TERTIARY STUDENT INTENTION TO USE BLOCKCHAIN-BASED ACADEMIC RECORDS: A CASE STUDY OF UBON RATCHATHANI PROVINCE, THAILAND

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Abstract

Blockchain-based applications possess the disruption of several industries worldwide. Researchers applied blockchain to transform the educational industry in several approaches, including blockchain-based academic records system. In Thailand, major universities in the capital have applied blockchain-based academic records systems, but it is relatively new in rural areas. Therefore, this study aims to analyze the adoption behavior toward block chain-based academic records systems of tertiary students in Ubon Ratchathani Province, Thailand. We proposed an integrated research model based on the technology acceptance model and task-technology fit. The data were collected using online and offline questionnaires (Cronbach's alpha > 0.84). A total of 134 randomly selected participants responded to the questionnaires and the obtained data were analyzed. The partial least square structural equation model was applied for empirically testing of the hypotheses. Every hypothesis was statistically supported. However, the behavioral intention to use blockchain-based academic records was predicted by perceived usefulness and task technology fit with 50.6 percent of the variance. Perceived ease of use was the strongest predictor of perceived usefulness. Perceived privacy risk had a negative impact on perceived usefulness. Task technology fit was confirmed in our study. Finally, the paper discussed and provided the practical implications for stakeholders related to the blockchain-based academic records system.

Keywords: Academic Records System, Blockchain, Technology Acceptance, Task-Technology Fit, Tertiary Student

Introduction

The academic record is a formal track record of a student's academic history at the educational institutions. It is a certification of skills, level of education, etc. Employers need certification and academic records from candidates when applying for a job. Now, the job market is highly competitive, with limited job offers but increased job seekers. Thus, the human resource department receives many job applications every day. Therefore, it is impossible to verify all certification

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documents. This situation is happening worldwide, allowing illegal businesses to take advantage by offering fake diplomas or certificates. The fake degree is known as diploma mills, degree mills, and accreditation mills (Brown, 2006). In Thailand, the problem of degree mills still exists (Buasuwan & Jones, 2016). A quick search on the internet on the "buying fake diploma" shows many companies that provide the degree mills.

Recently, blockchains have emerged as powerful platforms across industries. It is a digital ledger that enables a decentralized infrastructure for keeping transaction records without any central authority. The blockchain enables a trustless network suitable for transactions in several contexts. Therefore, it has drawn the interest of stakeholders from lots of industries. Nakamoto (Nakamoto, 2009) introduced it in 2009 as a cryptocurrency named "Bitcoin". Cryptocurrency is an extremely successful application of blockchain technology. It is a decentralized digital currency that has the potential to eliminate the central bank (Tschorsch & Scheuermann, 2016).

Blockchain's characteristics, including transparency, traceability, security, etc., which, if applied to the academic records system, may help reduce the degree mills problems (Arenas & Fernandez, 2018; Han et al., 2018; Lizcano et al., 2020). However, Blockchain is still new for rural universities, especially in Ubon Ratchathani Province, Thailand. Hence, the study on the adoption of blockchain-based technology is still minimal.

Objective

The objective of this study is to analyze the factors affecting the adoption of blockchain-based academic records systems in the universities in Ubon Ratchathani Province, Thailand.

Literature Review

Blockchains

Blockchain technology is a combination of several techniques, including mathematics, algorithm, cryptography, etc. Overall, it can be considered a peer-to-peer distributed data structure. Blockchain is a consecutive chain of blocks, where each block can store data that be considered a transaction (Nakamoto, 2009). Therefore, the database's transaction is shared by entirely nodes participating in a system. Wright and De Filippi (2015) defined the blockchain in the database context as "A distributed, shared, encrypted database that serves as an irreversible and incorruptible public repository of information".

A blockchain started with a dataset referred to as a "block". Each block contains the reference to the preceding block in the blockchains, transaction data, and the data used to validate the data associated with that block, which comes from a complex mathematical puzzle (proof of work). The proof of work is complicated (costly, time-consuming) data to generate but simple enough for others to verify and satisfies specific requirements (Tschorsch & Scheuermann, 2016).

After a new block has been successfully added to the blockchain for a while, it will become permanent and computationally impractical to alter because every block after it will be invalid and have to be regenerated. In conclusion, blockchain has a mechanism that guarantees immutability, accuracy, and authenticity without a centralized regulating party. Therefore, blockchain technology has been applied to many industries, such as payment services with blockchain (Dam et al., 2020), supply chains with blockchain (Dujak & Sajter, 2019; Kamble et al., 2019), hotel services with blockchain (Miraz et al., 2020), blockchain as the financial instrument (Heidari, 2019; Sebastian & Venkatesh, 2021), the use of blockchain in e-government (Batubara et al., 2018).

Blockchain-based academic records system

The benefit of blockchain technology functionality, including decentralization, scalability, reliability, security, and cost reduction, can be applied to the educational industry. As a result, academic institutions worldwide have employed blockchain technology in different approaches.

European Commission's science and knowledge service (Grech & Camilleri, 2017) reported examples of potential scenarios that the educational institution will benefit from blockchains, such as issuing certificates, lifelong learning passports, intellectual property management, and personal data management. However, One of the most applications of blockchain is the academic records system. For example, EduCTX (Turkanović et al., 2018) is a global blockchain-based higher education credit platform based on the European Credit Transfer and Accumulation System (ECTS) concept. Unichain (Daraghmi et al., 2019) is a blockchain-based smart contract for Electronic Academic Records (EARs). Moreover, various researchers proposed a blockchain-based method for storing, verifying, and sharing academic records (Arenas & Fernandez, 2018; Han et al., 2018; Lizcano et al., 2020). The major frontier universities in Bangkok have applied blockchain technology in their process. However, the universities in the Ubon Ratchathani Province still have not fully adopted this technology yet.

Technology adoption

Over the decades, researchers have attempted to assess and identify the factors that increase users' adoption of a new system or technology. Several theories and research models have been proposed in different contexts. One of the oldest models still famous is the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1977). It seeks to explain that attitudes and subjective norms predict behavioral intention. Furthermore, the same researcher presented the Theory of Planned Behavior (TPB) (Ajzen, 1991) as the upgraded version of TRA. The TPB adds a factor called perceived behavioral control. However, TRA and TPB were not explicitly designed for the information technology context.

Davis (1989) proposed a new model specifically for technology adoption based on TRA, namely Technology Acceptance Model

(TAM). The TAM consisted of two primary predictors: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Those predictors were used to predict the behavioral intention to use technology. It is one of the most widely applied among researchers in the field of information technology acceptance. Moreover, TAM was used as a core model for the broader context of technology adoption (King & He, 2006). The TAM's research model is shown in Figure 1.

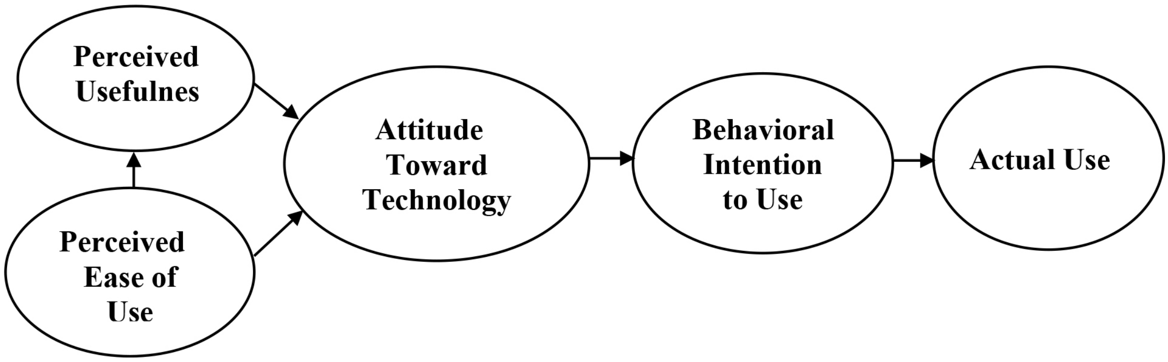

Figure 1 TAM research model (Davis, 1989)

Recent literature also used TAM to investigate the adoption of blockchain. For example, Kamble et al. (2021) predict an institute's chance of successful blockchain adoption using a machine learning technique and TAM. Almekhlafi & Al-Shaibany (2021) reviewed the papers on blockchain adoption from 2017 to 2021. They suggested that TAM is the most common model to assess the adoption of blockchain. However, the number of studies on blockchain adoption in education is still limited.

Task-Technology Fit

The Task-Technology Fit model (TTF) explains the information system's performance by investigating the suitability between two factors: task characteristics and technology characteristics. Those two factors predicted the task-technology fit in order to assess the user's performance and utilization. The original TTF model shows in Figure 2. TTF is widely used for evaluating in several contexts (Dishaw & Strong, 1999; Isaac et al., 2017; Klopping & Mckinney, 2004; Wu & Chen, 2017).

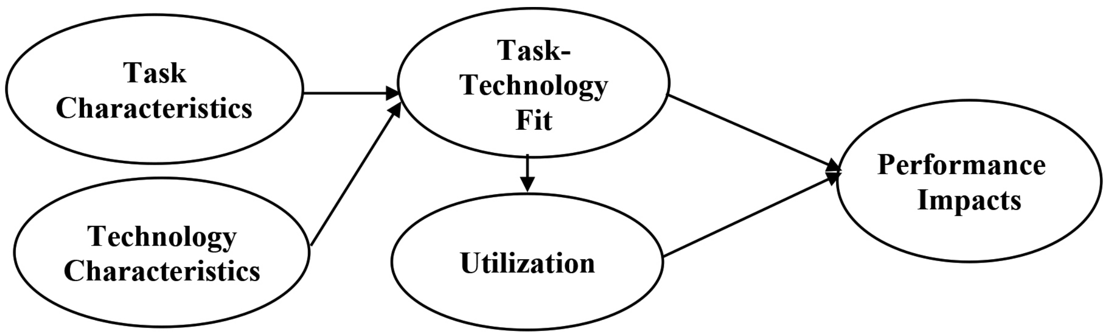

Figure 2 TTF research model (Ballarini et al., 1995)

Methodology

Designing the conceptual model

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) were widely used for predicting the intention to use technology (Davis, 1989). However, since blockchain in academic records is an entirely new experience, the Task-Technology Fit (TTF) (Ballarini et al., 1995) was added to predict behavioral intention. The TTF has two factors: Technology Characteristics (TC) and Task Characteristics (TFC). Furthermore, academic records are considered sensitive information. Therefore, the Perceived Privacy Risks (PPR) (Featherman & Pavlou, 2003) was added to the model.

Perceived Usefulness (PU)

David (1989) defined PU as "the degree to which a person believes that using a particular system would enhance his or her job performance (Davis, 1989)". It is one of the most common constructs used for assessing behavioral intention. Prior research study on the effect of perceived usefulness toward blockchain technology found that it has a positive influences blockchain adoption in a different context (Dam et al., 2020; Heidari, 2019; Kamble et al., 2019; Lee et al., 2019; Miraz et al., 2020; Sebastian & Venkatesh, 2021). Assume that users feel that by using blockchain to manage academic records, they will be able to manage their academic information more securely and reliably, as well as enhance their overall effort to manage their academic information. In that case, it may help to create a positive perception of using these systems. Thus, for our context, PU is defined as "the extent to which using blockchain technology in academic records will provide direct benefits to the users with their activities in academic information". Therefore, the hypothesis is:

H1: Perceived usefulness positively affects the behavioral intention to use block-chain-based academic records.

Perceived Ease of Use (PEOU)

PEOU is defined as "the degree to which a person believes that using a particular system would be free of effort (Davis, 1989)". PEOU has a positive effect on the intention to use technology (Legris et al., 2003; Mitzner et al., 2010). Especially with the brand new technology, it will have a strong influence on using the system. Previous research on the adoption of blockchain technology also adopted PEOU as a factor influencing the adoption (Dam et al., 2020; Heidari, 2019; Kamble et al., 2019; Lee et al., 2019; Miraz et al., 2020; Sebastian & Venkatesh, 2021). We therefore hypothesize:

H2: Perceived ease of use positively affects the perceived usefulness of blockchain-based academic records.

Perceived Privacy Risks (PPR)

Academic information is a sensitive information. Therefore, It is crucial to have control over the academic information's visibility and reliability. Users, on the other hand, will sense a risk to their academic information privacy. The privacy risk is defined as "Potential loss of control over personal information, such as when information about you is used without your knowledge or permission (Featherman & Pavlou, 2003)".

Perceived privacy risk is one of the most salient concerns for adopting e-services (Featherman et al., 2010; Featherman & Pavlou, 2003). It is also a common concern in the adoption.

H3: Perceived privacy risk negatively affects the behavioral intention to use blockchain-based academic records.

Task-Technology Fit (TTF)

TAM focuses on the influence of an individual's perception of technology adoption. On the other hand, TTF explained how technology leads to performance impacts (Ballarini et al., 1995). TTF is defined as "the degree to which a technology assists an individual in performing his or her portfolio of tasks (Ballarini et al., 1995)". It is considered the linkage between individual performance, task condition, and the technology's functionality. Therefore, we added the TTF to our model and TAM to profoundly investigate the adoption of blockchain-based academic records for both perception and appropriateness of the technology.

H4: Task technology fit positively affects the behavioral intention to use blockchain-based academic records.

The TTF is predicted by Technology Characteristics (TC) and Task Characteristics (TFC). Reference (Dishaw & Strong, 1999; Heidari, 2019; Klopping & Mckinney, 2004) integrated the TTF with the TAM model. Therefore, we proposed that:

H5: Task technology fit positively affects the perceived usefulness of blockchain-based academic records.

H6: Task technology fit positively affects the perceived ease of use of blockchain-based academic records.

H7: Technology characteristics positively affect the Task technology fit of blockchain-based academic records.

H8: Technology characteristics positively affect the perceived ease of use of blockchain-based academic records.

H9: Task Characteristics positively affect the task technology fit of blockchain-based academic records.

The conceptual research model of this study is shown in Figure 3.

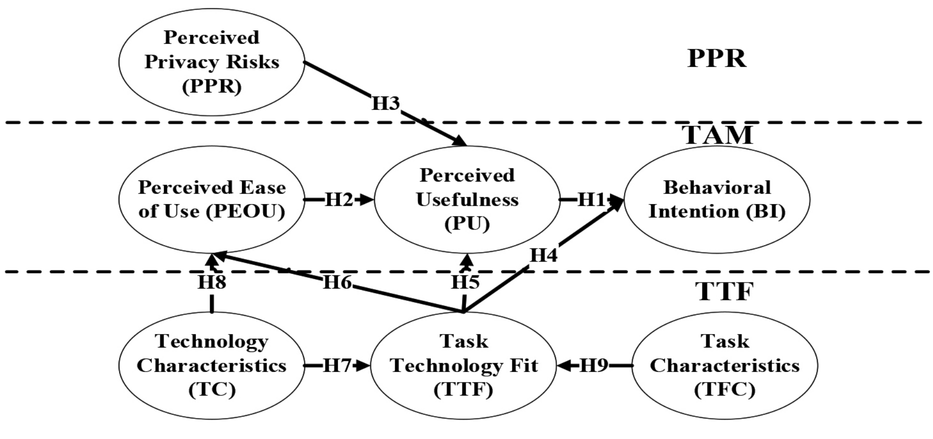

Figure 3 Proposed research model

Participants and data collection

This study's target population is tertiary students from Ubon Ratchathani University (36 participants) and Ubon Ratchathani Rajabhat University (98 participants). The number of populations is 26,896. The participants of the study were selected using a convenience sample method. The data was collected using a self-administered online and offline questionnaire. We sent the questionnaire link to students' university email and online social networking groups. The questionnaire was active for a month (January 2021). One hundred thirty-nine participants answered the questionnaires, but five of them did not pass the screening requirements. The final analysis used 134 participants to test the hypotheses (N = 134). Of these, 29 are male, and 105 are female. The age of participants ranges from 18 to 25 years old because they are tertiary students.

Instrument of constructs

The constructs of the questionnaire were tested and validated from previous studies. We integrated the TAM and TTF based on the evidence that it should help predict the adoption of both individual perception and the fitness of task to the technical aspects (Dishaw & Strong, 1999; Klopping & Mckinney, 2004). The PPR was also added to the proposed model (Featherman & Pavlou, 2003).

The constructs were modified to be a more specific context of using blockchain in academic records. The modified constructs are shown in Table 1. In order to keep the questionnaire short, each construct contains two items: the minimum number of items as arrows points to a latent variable in the model (Wong, 2013).

We added a friendly introduction that explains how the blockchain works, the application in academic records, and its benefits.

The questionnaire consists of two parts. The first part asked about demographic information. The second part contains the constructs from the proposed research model. The variables' constructs have been evaluated with a 7-point Likert scale (1 = "strongly disagree" to 7 = "strongly agree").

Data Analysis

The collected data are analyzed using Partial Least Square Structural Equation Modelling (PLS-SEM) (Hair et al., 2014) with a software package name SmartPLS version 3.3.3 (Ringle et al., 2015). The PLS-SEM does not require that data need to have a normal distribution. The PLS is famous for analyzing small sample sizes (Hair et al., 2014; Ringle & Sarstedt, 2011; Wong, 2013). Previous literature suggested that a sample size of 100 to 200 is enough for carrying out path analysis modeling (Hoyle, 1995; Wong, 2013).

For testing the hypotheses, the bootstrapping will test the hypothesis by creating a bootstrap sample from a repeated random sample of the original sample (Vinzi et al., 2010; Mooney et al., 1993; Ringle & Sarstedt, 2011).

Table 1 Instrument of constructs

Constructs		Questions	Ref.
BI	BINT1	I will definitely use the academic records system using blockchain when it is ready.	(Davis, 1989; Fishbein & Ajzen, 1977)
	BINT2	I will often use the academic records system using blockchain if I have a chance.	
PEOU	PEOU1	In general, the academic records system using blockchain is easy to use.	(Davis, 1989)
	PEOU2	Learning how to use the academic records system using blockchain is easy for me.	
PPR	PPR1	Using the academic records system using blockchain would lead to a loss of privacy because my personal information would be used without my knowledge.	(Featherman & Pavlou, 2003)
	PPR2	What are the chances that my academic records will not be private anymore if I use The academic records system?	
PU	PU1	I find that using the academic records system using blockchain will increase the performance of related work.	(Davis, 1989)
	PU2	The academic records system using blockchain will be useful in my professional life.	
TC	TC1	The academic records system using blockchain can be accessed securely.	(Ballarini et al., 1995; Heidari, 2019)
	TC2	The academic records system is very transparent.	
TFC	TFC1	I want to access my academic records ubiquitously.	(Ballarini et al., 1995; Heidari, 2019)
	TFC2	I want to share my academic records ubiquitously and securely.	
TTF	TTF1	I believe that blockchain technology is suitable for applying to academic records.	(Ballarini et al., 1995; Klopping & Mckinney, 2004)
	TTF2	I believe that The academic records system is pretty much what I need to carry out my task requirements.	

Results

We applied the recommended processes from (Hair et al., 2016). The first process evaluates the measurement model in terms of reliability and validity, Followed by examining the structural model for testing the hypotheses. This section presents the detail of the results from those analyses.

Evaluation of the measurement models

Table 2 presents the descriptive statistic of the constructs. The PLS suggested that data distribution is skewed (Wong, 2013). The acceptable skewness and kurtosis are from -2 to +2 (George & Mallery, 2019). Therefore, the data of this study have an acceptable level of kurtosis and skewness.

Table 2 Descriptive statistics

Factors	Mean	S.D.	Kurtosis	Skewness
BINT	5.43	1.194	-0.324	-0.384
PEOU	5.47	1.248	0.304	-0.669
PPR	4.67	1.717	-0.61	-0.509
PU	5.52	1.235	1.301	-0.932
TC	5.43	1.173	-1.150	-0.100
TFC	5.74	1.188	-0.895	-0.521
TTF	5.42	1.157	-1.043	-0.127

Since this study uses a reflective measurement model, it needs to be assessed on its internal consistency reliability, convergent validity, and discriminant validity. The results of the evaluation assessment are shown in Table 3.

The Index of Item Objectives Congruence (IOC) analysis was used to test the questionnaire's validity. It was sent through 3 experts. Each question has an IOC value of more than 0.67; hence, the questions are considered valid.

The Cronbach's alpha coefficient is used to evaluate the reliability. It approximates the reliability based on the intercorrelations of the constructs. The Cronbach's alpha coefficient threshold exceeds 0.70, but not more than 0.95 will be considered satisfactory, reliable constructs (Featherman & Pavlou, 2003) (Legris et al., 2003). The constructs of this study have the lowest value of Cronbach's alpha coefficient at 0.84; therefore, the constructs are highly reliable.

We also assess the reliability of the constructs with the Rho_a coefficient and composite reliability. The Rho_a coefficient value should be more than 0.60 (Dijkstra & Henseler, 2015). The composite reliability value must be more than 0.70 (Hair et al., 2016).

The results indicate that the Rho_a and the composite reliability have values higher than 0.70, so it is reliable.

Each construct was tested for convergent validity using the outer loading and Average Variance Extracted (AVE). The outer loading should be 0.708 or higher (Hair et al., 2018; Hair et al., 2016). It reveals how much of the variation in an item.

The AVE's threshold value should be more than 0.5 (Hair et al., 2018; Hair et al., 2016). Therefore, the corresponding constructs' outer loading and AVE of this study pass the convergent validity.

Table 3 Evaluation of measurement model

Factors	Items	Factor Loading	Cronbach's alpha	Rho_a	Composite Reliability	AVE
BINT PEOU	BINT1	0.921	0.841	0.847	0.926	0.862
	BINT2	0.936				
PPR PU	PEOU1	0.939	0.843	0.853	0.927	0.864
	PEOU2	0.920				
TC TFC	PPR1	0.929	0.855	0.859	0.932	0.873
	PPR2	0.940				
TTF BINT	PU1	0.960	0.917	0.917	0.960	0.923
	PU2	0.962				
PEOU PPR	TC1	0.959	0.913	0.913	0.958	0.920
	TC2	0.960				
PU TC	TFC1	0.946	0.882	0.882	0.944	0.894
	TFC2	0.945				
TFC	TTF1	0.960	0.914	0.914	0.959	0.921
	TTF2	0.959				

For the discriminant validity, we test the model with the Fornell-Larcker coefficient. The Fornell-Larcker metric can also determine that a construct is distinct from other constructs in the structural model (Fornell & Larcker, 1981; Hair et al., 2018). However, recent literature argued that the Fornell-Larcker criterion has issues when performing with a strong variety of indicator loading. Hence, the Heterotrait-monotrait ratio (HTMT) was proposed as a remedy for assessing the discriminant validity. It is defined as "the mean of all correlations of indicators across constructs measuring different constructs (Henseler et al., 2014)".

Table 4 shows the Fornell-Larcker coefficient and HTMT value of this study. For the Fornell-Larcker, the discriminant validity is passed if the value has greater than its highest correlation (Fornell & Larcker, 1981), which is matched with our situation.

The HTMT value has a conservative threshold of .85. However, the HTMT value of less than 1 is still acceptable (Henseler et al., 2014). The reliability and validity of the measurement model are confirmed.

The PLS analysis using bootstrapping algorithm was used to evaluate the path coefficient for testing the hypotheses. It reveals the effect of an independent variable assumed to be a cause on a dependent variable. The bootstrapping was used with the maximum number of subsamples (5,000).

Table 4 The Fornell-Larcker and Heterotrait-monotrait ratio metric

Factor	BINT		PEOU		PPR		PU		TC		TFC		TTF	
	FLM	HTMT	FLM	HTMT	FLM	HTMT	FLM	HTMT	FLM	HTMT	FLM	HTMT	FLM	HTMT
BINT	**0.929**	1.000												
PEOU	0.650	0.769	**0.929**	1.000										
PPR	0.246	0.293	0.403	0.474	**0.934**	1.000								
PU	0.651	0.737	0.782	**0.887**	0.239	0.269	**0.961**	1.000						
TC	0.641	0.733	0.756	**0.858**	0.380	0.429	0.623	0.680	**0.959**	1.000				
TFC	0.608	0.708	0.630	0.731	0.405	0.466	0.540	0.599	0.700	0.781	**0.946**	1.000		
TTF	0.638	0.729	0.735	0.833	0.407	0.458	0.642	0.701	0.850	**0.931**	0.765	**0.852**	**0.960**	1.000

FLM = Fornell-Larcker, HTMT = Heterotrait-monotrait

We also report the t-statistic value and p-value along with the path coefficient (Hair et al., 2018; Hair et al., 2016).

Table 5 shows the results of the bootstrapping. It shows that every hypothesis is supported. The f^2 values of 0.02, 0.15, and 0.35 correspondingly represent small, medium, and large effects (Cohen, 2013). Moreover, f^2 values of less than 0.02 mean that there is no effect. Furthermore, f^2 shows that every construct has enough effect size. However, H1, H5, and H6 have a negligible effect size. H1, H4, H7, H8, and H9 have a high statistical significance level ($p < 0.001$). The H3 is the only hypothesis that shows a negative beta coefficient (PPR->PU). The H5 (TTF->PU) has the weakest positive path coefficient value.

Discussion

One of the critical criteria that evaluate the quality of the structural model in PLS-SEM is the R^2 (Hair et al., 2016). It is the variance explained in the model. The R^2 value ranges from 0 to 1. The higher value means higher levels of predictive accuracy. Figure 4 shows the results of the proposed model along with R^2 and Q^2.

Overall, the results indicated that the perceived usefulness and task technology fit could explain 50.6% of the behavioral intention variance. Moreover, the other R^2 values are more than 0.50 and 0.75, which is considered moderate and substantial.

For assessing a relative measure of predictive relevance, we test the proposed model with a blindfolding algorithm with an omission distance of seven (Hair et al., 2016).

Table 5 The results of hypotheses testing

Hypothesis	Relationship	β Coefficients	*t*-statistics	*p*-values	Results	f^2	VIF
H1	PU -> BINT	0.411	3.107	< 0.01	Confirmed	0.201	1.701
H2	PEOU -> PU	0.701	6.799	< 0.001	Confirmed	0.596	2.240
H3	PPR -> PU	-0.115	2.273	<0.05	Confirmed	0.029	1.233
H4	TTF -> BINT	0.374	3.646	< 0.001	Confirmed	0.167	1.701
H5	TTF -> PU	0.174	2.105	< 0.05	Confirmed	0.036	2.248
H6	TTF -> PEOU	0.335	2.629	< 0.01	Confirmed	0.078	3.611
H7	TC -> TTF	0.617	8.963	< 0.001	Confirmed	0.881	1.962
H8	TC -> PEOU	0.471	3.88	< 0.001	Confirmed	0.154	3.611
H9	TFC -> TTF	0.333	5.253	< 0.001	Confirmed	0.256	1.962

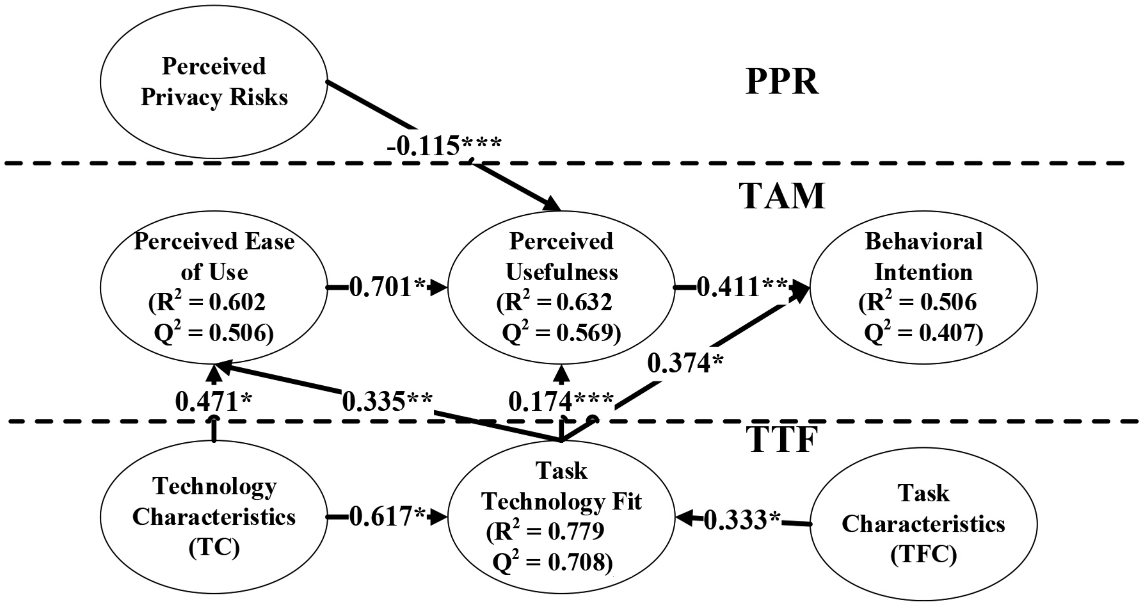

Figure 4 Results with R^2 and Q^2

* $p < 0.001$
** $p < 0.01$
*** $p < 0.05$

The Q^2 values estimated by the blindfolding procedure represent a level of relevance that the path model predicted the dependent value. The Q^2 must be more than 0 to have small predictive relevance. The value higher than 0.25 and 0.5 depict the path model's medium and large relevance (Hair et al., 2016). Most of our Q^2 is more than 0.5, which means the path model has high predictive relevance.

Conclusion

This study aimed to analyze the factors affecting intention to use blockchain-based academic records systems. We proposed an integrated model with the combination of TAM, PPR, and TTF. The model has seven factors: behavioral intention to use, perceived ease of use, perceived privacy risks, perceived usefulness, technology characteristics, task characteristics, and task technology fit. Nine research hypotheses were developed based on these factors. Data collected from the online and an offline questionnaire were analyzed using PLS-SEM. The results show that the model has a good fit, and every hypothesis is statistically significantly confirmed. The path model has a strong effect ($\beta > 0.30$) in every relationship.

The behavioral intention to use a blockchain-based academic system is predicted by PU ($\beta = 0.411$) and TTF ($\beta = 0.374$). The PU is also predicted by PEOU ($\beta = 0.701$), consistent with the original TAM result. Moreover, the effect of TTF supports evidence from previous research that integrated TTF and TAM (Dishaw & Strong, 1999; Heidari, 2019; Klopping & Mckinney, 2004). What is surprising is that TTF has a weak effect on PU ($\beta = 0.174$). Previous literature suggested that TTF could be both a strong (Klopping & Mckinney, 2004) and weak (Dishaw & Strong, 1999) effect. PEOU was predicted by TC ($\beta = 0.417$), and TTF ($\beta = 0.335$). The results from the TTF model also confirm the original model (Ballarini et al., 1995).

The PPR is the only factor with a negative relationship with PU ($\beta = -0.115$). If the perception of the PPR is high, it will decrease PU. These results reflect Featherman (2003), who also obtained the same results when applying PPR with e-services. Furthermore, these results corroborate the ideas that PPR has negatively reduced intention and trust (Lee, 2008; Pavlou, 2003). This result may be related to the new Personal Data Protection Act (PDPA) of Thailand, which will be effective in May 2022 (Thai Government, 2019). It is raising awareness of Thai people's privacy concerns.

Suggestions

This combination of findings provides some implications for this research to help increase the adoption rate of blockchain-based academic records. Firstly, the procedure of using the system must be easy enough. It has a strong effect on the perception of usefulness, which will lead to the intention to use. For example, use the same interface as in the old system to ensure that the users do not need to learn much or make the user interface as simple as possible. Secondly, since the PU affects the intention, the system should extend its features to be more useful. For example, the ability to notify about academic records' status to the social network and one-click verification for checking if the academic records are genuine or not.

Finally, the academic records issuer also needs to be serious about privacy and security of the information. The best way to accomplish this is to follow the rules and regulations for privacy, such as GDPR or PDPA. It depends on each country in which privacy laws are applied.

Limitations and Future Works

Blockchain technology is relatively new for the participants in this study. The tertiary student from the technology departments such as information technology or computer science, seems to realize the system's idea. However, it took some time to make the students from the non-technology department fully understand the idea of a blockchain-based academic records system.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Almekhlafi, S., & Al-Shaibany, N. (2021). The literature review of blockchain adoption. *Asian Journal of Research in Computer Science, 7*(2), 29-50.

Arenas, R., & Fernandez, P. (2018). Creedence ledger: A permissioned blockchain for verifiable academic credentials. In *2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)* (pp. 1-6). IEEE.

Ballarini, P., Guido, R., Mazza, T., & Prandi, D. (1995). Task-technology fit and individual performance. *MIS Quarterly, 10*(3), 213-236.

Batubara, F. R., Ubacht, J., & Janssen, M. (2018). Challenges of blockchain technology adoption for e-government. In *The 19th Annual International Conference on Digital Government Research: Governance in the Data Age* (pp. 1-9). Association for Computing Machinery.

Brown, G. M. (2006). Degrees of doubt: Legitimate, real and fake qualifications in a global market. *Journal of Higher Education Policy and Management, 28*(1), 71-79.

Buasuwan, P., & Jones, M. E. (2016). *Asia pacific graduate education*. Palgrave Macmillan.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic press.

Dam, H. N., Phan, D. T., Vu, D. T., & Nguyen, L. T. N. (2020). The determinants of customer's intention to use international payment services by applying blockchain. *Uncertain Supply Chain Management, 8*(3), 439-456.

Daraghmi, E. Y., Daraghmi, Y. A., & Yuan, S. M. (2019). Unichain: A design of blockchain-based system for electronic academic records access and permissions management. *Applied Sciences (Switzerland), 9*(22), 4966.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics and Data Analysis, 81,* 10-23.

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task-technology fit constructs. *Information & Management*, *36*(1), 9-21.

Dujak, D., & Sajter, D. (2019). *SMART supply network*. Springer, Cham.

Featherman, M. S., Miyazaki, A. D., & Sprott, D. E. (2010). Reducing online privacy risk to facilitate e-service adoption: The influence of perceived ease of use and corporate credibility. *Journal of Services Marketing, 24*(3), 219-229.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451-474.

Fishbein, M., & Ajzen, I. (1977). Belief, attitude, intention, and behavior: An introduction to theory and research. *Philosophy & Rhetoric, 10*(2), 130-132.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

George, D., & Mallery, P. (2019). *IBM SPSS statistics 26 step by step: A simple guide and reference.* Routledge.

Grech, A., & Camilleri, A. F. (2017). *Blockchain in education*. Publications Office of the European Union.

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial Least Squares Structural Equation Modeling (PLS-SEM): An emerging tool in business research. *European Business Review, 26*(2), 106-121.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2018). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24.

Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).* Sage Publications.

Han, M., Li, Z., He, J., Wu, D., Xie, Y., & Baba, A. (2018). A novel blockchain-based education records verification solution. In *The 19th Annual SIG Conference on Information Technology Education* (pp. 178-183). Association for Computing Machinery.

Heidari, H. (2019). Evaluating the factors affecting behavioral intention in using blockchain technology capabilities as a financial instrument. *Journal of Money and Economy, 13*(2), 195-219.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135.

Hoyle, R. H. (1995). *Structural equation modeling: Concepts, issues, and applications.* Sage Publications.

Isaac, O., Abdullah, Z., Ramayah, T., & Mutahar, A. M. (2017). Internet usage, user satisfaction, task-technology fit, and performance impact among public sector employees in Yemen. *The International Journal of Information and Learning Technology*, *34*(3), 210-241.

Kamble, S., Gunasekaran, A., & Arha, H. (2019). Understanding the blockchain technology adoption in supply chains-Indian context. *International Journal of Production Research, 57*(7), 2009-2033.

Kamble, S. S., Gunasekaran, A., Kumar, V., Belhadi, A., & Foropon, C. (2021). A machine learning based approach for predicting blockchain adoption in supply chain. *Technological Forecasting and Social Change, 163*, 120465.

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management, 43*(6), 740-755.

Klopping, I. M., & Mckinney, E. (2004). Extending the technology acceptance model and the task-technology fit model to consumer e-consumer. *Information Technology, Learning, and Performance Journal, 22*(1), 35-48.

Lee, C. C., Kriscenski, J. C., & Lim, H. S. (2019). An empirical study of behavioral intention to use blockchain technology. *Journal of International Business Disciplines, 14*(1), 1-21.

Lee, M. C. (2008). Factors influencing the adoption of internet banking: An integration of TAM and TPB with perceived risk and perceived benefit. *Electronic Commerce Research and Applications, 8*(3), 130-141.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191-204.

Lizcano, D., Lara, J. A., White, B., & Aljawarneh, S. (2020). Blockchain-based approach to create a model of trust in open and ubiquitous higher education. *Journal of Computing in Higher Education, 32*(1), 109-134.

Miraz, M. H., Hasan, M. T., & Masum, M. H. (2020). Factors affecting consumers intention to use Blockchain Based Services (BBS) in the hotel industry. *International Journal of Mechanical and Production Engineering Research and Development, 10*(3), 8891-8902.

Mitzner, T. L., Boron, J. B., Fausset, C. B., Adams, A. E., Charness, N., Czaja, S. J., Dijkstra, K., Fisk, A. D., Rogers, W. A., & Sharit, J. (2010). Older adults talk technology: Technology usage and attitudes. *Computers in Human Behavior, 26*(6), 1710-1721.

Mooney, C. Z., Mooney, C. F., Mooney, C. L., Duval, R. D., & Duvall, R. (1993). *Bootstrapping: A nonparametric approach to statistical inference*. Sage Publications.

Nakamoto, S. (2009). *Bitcoin: A peer-to-peer electronic cash system.* Bitcoin. http://www.bitcoin.org

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101-134.

Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 139-152.

Ringle, C. M., Wende, S., & Becker, J. M. (2015). *SmartPLS3.* SmartPLS. http://www.smartpls.com

Sebastian, S., & Venkatesh, V. (2021). Blockchain, adoption, and financial inclusion in India: Research opportunities. *International Journal of Information Management*, *52*, 101936.

Szabo, N. (1997). *Formalizing and securing relationships on public networks*. Firstmonday. https://firstmonday.org/ojs/index.php/fm/article/view/548/469

Thai Government. (2019). *Personal data protection act*. https://drive.google.com/open?id=1MzGNi3kdDPA0E52n8bDybeuDNklM8xJe

Tschorsch, F., & Scheuermann, B. (2016). Bitcoin and beyond: A technical survey on decentralized digital currencies. *IEEE Communications Surveys and Tutorials, 18*(3), 2084-2123.

Turkanović, M., Hölbl, M., Košič, K., Heričko, M., & Kamišalić, A. (2018). EduCTX: A blockchain-based higher education credit platform. *IEEE Access, 6,* 5112-5127.

Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of Partial Least Squares.* Springer.

Wong, K. K. K. (2013). Partial Least Squares Structural Equation Modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin, 24*(1), 1-32.

Wright, A., & De Filippi, P. (2015). *Decentralized blockchain technology and the rise of lex cryptographia*. SSRN. https://ssrn.com/abstract=2580664

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCS: Integrating the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) Model. *Computers in Human Behavior, 67,* 221-232.

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