variance of the dependent variable. All four hypotheses are accepted. The R^2 indicate 48% variance of the cryptocurrency adoption. Figure 2 and Table 5 show the path

TABLE 5. Structural model testing.

	Path	Path Values	St. Dev	t-value	p-value	Findings
H1	OPTI → CA	0.322	0.04	0.140	0.010 *	+ve and significant
H2	INNO → CA	0.626	0.04	0.126	0.000 **	+ve and significant
H3	INSE → CA	-0.147	0.07	0.149	0.020 *	-ve but significant
H4	DISC → CA	-0.104	0.09	0.145	0.030 *	-ve but significant
Optimism (OPTI), Innovativeness (INNO), Discomfort (DISC), Insecurity (INSE), Cryptocurrency Acceptance (CA) **Significant at the 0.05 Level, *Significant at the 0.001 Level.						

TABLE 6. PLS Predict results.

	RMSE		MAE		MAPE		Q2	
	LM	PLS-SEM	LM	PLS-SEM	LM	PLS-SEM	LM	PLS-SEM
CA1	1.54	1.32	1.23	1.02	44.20	34.07	0.09	0.22
CA2	1.64	1.53	1.42	1.31	64.34	62.71	0.08	0.17
CA3	1.52	1.34	1.14	1.03	42.49	40.12	0.10	0.22
CA		0.572	-	0.437	-	-	-	0.316
Notes: CA: Cryptocurrency adoption output. PLS-SEM < Linear Model (LM); Q2 > 0; Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)								

testing. The results show that Optimism and Innovativeness have a positive impact, while Discomfort and Insecurity have a negative impact on cryptocurrency adoption.

Furthermore, to assess the predictive relevance for measuring the cross-validated redundancy Q^2 Stone-Geisser criterion uses the blindfolding method [38]. Q^2 values (i.e., cryptocurrency adoption = 0.316) exceed the threshold value of 0, which signifies a robust predictive relevance. Moreover, the PLSpredict algorithm is also used to prove the predictive relevance to predict the PLS model performance for the Latent Variables (LV) and the Manifest Variables (MV) [39]. PLSpredict includes the linear model (LM) predictions and the Q^2 mean values to measure the predictive quality using Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) of the PLS path model estimations. Table 6 shows the latent construct's PLSpredict performance (cryptocurrency adoption) and its manifest factor three items. The findings show the lower PLS-SEM values than the simple linear model (LM) values, and Q2 values are also higher than zero specify higher predictive power [40].

VI. DEEP LEARNING NEURAL NETWORK ANALYSIS

ANN is used in the second step of the analysis to complement the PLS-SEM findings and to highlight each predictor's factor relevant importance. ANN has a higher prediction accuracy than SEM because of the linear or non-linear relationship assessment capabilities [15]. The ANN analysis using the Multilayer Perceptron (MLP) method is modeled using SPSS v22. The MLP analysis consists of inputs, hidden layers, and output. In this study, the ANN recommendations are followed from [15]–[18]. However, deep learning using two hidden layers in ANN was employed [19], [20]. The benefit of using two-hidden layers is to allow deeper learning on the ANN model for the output neuron node [19]. The ANN deep learning model uses the sigmoid function for both the hidden and output neurons as the activation function. Moreover, the range between 0, 1 for both input and output neurons is normalised to enhance the ANN deep learning model's performance. The ANN model has four input factors: Optimism, Innovativeness, Discomfort and Insecurity and one output - Cryptocurrency adoption. Figure 3 shows the deep learning ANN model.

The ANN was calculated by the root mean square error (RMSE) for the testing (10%) and training (90%) data sets [16]. Table 7 shows the results. Lower RMSE values signify higher predictive accuracy [15], [18].

Furthermore, sensitivity analysis [15] was performed to find the relative importance of each input Optimism, Innovativeness, Discomfort and Insecurity predictor. Table 8 shows the results. The relative importance findings show that Optimism is the first predictor in adopting cryptocurrency, followed by Innovativeness as the second significant predictor. However, Insecurity has a weaker impact, followed by Discomfort.

TABLE 7. ANN model RMSE values.

Output: Cryptocurrency adoption				
ANN	Training (90% of data sample)		Testing (10% of data sample)	
	SSE	**RMSE**	**SSE**	**RMSE**
ANN1	0.127	0.032	0.110	0.087
ANN2	0.124	0.031	0.106	0.086
ANN3	0.126	0.031	0.117	0.097
ANN4	0.132	0.032	0.128	0.098
ANN5	0.132	0.032	0.117	0.092
ANN6	0.112	0.028	0.106	0.087
ANN7	0.114	0.029	0.107	0.088
ANN8	0.115	0.027	0.118	0.093
ANN9	0.114	0.026	0.116	0.093
ANN10	0.113	0.029	0.117	0.091
	Mean	0.030	**Mean**	0.090

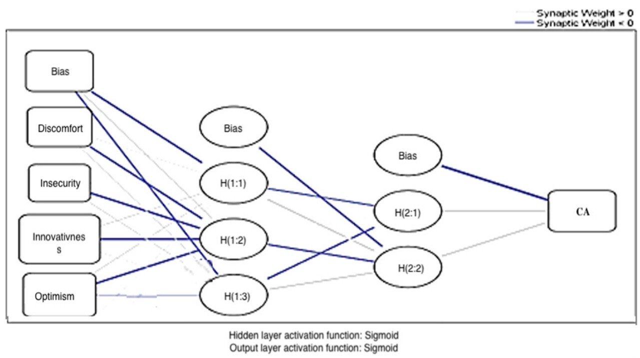

FIGURE 3. ANN model.

VII. DISCUSSIONS AND CONCLUSION

This study extended the Cryptocurrency adoption research with deep learning based neural network method. The multi-step approach of using PLS-SEM and deep learning ANN

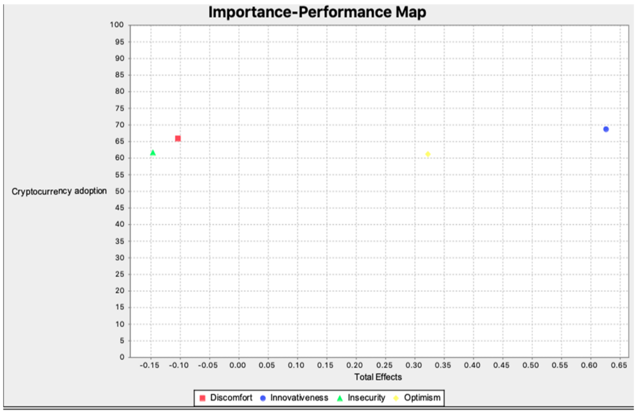

FIGURE 4. IPMA analysis.

TABLE 8. Input predictors relative importance.

Output: CA	Average relative importance	Normalized relative importance (%)	Ranking
Optimism	0.390	100	First
Innovativeness	0.290	72.1	Second
Insecurity	0.209	52.3	Third
Discomfort	0.110	25.3	Fourth

TABLE 9. Summary of ranking importance.

Output: Cryptocurrency adoption	PLS-SEM	IPMA	ANN sensitivity ranking
Optimism	2	2	1
Innovativeness	1	1	2
Insecurity	4	4	3
Discomfort	3	3	4

method shows useful information regarding the cryptocurrency adoption by predicting the relative importance of the input TR factors (Optimism, Innovativeness, Insecurity and Discomfort). The PLS-SEM findings show that Innovativeness has the most potent positive effect on cryptocurrency adoption, followed by Optimism. ANN model recommends by ranking Optimism first and innovativeness second. Also, the PLS-SEM findings show that Discomfort has a negative effect on cryptocurrency adoption, followed by Insecurity the ANN prediction ranked Insecurity than the Discomfort. This fascinating disagreement is due to the power of deep ANN modelling.

Importance-Performance Map Analysis (IPMA) was implemented [41] to further elaborate the findings for managerial implications. The IPMA findings consist of two dimensions, which are performance and importance [41], [42]. Performance is usually assessed from a 0 to 100 scale. Importance-Performance Map Analysis involves defining a target construct in the PLS path model, which is cryptocurrency adoption in our case.

Figure 4 shows Innovativeness is highly significant for increasing cryptocurrency adoption due to its strong effect. Optimism has the second highest importance. Though, this Innovativeness has minimum potential for an additional boost because it already has an increased effect. Therefore, Innovativeness and Optimism be maintained. Comparably, Insecurity followed by Discomfort has a somewhat low impact and are less importance towards cryptocurrency adoption. Thus, managerial efforts should be directed addressing the Insecurity and Discomfort to improve cryptocurrency adoption.

Table 9 summarizes the PLS-SEM, ANN and IPMA relative importance results. PLS-SEM and IPMA findings show the relative importance ranking of predictive variables Optimism, Innovativeness, Insecurity, and Discomfort. However, the ANN model shows innovativeness is the most significant predictive input to cryptocurrency adoption, followed by Optimism, Insecurity, and Discomfort.

In conclusion, the findings confirm that innovative and optimists' individuals are eager to try new things such as cryptocurrency adoption. But Insecurity and Discomfort signifying the complexities and uncertainties in adopting new technology. Limitations of this study include data collection from student only. Therefore, the results are less generalizable. Future studies should extend the research to other countries. In addition, comparison of the shallow ANN approach and the deep ANN using the data set and the same research model is required.

ACKNOWLEDGMENT

The authors acknowledge Taif University support for this research through Taif University researchers supporting project (TURSP -2020/231), Taif University, Saudi Arabia.

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