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Factors Influence Blockchain Adoption in Supply Chain Management Among Companies Based in Ho Chi Minh City

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ABSTRACT
In recent years, the devastating effects of the COVID-19 pandemic have threatened supply chain management. Blockchain technology has emerged as the resource that is used to mitigate the challenges caused by the COVID -19 pandemic. This study aims to figure out the effects of the performance expectancy (PE), effort expectancy (EE), facilitating condition (FC), and technology readiness (TECHR) on behavioral intention (BI), and examine the mediating role of trust (TR) between the exogenous and endogenous – behavioral intention in implementing blockchain in supply chain management among companies based in Ho Chi Minh city. The researcher combined two models involving the Technology-Organization-Environment framework and the Unified Theory of Acceptance and Use Technology theory that could cover most existing perspectives of the business. Data was accumulated from respondents who work in a supply chain firm and will be investigated by using SmartPLS. The finding reveals that performance expectancy and effort expectancy have significant effects on trust and behavioral intention. Hence, the result reflects that the respondents can perceive the performance expectancy and effort expectancy for operating the blockchain technology in supply chain management. Meanwhile, technology readiness and facilitating conditions are indirect predictors which were mediated by trust. The mediating effect of trust was found to be impactful on behavioral intention. This means the behavioral intention mainly operates whether the firms have enough trust in adopting the novel technology. This paper contributes new knowledge to the literature on factors that influence the adoption of blockchain and justifications also are discussed accordingly.

Keywords: *Vietnam, Supply chain management, Blockchain, Adoption, TOE framework, UTAUT theory.*

1. INTRODUCTION

The supply chain is a channel for delivering the form-both intangible and tangible products beginning with the suppliers to the end-users. Supply chain management and logistics recently are becoming an important, strategic trend for companies in Vietnam [1]. Since late 2019, the highly infectious Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) has been wreaking havoc around the world, causing the unique coronavirus disease (hereafter called COVID-19). The COVID-19 has overburdened supply chain systems across the world, particularly those engaged in resource-limited settings with poor disease surveillance mechanisms. Blockchain technology adoption is considered as a method to improve supply chain resiliency which was damaged by the COVID-19. Blockchain can expedite and automate various business transaction processes which enable more direct relationships between participants, as a result, it has been regarded as the backbone of the supply chain digitization. Blockchain is defined as a mechanism for businesses, industries, and government agencies to transact and verify transactions in near real-time by using a distributed ledger without relying on central authority [2]. Blockchain makes the supply chain secure, transparent, decentralized, and immutable that has the potential to revolutionize businesses [3].

A variety of past studies have proven that blockchain technology can tremendously improve and empower supply chain management. Blockchain technology is a vital instrument to effectively and efficiently operate the supply chain[4], [5]. Recent studies mainly paid attention to the surrounding areas of the blockchain [6], and the use of blockchain in addressing the supply chain management objectives [7] such as double marginalization [8], traceability [9]. The present study mainly focuses on addressing the paucity of blockchain adoption in supply chain management by examing the multiple elements related to behavioral intentions.

Inadequate literature still exists and lack of empirical study researching about the relationship between behavioral intention toward using blockchain in the supply chain in Vietnam, they mainly dedicated theory and definition about blockchain and its possibilities of use in a variety of firms, they forgot to mention the determinants of blockchain adoption. Still, some writers have recognized the potential of blockchain in the duration of the COVID-19 outbreak [10], [11], but they also forgot to mention the shifting of user behavioral intention toward managing the supply chain.

2. MATERIALS AND METHODS

2.1. Adoption Models

To investigate the relationship between user's psychological significance toward user's behavioral intention on adopting blockchain technology in supply chain management. The UTAUT model forms the underlying theoretical basis of the research model while the TOE model acts as a framework that comprises the construct variables of the UTAUT theory. The research more aims at extending the TOE framework through forming independent variables in terms of expectancy in utilizing blockchain and the readiness of adopting to blockchain separately rather than concentrating on the readiness of the company heading to technological innovation decision making in both – form of technology, organization, and environment

2.1.1. TOE Framework

Technology-Organization-Environment framework (referred to hereafter as TOE) was proposed by Tornatzky and Fleischer (1990) for analyzing the impact of the organizational adoption process and implementation of technological innovations. The TOE framework consists of three distinct main dimensions including technological context, organization context, and environmental context. The framework of TOE has a strong theoretical foundation and good evidence since it is demonstrated by a plethora of papers that use the TOE framework to explore and forecast variables that impact the adoption of a wide range of technologies at the enterprise level. The TOE framework has been utilized to describe the application, implementation, and impact of innovations [12]. Additionally, there is a link between TOE components and e-business value by discovering that variables such as technical readiness, financial resources, global scope, and regulatory environment all contributed considerably to e-business value [13]. Subsequently, the TOE concept was combined with the theory of resource-based view to clarify relationships between e-business, consumption, and valuation in the retail industry [14]. It is also discovered that for developed nations, competitive pressure, and regulatory support are essential considerations.

2.1.2. The Unified Theory of Acceptance and Use Technology

The Unified Theory of Acceptance and Use Technology (UTAUT), proposed by Venkatesh [15] is one of the most up-to-date models for analyzing technology adoption. Gender, age, experience, and voluntariness of usage affect the four moderators of performance expectation, effort expectancy, social influence, and enabling circumstances, which are direct drivers of behavioral intention and ultimately action [15]. Three main constituents affect intention to use including performance expectancy, effort expectancy, and social influence, and two direct elements that influence user action involving behavioral intention and facilitating condition.

The UTAUT theory in conjunction with the network theory was utilized to explain the rationale for adopting blockchain among supply chain management experts in the USA and India [16]. Similarly, the TAM constructs such as the perceived usefulness and perceived ease of use have similar features in comparison with PE and EE. Both these constructs are used as factors to forecast the desire into using blockchain technology in India [17].

2.2. Hypotheses Development

2.2.1. The Technology Dimension

In this research, the Technological dimension is seen as blockchain itself, it represents the benefits that users expect to gain from using the technology - blockchain. The Technology frame is constructed with Performance Expectancy and Effort Expectancy in the context of this paper.

2.2.1.1. Performance Expectancy

In the current studies related to blockchain technology, PE was found to be a predictor of behavioral intention to use cryptocurrency [18] and supply chain [19], which is in line with other research [20]. According to Wamba, & Queiroz [16] and Sanmukhiya [21], there is the positive effect of PE on behavioral intention (= 0.005; = 0.053).

The following hypothesis is formulated based on validations on these past studies:

H1a: PE has a positive influence on BI in implementing blockchain technology in supply chain management.

2.2.1.2. Export Expectancy

Considering as resemble performance expectancy, effort expectancy is a construct that discovers the ease of use of the systems. In terms of the blockchain, it was expected that the complexity of the various activities will drop significantly [22]. Hence, enabling more efficiency across supply chain activities [23]. Wamba, & Queiroz [16] and Wong et al. [24] mutually found out the significant positive effect of EE respectively on BI (= 0.12; = 0.267), The following hypothesis is formulated with these arguments:

H2a: EE has a positive influence on BI in implementing blockchain technology in supply chain management.

2.2.2. The Organization and Environment Dimension

In this research, the Environment dimension and the Organization dimension are merged into one frame and categorized as the readiness variable of the company. The Organizational and Environmental dimension is constructed with Facilitating Condition and Technology Readiness whereas Facilitating Condition is known as environmental factors, Technology Readiness is known as an organizational factor.

2.2.2.1. Technology Readiness

Technology readiness is considered as the element that represents the aspect of the organizational context [3]. Technology readiness is seen as a critical component in influencing a company's IT adoption. The two primary reasons which are identified namely the compatibility of the firm’s current information systems and network technologies, and conversion cost [25]. Moreover, technology readiness renders the right infrastructure and trust in one’s ability to attain the completion of blockchain technology. Alkhater et al. [26] and Wong et al. [24] figured out the significant positive impact of TECHR on BI respectively (= 0.118; = 0.32). Accordingly, the following hypothesis is formulated:

H3a: TECHR has a positive effect on BI in implementing blockchain technology in supply chain management.

2.2.2.2. Facilitating Condition

Facilitating condition (FC) is considered as a direct effect toward the behavioral intention [27]. In the context of this study, FC refers to the perceived presence of relevant resources such as knowledge infrastructure available to firms to implement blockchain in supply chain management. The study hypothesizes that if firms perceive that they have the necessary supporting technological infrastructures, they are more likely to adopt blockchain in supply chain management. Sanmukhiya [21] and Wong et al. [24] figured out is the significant positive effect of FC on BI respectively (= 0.640; = 0.19). Therefore, the following hypothesis has been posited:

H4a: Facilitating condition (FC) has a positive effect Behavioural Intention (BI) on implementing blockchain technology in supply chain management.

2.2.3. Trust as a Mediator

Trust is a reliable indicator of behavioral intention on several occasions [28]. Trust is a rational expectation that the trustworthy party will fulfil its responsibilities as intended by the trusting party [29], and it shows the risk propensity of a person to meet the needs. The study posits that lacking trust is going to be hindering the adoption of blockchain in supply chain management, especially in Vietnamese culture. A corporate that holds the belief that blockchain technology can mitigate and ease their work, will be more likely to accept and use the technology. Leong, Chiek, and Lim [30] and Enaizan et al. [31] found a positive relationship between TR and BI respectively (= 0.162; = 0.110). PE is related to the belief of the organization that utilizing blockchain technology will contribute to supply chain performance. In the recent survey on non-financial blockchain adoptions, all respondents who have experience with blockchain believed that blockchain would be useful in different areas of supply chain management [32]. Sanmukhiya [21] and Wei et al. [22] found the significant positive effect of PE on trust respectively (= 0.216; = 0.4). Faridi, Kavoosi-Kalashami, and Bilali [33] and Leong et al. [30] also discovered the substantial positive influence of EE on trust respectively (= 0.369; = 0.642). People stopped using computers as a result of their inherent fear of technology [34]. The explanations for this may be related to people's scepticism and the lack of preparation for emerging technology. Walczuch, Lemmink, and Streukens [35] figured out the positive relations between TECHR and TR respectively (= 0.08; = 0.09). In their electronic commerce study, Nicolaou and McKnight [36] demonstrated that facilitating conditions increase customers purchasing intent and also have a positive effect on consumers’s trust. Furthermore, those enabling factors are critical to maintaining a trusting environment [37]. Kaium et al [38] and Sanmukhiya [21] figured out the significant and positive influence of FC on TR correspondingly (= 0.225; = 0.215).

With these arguments, the following hypotheses are posited accordingly:

H1b: TR mediates the relationship between PE and BI on implementing blockchain technology in supply chain management.

H2b: TR mediates the relationship between EE and BI on implementing blockchain technology in supply chain management.

H3b: TR mediates the relationship between TECHR and BI on implementing blockchain technology in supply chain management.

H4b: TR mediates the relationship between FC and BI on implementing blockchain technology in supply chain management.

H5: TR has a positive effect on BI in implementing blockchain technology in supply chain management.

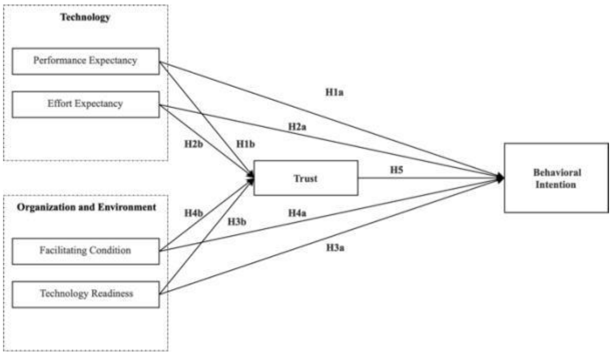

Figure 1 Proposed Model

2.3. Methodology

The targeted group of this paper is workers who are working in the field of the supply chain. The sampling is non-probability and the judgmental sampling technique is opted to accumulate the data due to the accuracy and the cost constraint. Ho Chi Minh city opted because the city is the ground for 281 supply chain and supply chain-related companies building, and the city is also the main economic center of Vietnam The study used the questionnaire which was prepared and delivered in Google Form to obtain an adequate sample size. Also, the questionnaire was developed based on validated measurement which was used in previous studies. A screening note was attached to ensure that every respondent in the sample has a clear view of blockchain technology and to avoid common method bias. The analysis was based on a calculation of the seven-point Liker-type scale ranging from 1 (strongly disagree) to 7 (strongly agree).

3. RESULTS AND DISCUSSION

3.1. Statistical Analysis

Table 1 presents the demographic characteristics of the sample.

Table 1. Demographic characteristics

Demographic characteristics		**Frequency Total: 308**	**Percentage**
Which of the following best describes your present level of understanding of blockchain technology?	Learning the technology	152	49.35%
	Testing the technology	47	15.26%
	Implementing the technology	32	10.39%
	None	77	25%
Age of organization (years)	5 or less	121	39%
	6 – 10 years	104	34%
	Above 10 years	83	27%
Category of your organization's products	Logistics and Transportation	69	22%
	Food	31	10%

	Retail	68	22%
	Construction and building material	33	11%
	Plastic	31	10%
	Processed product	33	11%
	Other	43	14%
Number of employees in your organization	Less than 50	113	37%
	50 – 100 employees	72	23%
	101 – 200 employees	60	19%
	Above 200 employees	63	20%

3.2. Assessing The Outer Measurement Model

The study used composite reliability (CR) and Dijkstra-Henseler's rho (rho_A) to test construct reliability [39]. According to previous studies, CR and rho_A ≥ 0.7 are considered good reliable [40]. As a result, in Table 2, the CR exceeds the minimum value of 0.7 for both indices indicating that the measurement model has good reliability.

Convergent validity shows the degree to which constructs are familiar with each other in the concept, will be examined by factor loading (FL) and average variance extracted (AVE). As shown in Table 2, all the AVE values for the constructs are higher than the recommended value of 0.5 [41]. The lowest value of AVE is 0.754 for the construct PE which is also greater than the minimum threshold of 0.5. Additionally, all factor loadings shown in Table 2 ranging from 0.861–0.939 were above the recommended value of 0.7 which provides support for convergent validity [42].

Discriminant validity (DV) was assessed using the traditionally-used Fornell and Larcker [40] procedure, which indicated that when the AVE of an individual construct is greater than the square multiple correlations of that construct compared to other constructs. Table 2 confirmed DV in which the square root of AVE for all constructs on the diagonal was higher than the correlations coefficients with other constructs. Additionally, the study examined Discriminant Validity (DV) by using the Heterotrait-Monotrait (HTMT) inference ratio of correlations through a non-parametric bootstrap approach [43]. All values in Table 3 show the lower and upper bounds of the 95% confidence interval and the values were lower than one for each relationship. This demonstrates that each concept in the sample is statistically distinct from the others and that discriminant validity has been established [44].

3.3. Inspecting The Inner Structural Model

The Standardized Root Mean Square Residual (SRMR) is used to evaluate the global goodness of fit of both the estimated and saturated models [45]. The saturated and estimated models were found respectively to be 0.041 and 0.051, which is less than 0.08 and shows that the model fit is satisfied [46]. The variance inflation factors (VIF) values for all constructs varied between 2.197 and 4.927, below the cut-off value of 5.0 [47], which suggests that multicollinearity did not exist.

Mediating effects can be examined based on the indirect effects of the mediators which are shown in Table 5. Based on the PLS analysis, it was found that there is a significant and positive mediating effect of trust ($t=3.456$, $\rho < 0.05$) in the relationship between effort expectancy and behavioral intention followed by performance expectancy ($t=2.437$, $\rho < 0.05$), facilitating condition ($t=2.229$, $\rho < 0.05$), technology readiness ($t=2.006$, $\rho < 0.05$). Henceforth, H2b, H3b, and H4b are confirmed to be supported.

Table 4 and figure 2 mutually show that 7 out of 9 hypotheses were supported. The result of the hypotheses testing with the respective p-values and t-statistics are shown in Table 4, which was generated by running smartPLS with 5000 sub-samples through bootstrap. The T-statistics is greater than 1.96 shows that the relationship is significant at a 95% confidence level ($\alpha = 0.05$). The results show that PE was positively related to BI ($t = 5.291$; $\rho < 0.01$). Therefore, H1a was confirmed. Moreover, EE positively affected on BI ($t = 4.218$; $\rho < 0.01$), which supported H2a. Furthermore, the structural model results also revealed that trust and behavioral intention are significantly related. This result corresponds to H5 of this study stating that there is a significant relationship between trust and behavioral ($t = 3.841$; $p < 0.01$). Contrary to our expectation, TECHR was not positively associated with BI ($t = 0.928$; $\rho < 0.01$), unsupporting H3a. Additionally, FC was not positively influenced on BI ($t = 0.190$; $\rho < 0.01$) which did not support H4a.

Table 6 shows that the research model accounts for 29.5 percent of variations in BI, which indicates the in-sample explanatory is at a high degree. On the other hand, R^2 quantified the model's in-sample explanatory capacity but not its out-of-sample predictive performance. Consequently, the research also follows PLS predict strategy by focusing on the main target construct. Table 8 shows that none of the root mean squared error (RMSE) indices in the PLS-SEM model exceed those in the linear model benchmark.

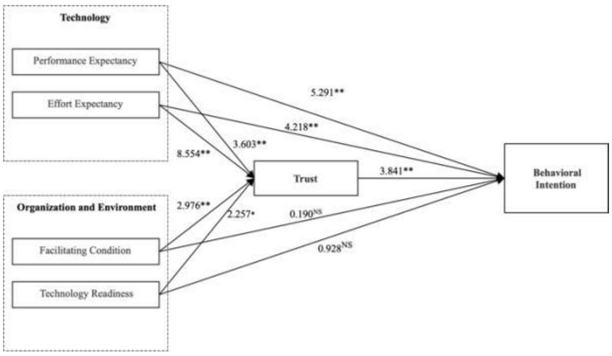

Figure 2 Structural model testing

3.4. Predictive relevance and effect size

Predictive relevance and effect size were examined using blindfolding with omission distance 6. The cross-validated communality was used to calculate Stone-Geisser's Q^2 in assessing the predictive relevance of this study Table 6 demonstrates that the research model can account for 64.3 percent of the variation in BI. Following the rule of thumb, a Q^2 value greater than zero signifies that the model has predictive relevance [48].

For the effect size, f^2 is assessed to establish the intensity of relationships among variables. Table 7 shows that FC (0.00) and TECHR (0.002) do not affect BI while EE (0.05), PE (0.077), and TR (0.025) have small effects on BI.

3.5. Importance-performance Map Analysis

The paper extends the PLS-SEM findings by analyzing importance-performance maps (IPMA). Table 7 indicated that the most important precursors of BI in implementing blockchain in supply chain management are EE (0.303), PE (0.299), TR (0.149), TECHR (0.036), and FC (-0.031). On a performance level, PE (64.152) is the most predictive of BI in implementing blockchain in supply chain management and followed by EE (59.674), TECHR (57.079), FC (56.317), and TR (50.163). The emphasis is on PE because it is less important (0.299), but high performance (64.152).

Table 2. Loading, composite reliability, Dijkstra Henseler (rho_A), and average variance extracted

Latent Constructs	Items	Loadings	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BI	BI1	0.892	0.922	0.940	0.797
	BI2	0.897			
	BI3	0.895			
	BI4	0.887			
EE	EE1	0.883	0.907	0.933	0.778
	EE2	0.888			
	EE3	0.867			
	EE4	0.890			
FC	FC1	0.866	0.950	0.943	0.806
	FC2	0.889			
	FC3	0.925			
	FC4	0.909			
PE	PE1	0.861	0.893	0.924	0.754

	PE2	0.869			
	PE3	0.879			
	PE4	0.864			
TECHR	TECHR1	0.915	0.934	0.947	0.818
	TECHR2	0.913			
	TECHR3	0.909			
	TECHR4	0.880			
TR	TR1	0.915	0.949	0.963	0.867
	TR2	0.938			
	TR3	0.939			
	TR4	0.933			

*Note (s):*BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; PE: Performance Expectancy; TECHR: Technology Readiness; TR: Trust

Table 3. Hetero-Trait-Mono-Trait (HTMT inference)

	Original Sample (O)	Sample Mean (M)	2.5%	97.5%
EE -> BI	0.500	0.499	0.407	0.586
FC -> BI	0.165	0.168	0.079	0.275
FC -> EE	0.359	0.359	0.249	0.469
PE -> BI	0.496	0.496	0.404	0.583
PE -> EE	0.563	0.563	0.470	0.645
PE -> FC	0.275	0.275	0.161	0.387
TECHR -> BI	0.219	0.219	0.111	0.325
TECHR -> EE	0.415	0.416	0.322	0.510
TECHR -> FC	0.653	0.653	0.583	0.721
TECHR -> PE	0.266	0.266	0.175	0.360
TR -> BI	0.347	0.346	0.261	0.429
TR -> EE	0.418	0.419	0.329	0.501
TR -> FC	0.038	0.061	0.024	0.140
TR -> PE	0.323	0.322	0.226	0.416
TR -> TECHR	0.018	0.049	0.021	0.110

*Note (s):*BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; PE: Performance Expectancy; TECHR: Technology Readiness; TR: Trust

Table 4. Results of the hypothesized direct effects of the variables in the structural model.

PLS Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	2.5%	97.5%	Remarks
PE -> BI**	0.276	0.277	0.052	5.291	0.000	0.173	0.378	Supported
EE -> BI**	0.245	0.244	0.058	4.218	0.000	0.130	0.352	Supported

TECHR - > BI^{NS}	**0.050**	**0.050**	**0.054**	**0.928**	**0.353**	**-0.056**	**0.161**	**Unsupported**
FC -> BI^{NS}	**-0.010**	**-0.009**	**0.051**	**0.190**	**0.849**	**-0.109**	**0.094**	**Unsupported**
TR -> BI**	0.149	0.148	0.039	3.841	0.000	0.073	0.224	Supported

*Note (s):*BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; PE: Performance Expectancy; TECHR: Technology Readiness; TR: Trust

* Significant at 5% level, $p < 0.05$.

** Significant at 1% level, $p < 0.01$.

^{NS} Not supported.

Table 5. Mediation effects of TRUST via bootstrapping.

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P-value2.5%		97.5%	Remarks
PE -> TR -> BI*	0.023	0.024	0.010	2.437	0.015	-0.042	-0.005	Supported
EE -> TR -> BI**	0.058	0.058	0.017	3.456	0.001	0.027	0.093	Supported
TECHR -> TR -> BI*	-0.015	-0.014	0.007	2.006	0.045	-0.030	-0.002	Supported
FC -> TR -> BI*	-0.021	-0.021	0.009	2.229	0.026	0.008	0.045	Supported

*Note (s):*BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; PE: Performance Expectancy; TECHR: Technology Readiness; TR: Trust

* Significant at 5% level, $p < 0.05$.

** Significant at 1% level, $p < 0.01$.

Table 6. Predictive relevance (Q^2)

Endogenous Construct	SSO	SSE	Q^2 (=1-SSE/SSO)	R Square
BI	2292	818.328	0.643	0.295

*Note (s):*BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; PE: Performance Expectancy; TECHR: Technology Readiness; TR: Trust

Table 7. Effect size f^2 and Importance performance map analysis

Predictor Construct/ Dependent Construct	**BI**	**Importance (Total Effect)**	**Performance (Index value)**
EE	0.050	0.303	59.674
FC	0	-0.031	56.317
PE	0.077	0.299	64.152
TECHR	0.002	0.036	57.079
TR	0.025	0.149	50.163

*Note (s):*BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; PE: Performance Expectancy; TECHR: Technology Readiness; TR: Trust

Table 8. PLS Predict

	PLS – SEM			**Linear model Benchmark**	
	RMSE	**MAE**	**Q²_ predict**	**RMSE**	**MAE**
BI1	1.114	0.876	0.261	1.115	0.876
BI2	1.150	0.892	0.208	1.158	0.904
BI4	1.203	0.936	0.194	1.221	0.951
BI3	1.165	0.893	0.147	1.171	0.894

*Note (s):*BI: Behavioral Intention; EE: Effort Expectancy; FC: Facilitating Condition; PE: Performance Expectancy; TECHR: Technology Readiness; TR: Trust

4. CONCLUSION

The finding shows that there are 7 out of 9 hypotheses were significant namely the effect of PE, EE on BI, and the effect of PE, EE, TECHR, and FC on TR. Besides, the mediating effect of the variable mediator also was tested by utilizing the indirect effect. The finding shows that performance expectancy has the strongest indirect effect on behavioral intention followed by facilitating condition, technology readiness, effort expectancy. Thus, there is a significant mediation effect of trust in the relationship between all the determinants and behavioral intention.

The findings from this research indicate that there is a significant effect of performance expectancy on behavioral intention. Compared to previous studies, the findings of this study are persistent with the prior study of Leong et al. [30]. The result from this study implies that trust plays a mediating role in this relationship and the performance expectancy resulting in trust and leading to behavioral intention in using blockchain in the supply chain. The effort expectancy is also exposed to have a significant effect on behavioral intention. It turns out that the result is in line with studies of Wong, Tan, et al. [24], and Queiroz & Fosso Wamba [16], also in an agreement with the previous study of Leong et al., [30] which implies that trust plays a mediating role in the relationship between the effort expectancy (ease of use) of blockchain technology resulting in trust and leads to intent to use blockchain.

In a difficult time like COVID – 19 outbreak, companies require the technology that can mitigate their difficulties in operations, especially for those who are engaged in supply chain management. The absence of workers in the workplace and the restriction in circulating lead to stagnancy in workload. And due to the importance and security of each procedure, so supply chain companies need technology that has appropriate characteristics, and blockchain is recognized as an immutable, secure, transparent, and traceable that meets the demand of companies in the pandemic outbreak. Therefore, the category of expectancy from blockchain including performance expectancy and effort expectancy has direct a relationship to behavioral intention. The category associated with trust also has a significant impact on behavioral intentions.

The finding of this paper exposed that there is an insignificant effect of facilitating conditions on behavioral intention to use blockchain. It is not in agreement with the prior studies of Sanmukhiya [21] and Wong, Tan, et al. [24] which mutually figured out the significant positive effect of facilitating conditions on behavioral intention to use blockchain. However, it is in line with the study of Kaium et al. [38] that figured out the significant and positive influence of facilitating conditions on trust. Coming to the technology readiness perspective, this study has a negative impact and is also in disagreement with the prior study of Alkhater et al. [26] and Wong, Tan, et al. [24] about the significant positive impact of technology readiness on behavioral intention. However, the finding is consistent with the study of Walczuch et al. [35] about the positive relations between technology readiness and trust.

Both facilitating conditions and technology readiness are considered as the property of the companies in form of intelligence and infrastructure. When the company decides to adopt new technology, they carefully examine the potential of this technology whether any risk arises during the operation management. Because risk may damage their available property. Instead of spending the labor force on accessing new technology that may possess risk, they can continuously use their conventional operating system. Training the employees to use the new technology can bring negative impacts if the technology does not have any positive and transformative effect on the company. Moreover, companies are likely to be anxious that blockchain may not be the best-optimized technology for their company. It could be a miss if the other technology was more appropriate with the characteristics of their company than blockchain. Among the respondents of this survey, there are 79 out of 308 people – accounting for 25.65 percent – are testing and implementing blockchain technology. This explained the reason why most people are likely to worry about the negative effects of blockchain technology because they have a lack knowledge and are full of suspicions about the technology. Especially, in the harsh time like the COVID-19 outbreak. Conversely, the companies that built on the right facilitating conditions and the technology readiness were more likely to believe that they could perform the new technology well. They have what it take to be trustful in their potential. Trust is associated with the relationship between facilitating conditions, technology readiness, and behavioral intention. Indeed, companies that are confident in what it takes are more likely to have more trust in blockchain, and it leads to more confidence in blockchain adoption. Consequently, facilitating conditions and technology readiness are considered as the determinants on blockchain adoption only be significant when it is associated with trust

The final result from this paper depicts a significant relationship between trust and behavioral intention. It is consistent with the prior studies of Leong et al. [30] and about the positive relationship between trust and behavioral intention. It can be understood that the user's demand from adapting to the advanced technology demand a shred of trustworthy evidence. For Vietnamese users who are timid to try new technology, trust-in-technology plays an important role to motivate the user to perceive the new technology in supply chain management among companies especially those based in Ho Chi Minh city in which is considered as the homeland of many big companies in the realm of supply chain management.

The first limitation of this study is that only Vietnamese enterprises are concentrated on. There arose a recommendation needed for future study to broaden the research by incorporating foreign companies which have the headquarter and now is running in Vietnam. The next limitation would be the lack of a moderating factor. Since this paper solely focused on the mediating factor of the Trust, the future paper should take into account incorporating moderating factors or a combination of both moderating and mediating effects, to gain further clarity on the relationship between the construct. Even though the research model is capable of explaining the relationship of the variance in behavioral intention, there may be other factors that can be incorporated into the research model in the upcoming studies.

The Organization and the Environment frame of the proposed framework were merged into one folder, hence it could be not clear to demonstrate and analyze both perspectives, the future research could find out one or more theories to associate well with the framework, also they may leverage the effects of each frame and properly select several components to empower the predictive power of the research model. Next, these aforementioned effective motivations did not go through the exploratory research step, so that perhaps it does not render the most ideal research models for observing the user's behavioral intention. Finally, the data was collected and analyzed in the Vietnamese cultural setting. Hence the findings may not be relevant to other geographical areas. Thus, future studies may be conducted in other geographical areas or cultural settings.

AUTHORS' CONTRIBUTIONS

Hieu-Ba Nguyen: Conceptualization, Methodology, Formal analysis, Investigation, Writing-original draft.
Luan-Thanh Nguyen: Conceptualization, Methodology, Writing-review & editing, Supervision.

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