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Applications of blockchain-based smart contracts in the field of health insurance

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Abstract
Purpose: This study specifically focus on to explore the user behavioral factors to use blockchain smart contracts for managing their healthcare insurance services in Malaysia.
Design/methodology/approach: Utilizing quantitative deductive research, this study tested the Unified Theory of Acceptance use of Technology (UTAUT), the task-technology fit (TTF) and initial trust model (ITM) concerning the user intenton towards blockchain smart contract in healthcare insurance services. Based on convenience sampling, the questionnaire distributed via google form and received 234 responses. The hypotheses is tested based on path coefficient analysis of SEM framework.
Findings: Results shows that the competency of the technology to perform the related tasks influence their intention to use this new technology advancement. Consumer initial trust on technology contributes to their intention especially in terms of structural assurances. The intention is increased when the benefits provided by utilizing this technology outweigh the costs.
Research limitations/implications: This research was conducted only in Malaysia with the awareness of the blockchain smart contract on insurance services still at initial stage, therefore the findings are inapplicable across countries. However, this study provides significant guidelines for policymakers and industry players in designing frameworks, products or strategies to enhance the development of blockchain smart contracts on healthcare insurance.
Originality/value: The research findings added insight to the current body of knowledge on the factors influencing behavioral intentions to use blockchain smart contracts to manage healthcare insurance services. There are limited studies focusing on this topic, especially for Malaysia.

Keywords: Blockchain, smart contract, healthcare insurance, initial trust, task technology fit

Introduction

People have relied significantly on insurance for many years to safeguard their assets and even their lives. However, the traditional insurance procedure is frequently cumbersome, prone to fraud, and delayed, making policyholders dissatisfied and mistrustful of the insurance company. Blockchain technology, which offers a decentralized, protection, and promote transparent mechanism to administer insurance coverage, has emerged as a practical solution to these issues. Smart contracts, on the other hand, are self-implement contracts with automatically enforce the terms and agreement without middlemen. They manage and complete insurance transactions on a secure, decentralized network, decreasing the need for human procedures and the possibility of fraud (Choudhary, Rane, Kothari & Chavan, 2023). Blockchain technology and smart contracts are gaining popularity in Malaysia. On October 18, 2016, the Central Bank of Malaysia released the Financial Technology Regulatory Sandbox Framework. Under the proper protections and regulatory restrictions, this regulatory sandbox will allow the testing of financial technology solutions in a real-world setting (Central Bank of Malaysia, 2018). As a result, the traditional financial sector has undergone a tremendous revolution since the introduction of blockchain technology which has also changed how financial services are delivered.

In accordance to Tursilli (2023), blockchain-based smart contracts able to transform insurance industry for more effective, secure, and transparent insurance solutions. Although the insurance business appears to benefit from the use of blockchain-based smart contracts, this cutting-edge technology has been slow to catch on. One of the causes is the absence of an efficient system, which allows both consumers and policymakers to take advantage of numerous loopholes, which undermines trust between the parties (Saeedi et al., 2020). In their study, Palma, Gomes, Vigil, and Martina (2019) pointed out that the insurance industry needs to consider certain crucial aspects of smart contract technology before they can be integrated into the system. Specifically, they emphasized that the technology should possess authoritative operations, scalability, and flexibility to ensure its effectiveness and successful implementation. These additional qualities are of utmost significance for the insurance industry to reap the benefits of smart contracts. Aside from that, Zheng et al. (2020) highlighted that most of current blockchain and smart contract systems lack mechanisms for protecting privacy, particularly for transactional privacy. For the most part, the transaction records are broadcast over the whole blockchain network and are still accessible to the public. These privacy and trust issues can cause smart contract usage in the insurance sector to be disrupted.

Despite the present increase in interest in blockchain research, little analysis has been done on how consumers use smart contracts in the practice of healthcare insurance services. The bulk of earlier research (e.g., Ch, Rajeshwari, Preethi & Achanta, 2023; Kalsgonda & Kulkarni, 2022; Xuan., 2021; Al Omar et al., 2021) focuses on the function, preparedness, benefits, and difficulties of implementing blockchain technology and smart contracts from the viewpoint of insurance players. It demonstrates how little attention is being paid to level of acceptance by users of using blockchain smart contracts for insurance services. Malaysian customers perceive the performance of smart contracts, as well as suitability the technology fits their needs. We expect that this paper will help programmers build safe and scalable smart contract applications to encourage user acceptance of blockchain-based smart contract in the healthcare insurance industry. Consequently, blockchain and smart contract technologies could be helpful for the insurance sector as well as other sectors.

Literature Review

Theoretical model

In advancement of technology environment , scholars have examined different models such as the task-technology fit (TTF), initial trust model (ITM), and Unified Theory of Acceptance Usage of Technology (UTAUT) individually. These models aim to comprehend the variables which contribute to the user acceptance and utilization of technology. We integrate three models to assess if users would embrace the incorporation of blockchain. Task Technology Fit (TTF) focuses on matching a certain technology to the tasks or activities that individuals or organizations must execute. It implies that a technology's usefulness in an organization is determined by how effectively it aligns with and supports the tasks or processes it is designed to help.

Goodhue and Thompson (1995), proposed on TFF theory which focused on the integration of technology on user tasks and the effects on user's satisfaction and system utilization. The formal concept of TTF expresses its capacity to asissts a task, to ensure the utilization of the technology align to the needs of the work and to examine the character. Dishaw & Strong (1999) concludes that the TTF able to complement TAM with more in-depth characterisation and operationalisation of TTF. Furneaux, (2011), as extended to TAM, TTF model incorporate the task affects use and technology adoption is influenced by suitability of latest technology matches with the given task. According to Larsen et al. (2019), the principle of TTF, an information system must be used and well-suited to the tasks to enhance a positive impact and propose two paths as IT-centric route through user pleasure and a work system-centric route through information system utilization.

UTAUT streamlining users' intentions to utilize information system and continuous usage behavior (Venkatesh et. al., 2003). Performance expectation (PE), effort expectancy (EE), social influence (SI), and enabling conditions (FC) serve as direct measures of usage intention and behavior. In addition, the moderating role of respondents demographic information would shape the relationship between independent variables and user intention. UTAUT capture the employees' motives of using blockchain, while network theory focuses on external aspects might contribute to the acceptance of the technology (Queiroz& Wamba, 2019), (Cheng, 2020) and (Caldarelli,2020). Mangle (2022) suggests that security and scalability correspond to UTAUT constructs of PE and EE. It is important to establish the significance of UTAUT. Indeed, most of the research utilize the UTAUT model to gauge how well new technologies are received and applied.

Trust is a basic component of human and social interactions and therefore in this study, initial trust model (ITM) development components are being explored. In 1998, McKnight et al. proposed a model that consists of several elements and methods to establish interpersonal trust; (1) trusting intention (focus on readiness to rely on the other party) and (2) trusting beliefs (a trustworthiness of the other party). Sun et al. in 2017, concluded that structural assurance emerged as the most significant component among all the other factors.

Hypothesis Development

Task technology Fit (TTF)

The TTF framework concentrates on technology that enables an individual to effectively perform a specific tasks in various scenarios. The success of a technological solution is dependent on how well it aligns with the actual requirements of the task and its compatibility with the user (Al-Maatouk et al., 2020). Experienced users prefer to opt for value gain techniques either in terms of enhanced productivity or better results (Tripathi & Jigeesh, 2015. The TTF model asserts that a team's performance positively influence the utilization of the technology among the teams to complete the specifc tasks that require precise information, requirement and coordination . Prior research reported that perceived TTF play a significant role to influence knowledge management systems. In summary, the TTF model become a useful framework to gauge the effectiveness of technology in supporting individuals and teams in completing their tasks. The model emphasizes the importance of technology compatibility with the user's requirements, and how it impacts productivity and results.

Technology Characteristic

In an analysis of technology characteristic, Tam and Oliveira (2016) found in today's rapidly evolving workplace, technology is becoming a more significant part of how even the most basic job functions are carried out. As a result, the connection between workplace technologies and employee performance has become even more crucial. This has led to a growing interest in exploring the relationship between technology and TTF. TTF is the measure of how much technology helps someone accomplish a task given the features and function of the technology (Tripathi & Jigeesh, 2015). In recent years, this particular concept has garnered a significant amount of attention due to its potential to significantly affect the efficacy and efficiency of work processes. The implications of this concept are profound, as it can transform work processes, resulting in an enhanced output and streamlined work procedures. Therefore, it is essential to understand and implement this concept, as it can be a game-changer for businesses and academic institutions alike.

The TTF framework is used as a predictor in the field of technology (Goodhue & Thompson, 1995). According to the authors, "fit" refers to how well a particular technology can handle the specific features or functionality required to perform a given task. Oliveira, Faria, Thomas, & Popovič (2014) recommend the implementation of the model is depend on the connection between the characteristic and the performance of a task. TTF model mainly focus on the interaction of information technology with human performance. This is an essential element of this paradigm by integrating the feature of the task with technology characteristics that must be compatible with each other. Therefore, the hypothesis is formulated as follows:

H1: Technology characteristics have a significant impact on Task-Technology Fit

Task Characteristic

Aljukhadar, Senecal, and Nantel (2014) highlight that the TTF framework act as a tools in evaluating the capability of the technology to enhance performance. It is measured by the influence and the alignment of the task and the features of the technology. Researchers are utilized TTF framework to forecast the uptake and application of new technologies across disciplines (Isaac, Abdullah, Ramayah, & Mutahar, 2017). The framework places significant emphasis on the need for task-technology adaptation, whereby information technology must be well-suited to the activity it facilitates, utilised efficiently, and increase user performance (Lin et al., 2020). By analyzing the TTF, organizations can ensure that they select and implement the right technology to enhance task performance and improve overall efficiency. Therefore, the hypothesis is formulated as follows:

H2: Task Characteristic has a significant impact on Task-Technology Fit

UTAUT- Performance Expectancy

Performance Expectation (PE) is used to measure the perceived benefits of adopting new technology to complete a job. Blockchain technology has emerged as a game-changing innovation for businesses looking to enhance the quality and efficiency of their operations. According to (Khazaei, 2020), blockchain technology offers a decentralized data-based solution for trustworthy transactions, leading to increased data quality and proficiency, and giving asset managers additional opportunities to monitor, trace, and apply resources. (Jain et al., 2022) conducted a study linking the UTAUT model with various factors influenced by a mindset of the individual and impersonal rules that influence behavioral intention. According to the results, an indivual behavioral intention to opt for blockchain technology will increase if they use it as a percentage of their intention to fulfill their actions.

Kapnissis, Vaggelas, Leligou, Panos, and Doumi (2022) identified the classic UTAUT model was modified by the "functional benefits" and "trust" of block chains among stakeholders in the shipping industry. Building from that, we include TTF and initial trust (ITM) as additional adoption criteria for blockchain technology. Chittipaka, Kumar, Sivarajah, Bowden, and Baral (2023) discover that by improving transparency, trust, and security for supply chain stakeholders, blockchain technology can significantly enhance firm performance. Al-Rahmi, Shamsuddin, and Alismaiel (2020) indicate that behavioral intention refers to an subjective probability and readiness of user to perform a particular behavior. It involved the user motivation factors on intentions and their effort towards the behaviour. As of technology usage perspective, behavioral intention is vital elements on user's acceptance and practically use the technology. It serves as a proxy factor that reflects users' attitudes, beliefs, and perceptions towards the technology and their willingness to adopt and use it. Therefore, the hypothesis is formulated as follows:

H3a: Task-Technology Fit has a significant impact on Performance Expectancy.
H3b: Task-Technology Fit has a significant impact on behavioural intention to use.
H4: Performance Expectancy has a significant impact on behavioural intention to use

Initial trust (ITM) plays a significant role in determining user's willingness to practice the services. This is especially true for users who are willing to take a risk with little or no prior experience. Kim, Shin, and Lee (2009) mention that credible and meaningful information also plays a crucial role in building trust. Mcknight, Carter, Thatcher, and Clay (2011), conclude that users more confidence in humans compared to technology and the features that lead to perceived risk. However, greater trust in technology improve their adoption of new technology (Miltgen, Popovič, & Oliveira, 2013). Even if potential users hesitate to use a new technology, trust in its reliability and efficiency can encourage them to perform the required tasks.

In a recent study conducted by Xie, David, Mamun, Prybutok, and Sidorova (2023), indicate that technological structural assurances can serve as possible indicators of customers' trusting beliefs. The study sheds light on the fact that customers' trust can be influenced by the level of technological structural assurance provided by the service provider. Aljaafreh, Al-Hujran, Al-Ani, Al-Debei, and Al-Dmour (2021) suggest that customers' ITM on internet banking services mainly determined by the reputation of banks and organizational structural assurance.This highlights the importance of establishing reliable and trustworthy organizational structures to foster customer trust in Internet banking services. Furthermore, Yoo, Li, and Xu (2021) highlight patients' internet self-efficacy aids fostering trust and enhancing patients' adoption of online health consultation (OHC). The study suggests that patients' trust in OHC services can be enhanced by factors such as verification, likelihood to trust, perceived informativeness, reputation of the platform, structural assurance, and perceived credibility of physicians. This would strengthen the security and reliablility of online health consultation platform that assures patients of their safety and privacy. Alarcon et al. (2018) suggests that trust propensity only significantly affects consumers' initial trust, but this effect usually fades as consumers get more accustomed to online shopping.

Jiang and Lau (2021) conducted a study where they found that trust in structural assurance had a negative correlation with continuance intention. This means that when consumers trusted the structural assurance of a platform, they were less likely to remain loyal to it. This is because the trust in structural assurance gave consumers more confidence to shift to different platforms due to various factors, like urgency or cost. Similarly, Tran et al. (2021) conducted a study on China's medical students to evaluate their behavioral intentions to adopt a diagnosis support system driven by artificial intelligence (AI). Their research demonstrated that ideas including perceived substitution crisis, effort expectancy, performance expectancy, and initial trust did not show any association with behavioral intentions.

Similarly, the study conducted by Farooq, Dubinina, Virtanen, and Isoaho (2021) revealed that initial trust contribute on the intention of European young adults to use password managers. The researchers observed that a company's reputation and structural assurance indirectly influence the desire to use password managers. Moreover, Liu and Tu (2021, the study highlights the significance of consumers' intention to adopt biometric recognition payment device (BRPD) technology in a Fintech company and discovered that initial trust when facing BRPD was not significantly impacted by trust propensity. These findings suggest that the ITM could play a pivotal mechanism in triggering the user's intention to use blockchain smart contract insurance services. Therefore, the hypothesis of this study is the ITM enhance the usage of blockchain smart contract insurance services. Therefore, the hypothesis is formulated as follows:

H5: Structural assurance beliefs have a significant impact on initial trust.
H6: Personal propensity to trust has a significant impact on initial trust.
H7a: Initial trust has a significant impact on performance expectancy.
H7b: Initial trust has a significant impact on behavioural intention to use.

Methods

The present research centered on the linkage of TTF, IT and PE on behavioral intention to manage healthcare insurance services through blockchain smart contracts. To examine the proposed research model shown in Figure 1, the questionnaire items is formulated using seven-point Likert scale (1 = strongly disagree to 7 = strongly agree). The survey began with a short description of the objective of the research. Then, it continues with a brief overview related to blockchain smart contracts on insurance services. The questionnaire was structured into two sections (section A include respondent demographic details and section B focus on measurement items related to each variable). An online administration survey questionnaire was carried out from August 2022 to December 2022 and distributed to 500 respondents aged 18 and older residing in Malaysia using convenience sampling. The final sample of 234 respondents with an overall response rate of 46.8%. To test and validate the measurement and structural model, we applied partial least square (PLS) modeling using SmartPLS 4.

By determining the level of divergence for dependent variables, the model was evaluated. The primary parameters used for calculating the structural model are the path coefficients and the R-squared (R^2) value. R^2 is a measure to demonstrate the percentage of variance of a dependent variable in a regression model that is explained by a combination of independent variables. Figure 1 shows the model has R^2 values of 47.5% for behavioral intention. This clarifies the behavioral intention has a moderate impact on the transaction applications employing the underlying blockchain technology 49.8% for performance expectancy, task technology fit (43.5%) and (34.7%) for initial trust. Therefore, the result explains the technology fit and initial trust has moderate impact on the blockchain technology involvement.

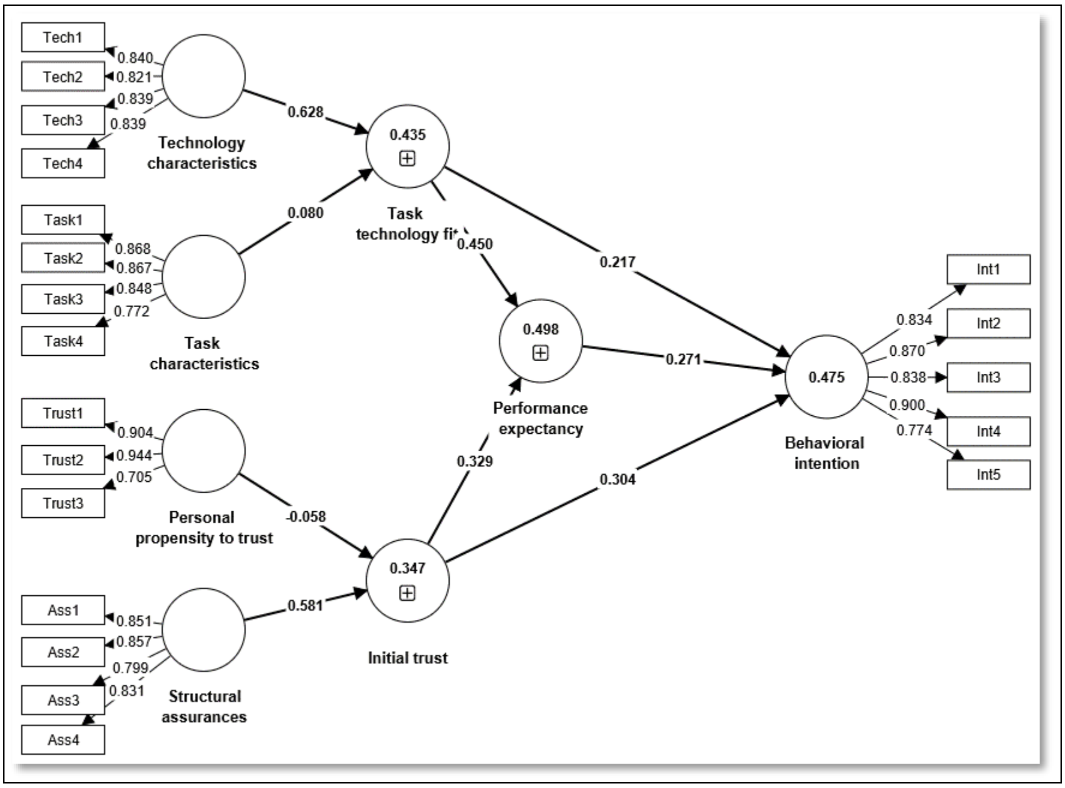

Figure 1: Path coefficients and factor loadings attained from PLS-algorithm

As shown in Table 1, the demographic profile of respondents is represented by 53% female and 47% male. About 85.47% of the respondents were above 21 years and the remaining 14.53% of respondents aged 20 years and below. Approximetly half of the sample possessed a bachelor's degree with 47.68%. Looking at the respondent's occupations, most of the respondents are students and working in the government sector with 31.2% and 29.91% respectively.

Table 1: Profile of respondent

Characteristic	**Freq**	**(%)**	**Characteristic**	**Freq**	**(%)**
Gender			Education		
Female	124	52.99	SPM/ O-level	38	16.24
Male	110	47.01	STPM/ A-level	21	8.97
Age			Diploma/ Advanced Diploma	38	16.24
≤ 20 years old	34	14.53	Bachelor's degree	112	47.86
21-30	91	38.89	Master's degree	23	9.83

31-40	53	22.65	Doctorate / PhD	2	0.85
41-50	33	14.10	Occupation		
More than 50 years old	23	9.83	Student	73	31.20
Ethnic			Government Sector	70	29.91
Malay	81	34.62	Private Sector	57	24.36
Chinese	102	43.59	Self-employed	30	12.82
Indian	50	21.37	Others	4	1.71
Others	1	0.43	Income Level		
Marital Status			Less than RM2,000	80	34.19
Single	133	56.84	RM2,000 – RM6,000	100	42.74
Married	93	39.74	RM6,001 – RM10,000	48	20.51
Divorced	6	2.56	More than RM10,000	6	2.56
Widowed	2	0.85			

Findings

Measurement Model

As for the measurement model in Table 2, the reliability and validity of the construct we tested. Constructs' validity is evaluated through convergent and discriminant validity, whereas to assess the items' internal consistency reliability, the constructs' reliability is used. (Ramayah et al., 2018)In this study, we evaluated the loadings, average variance extracted (AVE), and composite reliability (CR) using threshold values of 0.5 for loadings, 0.5 for AVE, and 0.7 for CR. The findings presented in Table 2 indicate that the AVEs for all constructs were greater than 0.5, and the CRs were all above 0.7.As for loadings, Trust4 for personal propensity to trust is deleted since the loading is less than 0.5. Overall, the result is valid and reliable.

Table 2: Measurement Model

Variable	**Items**	**Loading**	**CR**	**AVE**	**Full Collinearity VIF**
Structural_assurances	Ass1	0.851	0.902	0.697	1.630
	Ass2	0.857			
	Ass3	0.799			
	Ass4	0.831			
Performance_expectancy	Exp1	0.863	0.91	0.718	2.336
	Exp2	0.888			
	Exp3	0.868			
	Exp4	0.765			
Task _technology fit	Fit1	0.873	0.906	0.706	2.374
	Fit2	0.893			
	Fit3	0.807			
	Fit4	0.785			

Initial trust	Ini1	0.874	0.919	0.74	2.567
	Ini2	0.884			
	Ini3	0.922			
	Ini4	0.75			
Behavioral _intention	Int1	0.834	0.925	0.713	2.013
	Int2	0.87			
	Int3	0.838			
	Int4	0.9			
	Int5	0.774			
Task _characteristics	Task1	0.868	0.905	0.705	1.230
	Task2	0.867			
	Task3	0.848			
	Task4	0.772			
Technology _characteristics	Tech1	0.84	0.902	0.697	2.269
	Tech2	0.821			
	Tech3	0.839			
	Tech4	0.839			
Personal _propensity to trust	Trust1	0.904	0.891	0.735	1.058
	Trust2	0.944			
	Trust3	0.705			

Notes, CR = Composite Reliability, AVE = Average Variance Extracted, VIF = Variance Inflation Factor

We also tested the heterotrait-monotrait ratio (HTMT) and full collinearity variance inflation factors (VIFs) with the cut off for VIFs lower than 3.3 (Kock, 2020) and HTMTs not greater than 0.90 (Gold et al., 2001). Table 2 present the full collinearity VIFs is less than 3.3 and HTMT result in Table 3 significantly less than 0.9 showing sufficient discriminant validity. Hence, the discriminant validity of the measurement model is accepted, and no multicollinearity problem exists.

Table 3: Discriminant Validity (HTMT)

	Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	Behavioral _intention								
2	Initial trust	0.680							
3	Performance_expectancy	0.676	0.701						
4	Personal _propensity to trust	0.220	0.128	0.206					
5	Structural_assurances	0.400	0.657	0.417	0.135				
6	Task _characteristics	0.327	0.278	0.305	0.090	0.391			
7	Task _technology fit	0.663	0.723	0.758	0.167	0.487	0.314		
8	Technology _characteristics	0.664	0.663	0.760	0.222	0.413	0.369	0.761	

Structural Model

As suggested by Hair et al. (2017) we assessed the effect size (f^2) of each exogenous construct. The value of 0.02, 0.15 and 0.35 represent small, medium, and high effect size, respectively (Cohen, 1988). As illustrate in Table 5, technology characteristics and structural assurances belief have a large predicting effect of 0.62 and 0.514, correspondingly. Meanwhile, task technology fit, performance expectancy and initial trust have a small effect predicting the intention to use blockchain smart contracts with the value of 0.043,0.07 and 0.094 respectively. The hypothesis testing in this study separated into two main categories as presented in Table 4 (direct effect hypothesis) and Table 5 outlined the indirect effect hypothesis. The result in Table 4 reported the path coefficients, the standard errors, t-value, and p-value for the structural model using 10,000 subsample bootstrapping procedure. Out of nine hypotheses tested, only two was not supported namely hypothesis H2 (the effect of task characteristic on task technology fit) and hypothesis H6 (the effect of personal propensity to trust on initial trust) based on 95% bias-corrected confidence interval (BCI) and the p-value is more than 10% significant level.

Table 4: Hypothesis Testing (Direct Effect)

Hypo	**Relationship**	**Std Beta**	**Std Err**	**t-value**	**p-value**	**BCI 95% LL**	**BCI 95% UL**	**Decision**	**f^2**
H1	Technology -> TTF	0.628	0.059	10.584	0.000	0.524	0.718	Supported	0.620
H2	Task -> TTF	0.080	0.064	1.241	0.107	-0.029	0.183	Not Supported	0.010
H3a	TTF -> Performance	0.450	0.078	5.805	0.000	0.320	0.576	Supported	0.243
H3b	TTF -> INT	0.217	0.107	2.020	0.022	0.034	0.391	Supported	0.043
H4	Performance -> INT	0.271	0.104	2.612	0.005	0.102	0.440	Supported	0.070
H5	Assurances-> ITR	0.581	0.060	9.636	0.000	0.471	0.672	Supported	0.514
H6	Trust -> ITR	-0.058	0.064	0.896	0.185	-0.132	0.118	Not Supported	0.005
H7a	ITR -> Performance	0.329	0.083	3.950	0.000	0.188	0.461	Supported	0.129
H7b	ITR -> INT	0.304	0.079	3.829	0.000	0.168	0.433	Supported	0.094

Notes: n = 234. Bootstrap sample size = 10,000. LL = lower limit; UL = upper limit, CI = confidence interval, f2 = effect size, TTF = Task Technology Fit, ITR = Initial Trust and INT = Intention.

Table 5 presents the result of mediating effect analysis for indirect effects of performance expectancy on intention to use blockchain smart contracts on insurance services based on bootstrapping with 10,000 samples. The result reported performance expectancy has a strong predictive power in explaining task technology fit and initial trust towards intention to use blockchain smart contracts in insurance service, thus hypotheses H8 and H9 are supported.

Table 5: Hypothesis testing (Indirect effect)

Hypo	Relationship	Std Beta	Std Dev.	t-value	p-value	BCI 95% LL	BCI 95% UL	Decision
H8	TTF -> Performance-> INT	0.122	0.056	2.187	0.014	0.044	0.231	Supported
H9	ITR -> Performance -> INT	0.089	0.038	2.336	0.010	0.039	0.170	Supported

Notes: n = 234. Bootstrap sample size = 10,000. LL = lower limit; UL = upper limit, CI = confidence interval, TTF = Task Technology Fit, ITR = Initial Trust and INT = Intention.

Apart from that, we also evaluated the model the predictive validity based on blindfolding procedure. According to Henseler et al. (2009), this method is required to gauge the capability the proposed framework for prediction . Q^2 can be evaluated using an omission of distance of 5 – 10 (Akter et al., 2011), and if the Q^2 exhibit value larger than 0, it indicates that the model hold a predictive relevance of particular endogenous construct (Hair et al., 2017). The result reported in Table 6 concludes that the model achieves predictive relevance given all the items of construct Q^2 displays value is higher than 0. Addition to that, PLS-model present a smaller root means square error compared to the linear model estimation ($RMSE_{PLS} < RMSE_{LM}$). Therefore, we can conclude that, the proposed model develop in this study is significant to explain and predict customer intention to use blockchain smart contracts in insurance services under consideration of the relevant variable such as task technology fit, initial trust, and performance expectancy.

Table 6: PLS-predict Assessment.

		PLS		LM		PLS - LM	
Indicator	Q²	RMSE	MAE	RMSE	MAE	RMSE	MAE
Int1	0.215	1.036	0.790	1.007	0.738	0.029	0.052
Int2	0.198	1.087	0.817	1.124	0.808	-0.037	0.009
Int3	0.167	1.085	0.875	1.057	0.839	0.028	0.036
Int4	0.248	1.032	0.771	1.058	0.753	-0.026	0.018
Int5	0.165	1.156	0.926	1.168	0.910	-0.012	0.016
Ini1	0.269	0.951	0.738	0.912	0.704	0.039	0.034
Ini2	0.252	1.000	0.757	0.960	0.742	0.040	0.015
Ini3	0.298	0.916	0.705	0.865	0.672	0.051	0.033
Ini4	0.147	1.080	0.838	1.012	0.772	0.068	0.066
Exp1	0.229	1.013	0.749	1.016	0.760	-0.003	-0.011
Exp2	0.276	0.998	0.748	1.015	0.742	-0.017	0.006
Exp3	0.259	1.007	0.771	0.992	0.717	0.015	0.054
Exp4	0.248	1.051	0.868	1.018	0.788	0.033	0.080
Fit1	0.267	1.021	0.780	1.034	0.753	-0.013	0.027
Fit2	0.339	0.893	0.675	0.845	0.635	0.048	0.040
Fit3	0.309	0.881	0.711	0.901	0.705	-0.020	0.006
Fit4	0.250	1.065	0.800	1.074	0.798	-0.009	0.002

Notes: PLS-SEM = Partial Least Squares Structural Equation Modeling, LM = Linear Regression Model, RMSE = Root Mean Squared Error, MAE = Mean Absolute Error, Q2= Q2 Predict. Key: Behavioral intention, Initial trust, Performance expectancy, Task technology fit.

Discussion and Conclusion

Based on a sample of 234 respondents, our result reported the attributes of task characteristics enhance the task technology fit such as the adequacy, function, and accessibility of technology. This aligned with previous research by Lin et al. (2020) who reported that the framework places significant emphasis on the crucial aspect of task-technology adaptation. This essentially means that the information technology being used must be carefully selected and tailored to fit seamlessly to facilitate the task. It should also be utilized effectively to ensure optimal performance and productivity. Additionally, the technology should improve the user's experience, ultimately leading to a more positive outcome(Wu & Chen, 2017). It shows that whenever the technology effectively functions in time the customer needs, such as to review their healthcare insurance policy or opt for an administration policy, helps to boost the capability of the technology. However, the finding represents that technology characteristics are not an important element in task technology fit. It revealed that even though the blockchain smart contract managed to provide real-time and secure services, it does not a vital role in achieving compatibility when consumers perform tasks related to healthcare insurance services.

Other than that, the findings show that performance expectancy is affected by task technology fit and initial trust. Farooq, Dubinina, Virtanen, and Isoaho (2021), reported that a company's reputation and the structural assurances it provides are crucial in establishing initial trust among consumers. Structural assurance in building trust among customers through ensuring the safety and privacy of customers' financial transactions (Geebren, Jabbar, and Luo (2021). Yet, the research indicates that a personal propensity of the consumer towards trust does not bring important impact on initial trust. The study evaluated several structural assurances, including service guarantees, privacy rules, third-party recognition, and endorsement. The results suggest that companies should focus on building a positive reputation and providing structural assurances to gain the trust of consumers. Additionally, the study highlights the importance of service guarantees, privacy rules, third-party recognition, and endorsement in establishing initial trust among consumers. Consumers believe that the degree of technology assists in performing their tasks related to healthcare insurance services significantly contributes to the rewards of using the blockchain smart contract. Furthermore, the level of consumer initial trust is significantly influencing their performance expectancy. In healthcare insurance, if it is guaranteed that the blockchain smart contract was designed to assists the policyholder with secure and reliable transactions, consumers may put less pressure on performing the activities. However, consumer' propensity to trust plays an insignificant role in affecting their initial trust. As for the intention to use blockchain smart contracts on healthcare insurance services, task technology fit, performance expectancy and initial trust become the crucial contribution factors. Aljaafreh et.al (2021), highlight that the level of initial trust plays a critical role in shaping consumers' inclination toward using Internet banking services. The study revealed that individuals who display a strong initial trust in these services are more prone to embrace and utilize them. This highlights the importance of building trust with consumers at the outset of their interaction with Internet banking services. The capability of the technology with trust coupled with the performance expectancy to optimize their finances with no time constraint will increase their intention of managing healthcare insurance policies using blockchain-based smart contracts.

Implications, Limitations and Suggestions for Future Research

Although the study conducted on blockchain smart contracts in Malaysia was rigorous and comprehensive, it is subject to certain limitations. First, the research was carried out in Malaysia, where blockchain-based smart contracts currently at the inital stages of implementation. Consequently, voluntarily survey respondents, which may introduce self-selection bias (Roca, Chiu, & Martínez, 2006). However, this research provides crucial elements for strategic guideline for policymakers and adding other stakeholders designing strategies and promoting blockchain smart contracts on healthcare insurance. Second, the research was mainly cross-sectional. Given the dynamic nature of user behavior, longitudinal research could offer more profound insights into the changes of user behavior overtime. Thus, future research may consider longitudinal research designs to explore the correlations among variables related to technology acceptance. Furthermore, it is essential to incorporate additional constructs in future research such as consumer digital literacy, privacy and potential risk exposes blockchain-based smart contracts. We believe by including this variable, its enriched policy execution. The insights and ramifications highlighted in this study need to be broadened for external validation. This is because the study examined blockchain-based smart contracts and a particular user group in Malaysia only. Therefore, additional investigation is anticipated to extend the findings and discussions by encompassing diverse cultures perspective where blockchain based smart contracts are utilized.

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