Adoption of Blockchain Technology in Electronic Records Management in the Malaysian Public Sector

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Abstract—**As the Malaysian public sector undergoes digital transformation, its electronic records management faces challenges, including security issues, maintaining record integrity and record authenticity, audit trails, and trust in existing systems. Blockchain technology has the potential to solve these challenges through features such as distributed records, transparency, restricted immutability, and cryptographic security. However, the adoption of this technology in the Malaysian public sector is still underexplored. The main objective of the study is to identify factors that influence the adoption of blockchain technology in Electronic Records Management in the Malaysian public sector and to develop an adoption model. A quantitative method was used to collect data from 253 public-sector officials directly involved in electronic records management. The conceptual framework was developed by integrating the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Data analysis was conducted using the Partial Least Squares–Structural Equation Modeling (PLS-SEM) approach to test the relationship between variables and confirm the study hypotheses. Results show that users' behavioral intentions have a significant effect on actual usage of blockchain technology (H10 is accepted), with an R^2 of 0.633, indicating that the independent construct explains 63.3% of the variance in behavioral intentions. Individual, organizational, and environmental factors, including performance expectations, effort expectations, social influences, and facilitating conditions, have a significant effect on users' behavioral intentions, emphasizing that technology adoption requires a holistic approach. The study also finds that behavioral intentions act as a critical mediator before actual usage of the technology can occur.**

Keywords—Electronic records management; blockchain adoption; public sector; TAM; UTAUT

I. Introduction

Records management is essential to ensure that an organization runs smoothly, especially in the public sector. Organizations depend on systematic practices, including classification, storage, tracking, indexing, retention, and disposal for effective operations [1]. Non-compliance with these practices may result in record loss, inaccurate information, delays in record retrieval, and reduced efficiency in public service delivery [2]. With the Fourth Industrial Revolution (4IR), records management has transitioned from traditional paper-based systems to electronic records management (ERM). Thus, more adaptable, enabling large-scale storage, access, and processing of data with higher flexibility and scalability. In the public sector, ERM is essential to ensure the preservation, reliability, integrity, and availability of records throughout their lifecycle, while complying with legal requirements, such as the National Archives of Malaysia Act 2003. Failure to comply with this act may result in serious legal consequences [3]. ERM offers many benefits, but the shift to digital requires organizations to reassess their traditional records management principles, approaches, and strategies. Organizations must develop new skills, follow updated digital archiving standards, and use advanced preservation technologies [4]. Initiatives such as the Digital Document Management System (DDMS 2.0) by the National Archives of Malaysia are one example of governmental efforts to digitize public administration.

Blockchain technology is a promising innovation due to its decentralized, transparent, secure, and tamper-resistant properties. The integration of blockchain into ERM could improve data integrity, record tracking, and information security [5]. However, research on blockchain adoption in Malaysia's public sector remains underexplored [6]. Although international research on blockchain is increasing, studies on its adoption in public sector ERM in Malaysia are limited [7]. Previous studies have focused mainly on its technology, despite the significant influence of leadership, organizational support, social influence, and regulatory environment on successful technology adoption [8]. There is also a lack of a comprehensive and empirical adoption model that includes technological, organizational, and individual factors specific to the Malaysian context. Preliminary evidence from the National Archives of Malaysia indicates a lack of understanding among individuals and organizations regarding records management responsibilities. The uncoordinated bottom-up approach conflicts with ERM's requirements for strategic support and a top-down approach from senior management to ensure comprehensive planning, coordination, and implementation [9]. Furthermore, the lack of an ERM system that serves as a comprehensive reference for software, policies, procedures, and practices contributes to the inconsistent implementation of public ERM in the public sector [10].

This study was conducted to address the existing research gap by focusing on the adoption of blockchain technology in the ERM of the Malaysian public sector from individual, organizational, and environmental perspectives. This study integrates the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to develop a more comprehensive, contextually grounded adoption model [11]. The main objective of the study is to identify the factors influencing the adoption of blockchain technology and to develop a practical, empirically grounded model. The scope of the study focused on 24 public sector ministries and two main agencies, namely the National Archives of Malaysia and MAMPU, with a focus on management officers and professionals. This study assessed the adoption of blockchain technology from individual, organizational, and environmental perspectives to form a holistic, realistic, and appropriate adoption framework for the electronic records management needs of the Malaysian public sector. Although TAM and UTAUT are among the most established frameworks in technology adoption research, their application to blockchain-enabled electronic records management remains limited, particularly in the public-sector context. Most prior studies have focused either on general blockchain adoption or technical implementation issues, rather than on records governance and archival management environments. This study contributes to the literature by extending TAM and UTAUT through the inclusion of organizational and environmental factors, namely policy, security, leadership support, and infrastructure quality, which are highly relevant in government institutions. In addition, the Malaysian public sector provides an important context for emerging economies, where digital governance, accountability, and inter-agency coordination are increasingly significant.

II. Literature Review

Amid globalization and IR 4.0, effective records management is essential for ensuring the efficient dissemination of information by organizations and governments. ERM systems have been widely adopted, with approximately 87% of organizations utilizing them since 2017, especially in the healthcare sector, and this adoption rate continues to rise [12]. The shift from paper-based to electronic records results not only in a format change but also in the entire records management ecosystem, including record creation, classification, storage, access, security, preservation, and disposal [13, 14, 15]. In the public sector, e-government and digitalization efforts encourage the use of ERM to improve efficiency, transparency, and accountability [16, 17]. Successful implementation requires the right infrastructure, well-defined policies, sufficient resources, and an explicit governance framework [18, 19]. Electronic records have evolved alongside technological advances since the 1950s [20]. ERM is defined as a set of principles, policies, and systems for systematically managing digital records throughout their lifecycle, based on the principles of authenticity, reliability, integrity, and availability outlined in ISO 15489 [16].

A. ERM Challenges in the Public Sector

Implementing ERM in Malaysia's public sector poses several challenges, including technological, organizational, legal, and human resource issues [20]. One major challenge is that ministries and agencies develop their own ERM systems, leading to differences in the ERM framework and inconsistent records management. This makes it hard to integrate systems, share information, and coordinate records management nationwide, which affects how efficiently the government operates [21].

The National Archives of Malaysia is the main authority, but agencies still show different levels of compliance with ERM policies, guidelines, and standards. Many view ERM as just a support role rather than a key part of governance. Because of this view and limits on enforcement, ERM often gets low priority when put into practice [16, 22, 23]. The situation is even more complicated when agencies must comply with multiple laws and regulations, such as the National Archives Act 2003, the Public Sector ICT Security Policy, and MS ISO 15489. This is especially true in a digital setting, where they must balance transparency, public access, and confidentiality [24, 25, 26].

The lack of ERM specialist officers, limited specialized training, and frequent officer turnover also affect the effectiveness of ERM in the public sector [27]. In addition, bureaucratic culture and reliance on traditional working methods create resistance to change, including reluctance to use ERM systems and non-compliance with file classification, thereby increasing the risk of loss, duplication, and misuse of records [28]. Digital records are growing quickly in the Malaysian public sector as more applications, emails, and e-Government systems are used [29]. This increase leads to risks such as information overload, higher storage costs, and difficulties in disposing of records [30]. Electronic records can also be manipulated, have poor version control, or face cybersecurity threats such as system intrusions and data leaks [31, 32]. These issues can undermine their evidentiary value, reduce accountability, and weaken public trust. Long-term preservation of electronic records is a challenge due to the changing technologies and file formats [33]. It also takes significant resources to keep these records accessible and usable over time. While ERM can help save time and money, following strict rules to protect sensitive government data can make implementation more difficult.

B. Blockchain

Blockchain technology is a new digital tool that can help improve ERM by enabling transparent, secure, and immutable distributed ledgers [34]. This technology does not replace existing systems but provides a layer of trust to enhance the authenticity, integrity, reliability, and traceability of electronic records throughout their lifecycle [35]. One of the main challenges of ERM is the risk of unauthorized manipulation, modification, and deletion of records [36, 37]. Blockchain solves this issue by recording each transaction as a new, time-stamped entry, thus creating a complete and transparent audit trail [38]. This characteristic of blockchain is especially important in the public sector, where accountability, transparency, and responsibility are essential [39]. Blockchain uses cryptographic hashes, digital signatures, and consensus mechanisms to help keep records authentic and intact by making any changes easy to spot [40]. Key metadata, such as the user's identity, creation date, and record classification, is stored with the hash value to serve as digital proof of authenticity [41]. This method allows records to be verified without relying on just one authority [42].

Because blockchain is distributed, records are more widely available and accessible, and there is less risk of data loss if a single system fails. Using blockchain in records management, especially for recording metadata and transaction evidence, matches ERM requirements that focus on controlling, monitoring, and preserving records for the long term [43]. From a public-sector perspective, blockchain offers a range of benefits, including immutable recordkeeping, decentralization, enhanced security, automated processes via smart contracts, cost savings, interoperability across systems, and support for regulatory compliance [44]. The technology also has the potential to act as a cross-agency integration layer without requiring full ERM standardization, thereby reducing information silos and increasing national record management coordination [45]. The integration of blockchain technology into ERM has the potential to support compliance with the main principles of records management, improve public sector governance and accountability, and reduce manual work through automation and more objective, systematic technical mechanisms [13, 14].

C. Technology Acceptance Model (TAM)

TAM is the most widely cited and influential model for explaining technology acceptance and use for over two decades [46]. This model was proposed by Davis (1989) and further developed by Venkatesh and Davis (1996) based on the Theory of Reasoned Action (TRA), to understand the factors that influence individuals' decisions to accept or reject a technology [47]. TAM emphasizes two main constructs, namely Perceived Usefulness (PU) and Perceived Ease of Use (PEU), which significantly influence technology usage intentions and behavior [48]. Previous studies have shown that individuals are more likely to accept technology when they believe it improves work performance and is easy to use [49]. In addition, TAM is known as a simple, easy-to-understand model and has high predictive power across various information technology contexts [50, 51]. Although originally focused on individual factors, TAM also considers social and environmental influences, thereby broadening its application across sectors, including education and public services [52, 53]. Many empirical studies have proven that TAM is the most popular, reliable, and effective model in predicting the adoption of new technologies, including e-learning, internet banking, and educational technology [54]. A study by Ismail et al. (2023) also confirmed the validity of TAM in the context of video conferencing technology for online learning. However, it suggests adding motivational and economic factors, such as social influence, to strengthen the explanation of technology adoption. TAM remains a relevant and suitable primary theoretical framework for studying the adoption of new technologies in ERM, including blockchain, due to its ability to systematically and empirically explain technology usage intentions and behaviors [55].

D. Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT is one of the most recent and influential information technology acceptance models, introduced by Venkatesh et al. (2003) to integrate and empirically compare elements from various prior technology acceptance models. This model posits that users' behavioral intentions determine actual technology use; thus, UTAUT is widely used to assess the factors that influence technology acceptance intentions, including in the context of emerging technology [56]. UTAUT contains four main constructs, namely performance expectations, effort expectations, social influence, and facilitating factors, which have a direct effect on technology intention and use [57, 58]. In addition, the effect of the relationship between the constructs and technology use is influenced by moderating variables such as age, gender, experience, and willingness to use [57]. This model is widely recognized as one of the most well-known and widely used theories of technology acceptance in recent empirical studies [59]. Several researchers have expanded UTAUT to improve its accuracy. Because of this, researchers often combine TAM and UTAUT to predict technology acceptance better. UTAUT looks at behavioral intentions, while TAM explains how perceived usefulness and ease of use affect acceptance [57]. While UTAUT is a strong model, some have criticized its theoretical and methodological foundations. Criticisms include limited validity across settings, inconsistent explanations of behavioral intentions, and model complexity due to many constructs and moderating variables [57, 59, 60]. Some studies suggest that UTAUT should include factors such as trust, innovation, self-efficacy, perceived risk, and perceived threat to make it more useful in real-world settings [61, 62]. UTAUT is a key framework in technology acceptance research. However, it is often improved by modifying it or combining it with other models, such as TAM, to make predictions more accurate and relevant to the study context [63].

E. Factors and Hypothesis

Performance Expectations (PE) holds that using blockchain technology can make work more efficient and improve ERM in the public sector [64]. In UTAUT, performance expectations are the main factor determining users' behavioral intentions to adopt new technologies, especially in organizational environments involving large-scale, critical information systems [57, 60]. This concept is relevant to the study of public sector ERM, which focuses on efficiency, accuracy, and record reliability. Research shows that users are more likely to accept technology if they believe it will improve work quality, productivity, and task performance [65, 66]. For blockchain, features such as distributed ledgers, immutability, and traceability can make ERM more trustworthy and reliable [44]. Performance expectations are essential for understanding technology acceptance and for meeting the practical needs of public sector ERM [67]. Thus, it is reasonable to expect that performance expectations strongly influence users' intention to adopt blockchain technology [68].

Effort Expectations (EE) refers to the ease of use and the effort required for users to understand and operate a technology. In UTAUT, effort expectations are considered an important factor, especially in the early stages of technology adoption [57]. This concept also aligns with the perceived ease of use construct in the TAM, which asserts that easy-to-use technology increases users' tendency to adopt it [49]. In the context of blockchain technology, the perception of technical complexity is often identified as a major challenge to user acceptance, especially in the public sector, which relies on formal work structures and procedural compliance [69]. Previous studies have shown that even if a technology offers high strategic benefits, its level of acceptance still depends on how easy it is to understand and integrate into existing work routines [70, 71]. Therefore, effort expectations are a significant construct and should be retained in this study to explain blockchain technology adoption from the user perspective comprehensively.

Social Influence (SI) refers to the degree to which individuals perceive that important parties in the work environment, such as colleagues, management, and the organization, expect them to use a new technology [57]. In the public sector, decisions regarding technology use are not usually made individually, but are instead influenced by organizational norms, administrative hierarchies, and institutional work culture [72]. Previous studies have consistently shown that social influence plays an important role in influencing technology adoption, particularly in bureaucratic and structured organizations such as the public sector [73]. Support and legitimacy from top management, as well as acceptance from colleagues, can increase users' confidence in the technology's suitability. Therefore, social influence is a relevant construct and cannot be ignored in explaining the adoption of blockchain technology in electronic records management in the public archiving sector.

Facilitating Conditions (FC) refers to the level of user belief that the existing technical infrastructure and organizational support can support the adoption of new technologies [57]. This construct is particularly significant in the public sector context because successful technology implementation depends not only on individual readiness but also on organizational readiness, including infrastructure, training, technical support, and human resources [74]. Empirical studies have shown that facilitating conditions directly affect technology adoption behavior, especially for complex technologies such as blockchain [75]. Therefore, including this construct in the study aligns with the realities of public sector organizations and strengthens the study model's ability to explain the actual adoption of blockchain technology [76]. Empirical studies show that facilitating conditions directly affect how people adopt technology, especially complex technologies like blockchain [75]. Including this factor in the study matches the realities of public sector organizations and helps the model better explain how blockchain is used [77].

Attitudes Toward Technology (ATU) refers to whether users perceive a technology positively or negatively. In TAM, attitudes help explain how users' beliefs shape their intentions to use a technology [49]. Although UTAUT does not include attitudes directly, recent studies found that adding attitude factors can make technology acceptance models more effective, especially for new or high-risk technologies [57, 60]. Since blockchain is still seen as a disruptive technology, user attitudes are important for early acceptance and willingness to change [67]. Including attitudes toward technology in this study is logical both in theory and practice, and it supports the use of both TAM and UTAUT. In addition to individual and technological factors, organizational factors also play a critical role in influencing the adoption of blockchain technology. Infrastructure Quality (I), Policy (D), Security (K), and Leadership Support (SK) are widely identified in the literature as critical success factors for technology implementation in the public sector [78, 79]. The absence of adequate infrastructure, clear policies, security assurance, and leadership support can thwart technology implementation, even when individual readiness is high [80]. Therefore, including these organizational factors in the research framework not only strengthens the study's relevance but also ensures that the developed model can realistically and holistically explain the adoption of blockchain technology. Behavioral Intention to Adopt Blockchain (NTIM) is defined as an individual's subjective probability of accepting and using the technology in performing their work tasks [57, 81]. Behavioral intention is considered the closest predictor of actual behavior. In contrast, Usage Behavior (TLP) refers to the actual use of blockchain technology in the electronic records management of the public archiving sector [82]. Therefore, the following hypotheses are developed based on the factors. The conceptual research framework is shown in Fig. 1.

Hypothesis 1:' Performance Expectations ' has a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 2: 'Effort Expectations' has a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 3: 'Social Influence' has a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 4: 'Facilitating Conditions' have a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 5: 'Attitude towards technology' has a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 6: 'Infrastructure quality' has a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 7: 'Policy' has a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 8: 'Security' has a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 9: 'Leadership support' has a positive impact on behavioral intentions to adopt blockchain.

Hypothesis 10: Relationship Behavioral intention to adopt blockchain has a positive impact on blockchain usage behavior.

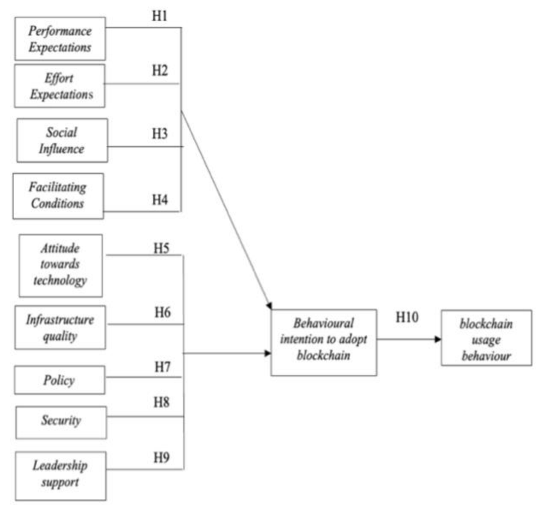

Fig. 1. Conceptual research framework

III. Methodology and Data Collection

This study uses a quantitative method to examine the factors influencing the adoption of blockchain technology in ERM in the Malaysian public sector. This approach was selected because it enables the systematic collection of numerical data, allowing objective analysis and application to a larger group. Data collection was done using a structured questionnaire with a five-point Likert scale, which was developed based on a literature review, records management standards (MS ISO 15489 and MS ISO 16175), and previous studies related to technology adoption.

The minimum sample size was determined using the Krejcie and Morgan (1970) table, with a target population of 2,828 officers and a minimum sample size of 338 respondents. The study respondents consisted of public sector officers from grades 9 to 14 involved in ERM. Of the 400 questionnaires distributed, 253 completed forms were returned, yielding a return rate of 63.2%. Data analysis was conducted using SPSS version 30 for descriptive analysis and Partial Least Squares–Structural Equation Modeling (PLS-SEM) to test the measurement and structural models, including direct and indirect relationships among the study constructs. Pilot studies and expert validation were conducted, and the results showed that all constructs achieved satisfactory levels of validity and reliability, thereby confirming the suitability of the study methodology and instruments for assessing the adoption of blockchain technology in the Malaysian public sector context.

IV. Results

A. ERM Challenges in the Public Sector

Table I presents a demographic analysis of respondents comprising Malaysian public sector officers to provide a descriptive picture of the respondent profile. A total of 400 questionnaires were distributed, and 253 complete responses were received, yielding a return rate of 63.2%, which is considered very good and sufficient for generalizing the study [83]. Most respondents were female (65.6%) and aged 30 to 39 years (69.6%). In terms of organization, most respondents came from ministries (83%), followed by agencies (13%) and departments (4%). Respondents were from various job schemes, with administrative officers (44.3%) and information technology officers (29.2%) forming the largest groups. The distribution of job grades showed that most respondents were in grades 9 and 10 (70%). In terms of length of service, most respondents had served between 6 and 10 years (41.5%) and 11 and 15 years (32.8%), in line with the age distribution of the respondents. Analysis of roles in ERM shows that most respondents are end users (73.9%), followed by information technology managers (17%), while the remainder are system administrators and technical support. Overall, this demographic profile reflects a group of respondents who are well-informed and experienced in public-sector ERM.

B. Measurement Model Analysis

This study uses SEM to simultaneously test the relationships among variables, combining factor analysis and multiple regression. The variance-based PLS-SEM approach is used to evaluate the measurement and structural models, with the main aim of predicting and explaining the variance of the dependent construct. A measurement model is the relationship between constructs and indicators [84]. A construct is an abstract concept that cannot be measured directly but is represented through several indicators or questionnaire items. It refers to a variable developed on theoretical grounds and used to represent psychological, social, perceptual, intentional, or behavioral phenomena that cannot be observed directly but can be measured indirectly through several questions that reflect these perceptions.

1) Indicator reliability: The level of consistency of items in measuring the study construct. The recommended indicator weight is at least 0.60, while indicators with values below 0.40 or above 0.95 should be excluded [84, 85]. Based on Table II, all indicators recorded weight values between 0.40 and 0.95. Therefore, all indicators were retained because they met the reliability requirements.

2) Construct reliability (CR): It assesses the internal consistency of indicators within a construct. In pls-sem, composite reliability is more appropriate than Cronbach's alpha because it takes into account the differences in indicator weight values [84, 86]. The accepted composite reliability value is $\geqslant$ 0.70 and not less than 0.60 [84, 85]. Table II shows that all constructs recorded composite reliability values between 0.896 and 0.974, indicating a high and reliable level of internal consistency.

3) For author-convergent validity: Convergent validity is assessed using AVEs to ensure that the indicators truly measure the specified construct [87]. An AVE value $\geqslant$ 0.50 is considered satisfactory because the construct can explain at least 50% of the indicator variance [84, 88]. In this study, all 11 constructs recorded AVE values between 0.665 and 0.818 in Table II, indicating that all indicators meet the requirements of convergent validity.

4) Discriminant validity: Ensures that each construct is distinct and does not overlap with other constructs. The assessment was carried out using the Fornell-Larcker criteria and the heterotrait-monotrait ratio as recommended by Hair et al. (2017). Based on Table II, the square root of AVE values for each construct was higher than the correlation values with other constructs, fulfilling the Fornell-Larcker criteria in Table III. In addition, Table IV shows that all HTMT values were less than 0.85 [85], confirming that the discriminant validity of the measurement model was satisfactory. The structural model is shown in Fig. 2.

TABLE I. Descriptive Analysis of Demographic Variables

Variable	Item	Frequency	Percentage %
Gender	Male	87	34.4
	Female	166	65.6
Age	20-29	23	9.1
	30-39	176	69.6
	40-49	37	14.6
	50 and above	17	6.7
Organization	Ministries	210	83
	Departments	10	4

	Agencies	33	13
Job schemes	Information Technology Officer	74	29.2
	Administrative Officer	112	44.3
	Finance Officer	9	3.6
	Human Resources	33	13
	Archive Officer	21	8.3
	Engineer	4	1.6
Grade	14	11	4.3
	13	17	6.7
	12	48	19
	10	73	28.9
	9	104	41.1
Years of service	1-5	22	8.7
	6-10	105	41.5
	11-15	83	32.8
	16-20	15	5.9
	More than 20 years	26	10.3
Roles in ERM	System Administrator	9	3.6
	Information Records Manager	43	17
	Support	14	5.5
	End User	187	73.95

TABLE II. MEASUREMENT MODEL ANALYSIS

Construct	Indicator	Loadings	CR	AVE	Discriminant Validity
PE	PE1	0.841	0.962	0.834	Yes
	PE2	0.809			
	PE3	0.851			
	PE4	0.711			
	PE5	0.829			
EE	EE1	0.917	0.922	0.747	Yes
	EE2	0.775			
	EE3	0.903			
	EE4	0.877			
	EE5	0.836			
SI	SI1	0.803	0.956	0.845	Yes
	SI2	0.853			
	SI3	0.921			
	SI4	0.900			
	SI5	0.916			
FC	FC1	0.891	0.905	0.656	Yes
	FC2	0.883			
	FC3	0.908			
	FC4	0.860			
	FC5	0.923			
ATU	ATU1	0.917	0.936	0.745	Yes
	ATU2	0.901			
	ATU3	0.938			
	ATU4	0.896			
	ATU5	0.912			
I	I1	0.895	0.974	0.902	Yes
	I2	0.943			
	I3	0.927			

	I4	0.912			
D	D1	0.823	0.952	0.798	Yes
	D2	0.884			
	D3	0.878			
	D4	0.872			
K	K1	0.921	0.953	0.802	Yes
	K2	0.947			
	K3	0.941			
	K4	0.941			
SK	SK1	0.932	0.945	0.774	Yes
	SK2	0.939			
	SK3	0.932			
	SK4	0.945			
NTIM	NTIM1	0.854	0.975	0.906	Yes
	NTIM2	0.916			
	NTIM3	0.948			
	NTIM4	0.907			
	NTIM5	0.849			
TLP	TLP1	0.888	0.947	0.818	Yes
	TLP2	0.906			
	TLP3	0.926			
	TLP4	0.899			

TABLE III. FORNELL-LARCKER CRITERION

	ATU	D	I	PE	EE	K	FC	NTIM	SI	SK	TLP
ATU	**0.913**										
D	0.205	**0.864**									
I	0.120	0.394	**0.919**								
PE	0.253	0.613	0.357	**0.810**							
EE	0.231	0.522	0.215	0.645	**0.863**						
K	0.236	0.639	0.336	0.503	0.646	**0.950**					
FC	0.182	0.617	0.355	0.741	0.598	0.483	**0.893**				
NTIM	0.116	0.330	0.178	0.675	0.630	0.295	0.638	**0.896**			
SI	0.276	0.571	0.334	0.661	0.659	0.541	0.656	0.578	**0.880**		
SK	0.377	0.585	0.252	0.578	0.412	0.347	0.554	0.460	0.455	**0.952**	
TLP	0.164	0.286	0.117	0.627	0.501	0.200	0.521	0.724	0.522	0.386	**0.905**

TABLE IV. HETEROTRAIT-MONOTRAIT RATIO (HTMT)

	ATU	D	I	PE	EE	K	FC	NTIM	SI	SK	TLP
ATU											
D	**0.190**										
I	0.134	**0.417**									
PE	0.249	0.694	**0.387**								
EE	0.217	0.575	0.222	**0.727**							
K	0.231	0.687	0.342	0.550	**0.688**						
FC	0.150	0.667	0.372	0.821	0.644	**0.507**					
NTIM	0.093	0.359	0.182	0.747	0.680	0.310	**0.677**				
SI	0.264	0.613	0.342	0.725	0.709	0.565	0.690	**0.613**			
SK	0.363	0.632	0.273	0.633	0.440	0.361	0.579	0.482	**0.469**		
TLP	0.151	0.308	0.136	0.701	0.544	0.211	0.557	0.777	0.557	**1.**	

C. Structural Model Analysis

Once the measurement model meets the reliability and validity criteria, the next evaluation is a structured model to assess the strength of the relationships among the constructs and the model's predictive ability. This evaluation involves collinearity analysis, hypothesis testing, coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) using SmartPLS software.

1) Collinearity assessment: Refers to high correlation between independent variables, which can affect the accuracy of the regression coefficients. The variance inflation factor (VIF) is used to check for collinearity. A VIF value of 5 or higher suggests possible collinearity, while a value below 5 indicates no issues [84]. In this analysis, all independent variables had VIF values below the threshold, as shown in Table V, meaning no collinearity problems in the study model.

2) Hypothesis testing (path coefficient): Conducted through bootstrap analysis with 500 random resamples. Table VI summarizes the hypothesis testing and path coefficients. The relationship between constructs was assessed using path coefficients (β), t-values (>1.65), and p-values (<0.05) in a one-tailed test. The results showed that nine hypotheses were supported with significant, positive relationships, while one hypothesis (h6: i → ntim) was rejected because the relationship was not significant and negative. The majority of relationships were consistent with the study hypothesis.

3) Coefficient of determination (r^2): The r^2 value in Table VII indicates the level of variance of the dependent construct that the independent construct can explain. The analysis found that the r^2 values for ntim and tlp were 0.633 and 0.524, respectively, both at a moderate level [84]. This means that the independent construct explained 63.3% of ntim variance, while ntim explained 52.4% of tlp variance, indicating that the model's predictive ability was moderate.

4) Effect size (f^2): The effect size (f^2) was used to assess the contribution of each independent construct to the predictive accuracy of the model. The results in Table VIII showed that most constructs had small effects on ntim, while the ntim → tlp relationship showed a large effect (f^2 =1.099). Construct: I did not show any effect, consistent with the non-significant path coefficient results. The majority of relationships in the model showed small effects, with one main relationship at a large level.

5) Predictive relevance (q^2): Predictive relevance was assessed using the Stone–Geisser (q^2) statistic via the plspredict procedure. Table IX shows the predictive relevance (q2) values. A q^2 value greater than zero indicates that the model has good predictive ability. The results show that the q^2 values for ntim (0.561) and tlp (0.410) are high, indicating that the study model has high predictive relevance.

TABLE V. CONSTRUCT COLLINEARITY ASSESSMENT (VIF)

Dependent constructs	Independent constructs	VIF
NTIM	ATU	1.229
	D	2.613
	I	1.269
	PE	2.979
	EE	2.584
	K	2.309
	FC	2.309
	SI	2.414
	SK	1.976
TLP	NTIM	1

TABLE VI. PATH COEFFICIENT TEST

Hypothesis	Construct relationship	β	t-value	p-value	Discussion
H1	PE -> NTIM	0.343	*3.065	*0.002	Supported
H2	EE -> NTIM	0.375	*3.187	*0.002	Supported
H3	SI -> NTIM	0.154	*2.494	*0.013	Supported
H4	FC -> NTIM	0.244	*2.061	*0.040	Supported
H5	ATU -> NTIM	0.108	*2.551	*0.011	Supported
H6	I -> NTIM	-0.030	0.450	0.653	Rejected
H7	D -> NTIM	0.268	*2.883	*0.004	Supported
H8	K -> NTIM	0.103	*2.339	*0.020	Supported
H9	SK -> NTIM	0.167	*2.442	*0.015	Supported
H10	NTIM -> TLP	0.724	*12.785	*0.000	Supported

TABLE VII. ANALYSIS OF MODEL PREDICTION ACCURACY BASED ON R^2 VALUE

Dependent constructs	R^2 Value
NTIM	0.633 (Moderate)
TLP	0.524 (Moderate)

TABLE VIII. RESULTS OF THE ANALYSIS OF THE EFFECT SIZE VALUE (F^2)

Dependent constructs	Independent constructs	Effect size (f^2)	Impact of change
NTIM	ATU	0.026	Small
	D	0.075	Small
	I	*0.002	No effect
	PE	0.108	Small
	EE	0.149	Small
	K	0.035	Small
	FC	0.059	Small
	SI	0.027	Small
	SK	0.038	Small
TLP	NTIM	1.099	Big

TABLE IX. RESULTS OF THE ANALYSIS OF THE EFFECT SIZE VALUE (Q^2)

Dependent constructs	R^2 Value	Q^2 Value
NTIM	0.633	0.561
TLP	0.524	0.410

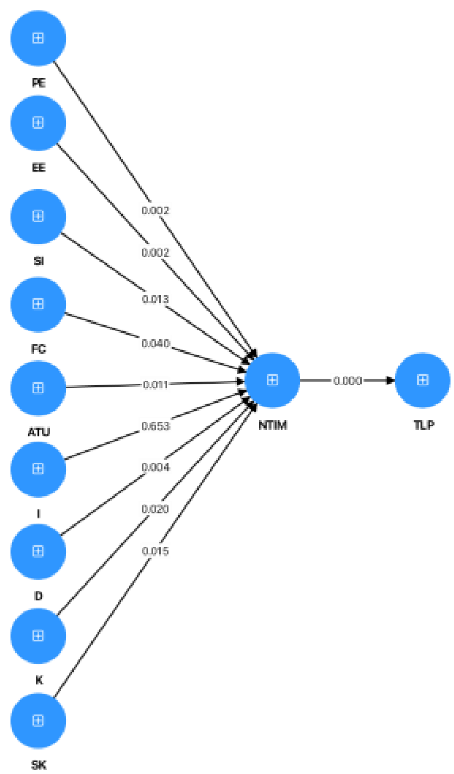

Fig. 2. Structural model.

V. CONCLUSION AND DISCUSSION

A. Hypothesis Testing Results

The results of the analysis showed that eight out of nine predictor factors had a positive and significant relationship with behavioral intention to adopt blockchain technology (NTIM), namely Performance Expectations (H1), Effort Expectations (H2), Social Influence (H3), Facilitating Conditions (H4), Attitudes Towards Technology (H5), Policies (H7), Security (H8), and Leadership Support (H9). On the other hand, Infrastructure Quality (H6) was found to be insignificant.

1) Individual factors: Performance expectations ($\beta = 0.343$, $P < 0.01$) and effort expectations ($\beta = 0.375$, $P < 0.01$) had a significant positive effect on adoption intention. This shows that perceptions of technology's benefits and ease of use are the main drivers of user intention, in line with the UTAUT theory [57]. In addition, attitude towards technology also significantly influenced intention, although with a smaller effect, indicating the importance of user openness to innovation.

2) Organisational and environmental factors: Social influence ($\beta = 0.154$, $P < 0.05$), facilitating conditions ($\beta = 0.244$, $P < 0.05$), Policy ($\beta = 0.268$, $P < 0.01$), security ($\beta = 0.103$, $P < 0.05$), and leadership support ($\beta = 0.167$, $P < 0.05$) were found to be significant in shaping adoption intentions. This finding underscores that organizational support, policy clarity, confidence in information security, and leadership commitment are important in a structured, rule-based public sector.

3) Infrastructure quality: Hypothesis H6 regarding infrastructure quality was not supported ($\beta = -0.030$, $P > 0.05$). This finding suggests that respondents considered technological infrastructure sufficient and that it is no longer a major determinant of intention formation. Instead, human and organizational factors are more dominant in influencing blockchain technology adoption.

4) Relationship between intention and usage behavior: The results of the analysis showed a very strong and significant relationship between behavioral intention (NTIM) and actual usage behavior (TLP) ($\beta = 0.724$, $P < 0.001$). This finding confirms that intention is a key predictor of actual technology usage, in line with TAM and UTAUT theories [49, 57].

B. Key Findings

The research model showed good explanatory power, with R^2 values of 0.633 for behavioral intention and 0.524 for usage behavior. The predictive analysis also showed a positive Q^2 value, indicating moderate to good predictive power. The effect size analysis showed that the NTIM → TLP relationship had a large effect ($f^2 = 1.099$), while other factors on intention showed small to medium effects. The study also found that people's intentions to adopt blockchain technology depend on individual, organizational, and environmental factors. Performance expectations, effort expectations, social influence, facilitating conditions, attitudes toward technology, policy, security, and leadership support all played important roles, but infrastructure quality did not have a significant impact. The link between intentions and actual use shows that intentions are key before people start using new technology. Even with good organizational and infrastructure support, adoption will not happen unless users have strong intentions. This supports the TAM and UTAUT theories for the Malaysian public sector ERM. The integration of TAM and UTAUT was theoretically motivated by the complementary strengths of both models. TAM examines user perceptions of usefulness and ease of use, while UTAUT captures broader social and facilitating influences. Rather than treating them as competing models, this study adopts an integrative approach suited to complex public-sector environments, where both individual beliefs and institutional conditions influence adoption decisions. The model's relatively strong explanatory power ($R^2 = 0.633$) suggests that the combined framework provides robust predictive capability. Future studies may conduct nested model comparisons to examine the incremental predictive contributions of each framework. In addition to R^2, predictive relevance (Q^2) and effect size (f^2) were assessed to provide a comprehensive PLS-SEM evaluation. The Q^2 values for behavioral intention (0.561) and usage behavior (0.410) were above zero, indicating strong predictive relevance. Effect size analysis showed that behavioral intention had a large effect on usage behavior ($f^2 = 1.099$), while other predictors demonstrated small to moderate effects.

1) Theoretical implications: The findings of this study confirm the relevance of TAM and UTAUT theories in explaining blockchain technology adoption in the public sector. The main construct of UTAUT shows a significant relationship with behavioral intention, and behavioral intention is a strong predictor of actual usage behavior. The moderate to high R^2 value and large F^2 effect size for the intention–usage relationship support the view that technology adoption is a gradual process driven by intention formation. The lack of significance of infrastructure quality suggests the need to adapt the technology adoption model to the local context, where policy, security, and leadership factors are more dominant in the public sector.

2) Practical implications: The findings highlight the importance of clear company rules, strong leadership, and a focus on keeping information secure to encourage the adoption of blockchain technology. Also, providing thorough training, good ways to share information, and designs that focus on users are needed to set clear goals for how well the technology should work and how much effort it will take, and to help people feel good about using it. Evenhough the quality of basic infrastructure is not the main issue, having good technical support and using resources effectively are still very important for making the technology work.

VI. Limitations and Future Work

Although this study followed a systematic approach and relied on a solid theoretical framework, it has some limitations. The research used a cross-sectional survey, collecting data at just one point in time. As a result, the findings show only respondents' views on adopting blockchain technology in ERM during the study period and do not capture how user attitudes or behaviors might change over time. The study only included respondents from the public sector in Malaysia. This means the results mainly apply to public-sector organizations in that country and may not fully reflect the private sector or organizations in other countries with different laws, cultures, or levels of technology. This study also used only quantitative methods through a questionnaire. While this works well for testing relationships in the model, it does not allow for a deeper look at the context, practical challenges, or real-world issues of using blockchain technology that could affect adoption in public sector organizations. Additionally, the study examines certain variables based on technology adoption models such as TAM and UTAUT. While these models are well supported by research, other factors such as legal issues, costs, infrastructure readiness, and data governance were not directly tested in this study.

Future research should include a longitudinal study to track changes in perceptions, behavioral intentions, and actual use of blockchain technology in ERM. This would help researchers understand how the technology adoption process develops over time. Research could also include private-sector organizations and quasi-governmental agencies, or compare results across countries that may show significant differences in the factors affecting the adoption of blockchain technology in ERM. A mixed methods approach could combine in-depth interviews, case studies, or document analysis. This can add valuable qualitative insights to support quantitative results, especially regarding operational-level challenges. Future research can also include variables such as information technology governance, organizational readiness, trust, technology costs and risks, and compliance with policies and laws, to expand the conceptual model. These variables may enhance the model's predictive ability and the relevance of the findings to policymakers and practitioners. Finally, experimental or pilot studies on blockchain-based electronic records management systems in public-sector organizations would be valuable. These studies could confirm current findings and help develop practical guidelines and policies for using blockchain in public records and archives management.

Acknowledgment

This study was funded by GUP-2024-045.

Declaration on the Use of Generative AI

The authors acknowledge the use of a generative AI tool to enhance language clarity and assist in correct grammar. However, all scientific ideas, conceptual design, interpretations, and conclusions were independently developed by the authors. All AI-supported content was carefully revised, improved, and validated by authors, and they accept full responsibility for the manuscript's quality and integrity.

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