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Understanding the Drivers of Intention to Adopt Blockchain-Based Certificate Verification: A PLS-SEM Analysis

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Abstract

Higher education institutions in developing countries continue to struggle with certificate authenticity due to the limitations of centralized verification systems. Although blockchain-based certificate verification offers a secure and transparent alternative, adoption intention remains low because behavioral determinants are insufficiently understood. This study develops and tests an integrated model combining Technology Readiness Index dimensions, diffusion of innovation factors, perceived complexity, compatibility, and resistance to change to explain intention to adopt blockchain-based certificate verification. Survey data were collected from 586 student record officers across 64 Iraqi universities and analyzed using PLS-SEM. Results indicate that innovativeness, optimism, discomfort, insecurity, and perceived compatibility significantly influence adoption intention, while perceived complexity is not significant. Resistance to change selectively moderates the effects of innovativeness and discomfort but no other predictors. The model demonstrates strong explanatory power, emphasizing the dominant role of psychological readiness and behavioral resistance over purely technical concerns. The study extends blockchain adoption literature by integrating multiple theoretical perspectives in an educational context and provides practical guidance for capacity building, training, and change management to support blockchain implementation in developing higher education systems.

I. INTRODUCTION

The rapid digitalization of higher education institutions has intensified the need for secure, transparent, and efficient mechanisms for managing academic credentials [1]. Traditional certificate issuance and verification systems are predominantly centralized, manual, and paper-based, making them vulnerable to forgery, loss, unauthorized modification, and verification delays[2,3,4]. These limitations pose serious challenges for universities, employers, and accreditation bodies, particularly in contexts characterized by increasing student mobility and cross-institutional credential recognition [5]. Consequently, emerging digital technologies are being explored to address persistent trust and efficiency issues in academic certificate management [6].

Individual technology readiness traits play a critical role in shaping adoption behavior [7,8]. Innovativeness (INNV) reflects an individual's willingness to experiment with and adopt novel technologies [9], while optimism (OPTM) represents positive beliefs regarding technology's potential to improve efficiency, transparency, and performance [10]. Users exhibiting high levels of innovativeness and optimism are more likely to perceive BBCV as beneficial and are thus more inclined to adopt it [11]. In contrast, negative readiness dimensions namely discomfort (DCFT) and insecurity (INSC) may inhibit adoption intentions [12]. Discomfort arises from perceived difficulty in understanding or controlling advanced technologies, whereas insecurity reflects concerns about data privacy, system reliability, and trust in blockchain infrastructures.

In addition to individual-level factors, system-related perceptions significantly influence adoption decisions [13]. Perceived complexity (PCXT) refers to the degree to which BBCV is perceived as difficult to learn or use [14,15]. High perceived complexity can increase cognitive effort and discourage adoption, especially among users with limited technical expertise [16]. Conversely, perceived compatibility (PCOM) the extent to which BBCV aligns with existing institutional practices, technological infrastructure, and user values facilitates adoption by reducing uncertainty and integration effort [17]. Organizational and behavioral barriers further affect adoption outcomes [18]. Resistance to change (RTC) represents users' tendency to prefer existing systems and routines over new technological alternatives [19]. In higher education institutions, where administrative processes are often deeply institutionalized, resistance to change can significantly impede the implementation of blockchain-based solutions, even when their advantages are evident [20].

The context of higher education institutions in Iraq presents a particularly relevant case for examining BBCV adoption [21]. Iraqi universities face persistent challenges related to certificate fraud, inefficient verification processes, and limited inter-institutional trust [22]. At the same time, ongoing digital transformation initiatives and increasing interest in e-governance create a favourable environment for blockchain-based innovations [23,24]. However, empirical evidence on the determinants of BBCV adoption in the Iraqi higher education sector remains limited, highlighting the need for systematic investigation. To address this research gap, this study aims to predict the intention to adopt blockchain-based certificate verification in higher education institutions in Iraq by examining the effects of innovativeness, optimism, discomfort, insecurity, perceived complexity, perceived compatibility, and resistance to change. A comprehensive research model is developed to capture the combined influence of individual, technological, and organizational factors on adoption intention.

Methodologically, most prior studies on technology adoption have relied on Partial Least Squares Structural Equation Modeling (PLS-SEM) to test hypothesized relationships [7,25,26,27,28]. While PLS-SEM offers strong explanatory capabilities, but it is limited in predictive accuracy. Recent research advocates integrating Machine Learning (ML) algorithms with SEM to enhance prediction and model validation [29,30,31]. Accordingly, this study adopts a PLS-SEM learning approach, leveraging the explanatory power of PLS-SEM and to provide robust insights into BBCV adoption behavior. The findings of this study are expected to contribute both theoretically, by extending technology adoption research in blockchain applications, and practically, by informing policymakers and university administrators on strategies to facilitate BBCV implementation in higher education.

II. RELATED STUDIES

A. FEATURES AND OPPORTUNITY OF BLOCKCHAIN

Blockchain technology is widely recognised for its core features, including decentralisation, transparency, immutability, security, and traceability, which collectively distinguish it from traditional centralised information systems [32]. Decentralisation eliminates reliance on a single authority by distributing data across a peer-to-peer network, thereby reducing single points of failure and enhancing system resilience [33]. However, while decentralisation improves trust and data integrity, it also introduces governance and coordination challenges, particularly in institutional settings where accountability and regulatory compliance are essential [34].

Transparency and immutability ensure that once records are stored on the blockchain, they cannot be altered without network consensus, strengthening data integrity and auditability [35]. These features are especially valuable in domains requiring long-term record preservation and verification, such as education, finance, and public administration. Nevertheless, the irreversible nature of blockchain records raises concerns regarding data privacy, error correction, and compliance with data protection regulations, including the right to be forgotten [36]. Security is another fundamental feature, achieved through cryptographic mechanisms and consensus protocols that protect data from unauthorised access and tampering [37]. Despite these advantages, blockchain systems are not immune to risks, such as smart contract vulnerabilities, scalability limitations, and high computational costs, particularly in public blockchains relying on energy-intensive consensus mechanisms [38].

Overall, while blockchain presents significant opportunities for enhancing trust, transparency, and efficiency, its practical value is contingent upon addressing technical, organisational, and regulatory challenges. A critical understanding of both its enabling features and inherent limitations is therefore essential for informed and sustainable adoption across sectors.

B. PREVIOUS RESEARCH ON BLOCKCHAIN TECHNOLOGY IN EDUCTION

The researcher [39] examines blockchain integration in higher education management amid growing data sprawl and post-COVID digitalization pressures. It evaluates the technology's benefits, limitations, and trade-offs, highlighting tensions between innovation, privacy, and regulation. Using mixed methods, the study assesses stakeholder experiences to inform realistic, secure, and transparent governance reforms. [40] reviews the nascent application of blockchain in education, critically assessing its advantages, limitations, and implementation challenges. It combines conceptual analysis with a practical case the BeCertify project to demonstrate certificate verification via blockchain. While showcasing technical feasibility and transparency gains, the study reflects early-stage adoption and limited empirical validation. [41] explores blockchain adoption in Chinese higher education, critiquing limitations of centralized credential verification systems. It argues that blockchain's decentralization can enhance efficiency, data traceability, and degree verification. However, the discussion remains largely conceptual, drawing heavily from financial analogies with limited empirical evidence or practical implementation analysis in educational contexts.

III. CONCEPTUAL MODEL AND HYPOTHESES

This study proposes an integrated conceptual model grounded in Technology Readiness Index (TRI), Diffusion of Innovation (DOI), and moderator of Resistance to Change (RTC) to explain stakeholders' intention to adopt Blockchain-Based Certificate Verification (BBCV) in higher education institutions (HEIs). The model recognises that the adoption of complex technologies such as blockchain is shaped not only by individual psychological readiness and innovation attributes, but also by behavioural resistance to change, which can attenuate otherwise positive adoption intentions.

A. THE TECHNOLOGY READINESS INDEX CONSTRUCTS AND INTENTION TO ADOPT BBCV

Innovativeness is widely recognised as a key driver of technology adoption. The innovativeness as the capacity of individuals or organisations to generate and implement novel ideas that lead to positive change. Prior studies consistently demonstrate a positive relationship between innovativeness and intention to adopt new technologies [8,42,43,44]. For example, [8] found a strong positive association between academic staff's personal innovativeness and e-learning adoption at the University of Nineveh. Similarly, [45] showed that organisational readiness for change significantly influences individual innovativeness in e-learning contexts. [46], in their study on IoT adoption among Malaysian SMEs, reported that although optimism existed, limited innovativeness and uncertainty constrained adoption. Collectively, these findings suggest that higher levels of innovativeness increase individuals' willingness to adopt emerging technologies such as BBCV.

Optimism represents a positive belief in technology's ability to enhance performance and overcome challenges. Empirical evidence highlights optimism as a significant predictor of technology adoption [46,47,48,49]. [39] demonstrated that optimism significantly predicts big data adoption, while [11] linked optimism to cryptocurrency adoption. These findings suggest that optimistic individuals are more likely to embrace innovative technologies. In the context of higher education, optimism may similarly enhance stakeholders' intention to adopt BBCV. Discomfort reflects feelings of unease or lack of control when interacting with new technologies [46,50,51]. Discomfort may arise from perceived complexity, data security concerns, or uncertainty regarding system effectiveness. For instance, [7] argue that individual comfort levels significantly influence organisational adoption decisions. Although discomfort is often viewed as a barrier, [52] suggest it can also trigger learning and adaptation by motivating individuals to seek training or support. Nevertheless, higher discomfort is generally expected to reduce adoption intention.

Insecurity refers to concerns related to trust, privacy, and perceived risks associated with new technologies. Studies show that insecurity can negatively affect technology adoption intentions [53]. For instance, job insecurity has been linked to lower adoption intentions [54], while data insecurity has influenced technology use in healthcare contexts [35]. [7] note that privacy and cyber-security concerns often heighten insecurity, making technologies appear more complex. [24] further indicate that insecurity indirectly shapes continuous usage intentions through user attitudes. Accordingly, insecurity is expected to significantly influence BBCV adoption to adopt. Thus, the present study is based on the following hypotheses:

H1: Innovativeness Influences Intention to Adopt BBCV
H2: Optimism influences Intention to Adopt BBCV
H3: Discomfort has a significant influence on the intention to adopt BBCV
H4: Insecurity has a significant influence on the intention to adopt BBCV

B. THE DIFFUSION OF INNOVATION CONSTRUCTS AND INTENTION TO ADOPT BBCV

The BBCV system in higher education can be examined through prior research on the role of technological complexity in adoption decisions. Numerous studies have consistently identified perceived complexity as a critical barrier to technology adoption (i.e [25,28,55,56,57]). For example, [58] demonstrated that organisations are less inclined to adopt technologies they perceive as complex, particularly when such technologies require specialised knowledge or disrupt existing workflows. Similarly, [59] found that increasing technological complexity reduces individuals' willingness to adopt new systems. These findings align with established technology acceptance theories, which argue that higher perceived complexity negatively shapes users' attitudes and behavioural intentions toward adoption [60,61]. In the context of BBCV, blockchain's technical sophistication may pose cognitive and operational challenges, thereby discouraging adoption in higher education institutions.

Perceived compatibility is another critical determinant of technology adoption. Defined as the extent to which a new technology aligns with existing systems, values, and practices, compatibility has been positively associated with adoption intentions across multiple studies [8,42,62]. [43] reported a strong positive relationship between perceived compatibility and technology adoption intention. Likewise, [63] found compatibility to be a significant factor influencing cryptocurrency adoption among Asia-Pacific e-retailers. In the context of cloud computing adoption, [64] further emphasised compatibility as a critical success factor for SMEs. Applied to BBCV, systems that integrate smoothly with existing certificate verification processes are more likely to be adopted. Thus, the following hypotheses are established

H5: Perceived Complexity of BT influences intention to adopt BBCV
H6: Perceived Compatibility of BT influences intention to adopt BBCV

C. RESISTANCE TO CHANGE AS A MODERATOR ON THE RELATIONSHIP BETWEEN TECHNOLOGY READINESS INDEX, DIFFUSION OF INNOVATION CONSTRUCTS AND INTENTION TO ADOPT BBCV

Resistance to Change (RTC) as a critical behavioural factor influencing technology adoption and its moderating role in the BBCV context. Psychologically, individuals tend to resist new technologies because they prefer routines and comfort zones, perceiving innovation as a potential threat [65]. RTC has been shown to significantly affect technology adoption, as individuals often resist innovation to preserve the status quo and avoid uncertainty [66,67,68]. Human beings are creatures of habit, and disruptions to established routines can generate discomfort and resistance [69]. Resistance may also arise when change conflicts with personal beliefs, self-concept, or job security, leading to scepticism and opposition [70].

Within technology adoption research, RTC is recognised as a key moderator that can weaken favourable perceptions of technology. Prior studies highlight that RTC shapes how users interpret perceived compatibility, complexity, insecurity, discomfort, optimism, and innovativeness, thereby influencing adoption intentions [71,72]. For instance, individuals are more likely to resist innovations perceived as complex, as complexity increases cognitive burden and uncertainty [66,73,74]. Empirical evidence confirms that RTC negatively moderates the relationship between perceived complexity and intention to adopt cloud computing and other technologies [75,76,77]. RTC also interacts with insecurity, discomfort, optimism, and innovativeness. Job insecurity has been linked to psychological distress and resistance, which can reduce openness to change [78,79]. Discomfort and negative emotions triggered by new technologies may further strengthen resistance [80,81]. Although optimism and innovativeness generally promote adoption [82,11,83], prior studies show that RTC can weaken these positive effects [84,77,66]. Accordingly, RTC is proposed as a moderator across all key relationships in the BBCV adoption model. Hence the following hypotheses (H7–H12).

H7: Resistance to change Moderate the Relationship between Perceived Compatibility of BT and Intention to Adopt BBCV

H8: Resistance to Change Moderate the Relationship between Perceived Complexity of BT and Intention to adopt BBCV

H9: Resistance to Change Moderate the Relationship between Insecurity and Intention to Adopt BBCV

H10: Resistance to Change Moderate the Relationship between Discomfort and Intention to Adopt BBCV

H11: Resistance to Change Moderate the Relationship between Optimism and Intention to adopt BBCV.

H12: Resistance to Change Moderates the Relationship between Innovativeness and Intention to Adopt BBCV

D. THE CONCEPTUAL FRAMEWORK

The conceptual framework of the present study aims to assess the determinants of stakeholders' intention to adopt Blockchain-Based Certificate Verification (BBCV) systems in higher education institutions (HEIs) by integrating TRI, DOI, and RTC. The framework is designed to provide a holistic explanation of BBCV adoption by simultaneously capturing individual psychological readiness, innovation-specific attributes, and behavioural resistance to organisational change. At the individual level, the framework incorporates the four core dimensions of TRI innovativeness, optimism, discomfort, and insecurity as key antecedents influencing intention to adopt BBCV. Innovativeness and optimism represent positive readiness drivers that enhance openness toward blockchain adoption, while discomfort and insecurity act as inhibitors that may reduce adoption intention due to perceived difficulty, lack of control, or concerns regarding system reliability and data security. These dimensions reflect users' cognitive and emotional predispositions toward emerging technologies, which are particularly salient in the context of complex and unfamiliar systems such as blockchain-based verification.

From the innovation perspective, the framework draws on DOI theory by including perceived complexity and perceived compatibility as critical technology attributes influencing adoption decisions. Perceived complexity captures the extent to which BBCV is viewed as difficult to understand or use, which can slow adoption in institutional environments with limited technical expertise. Conversely, perceived compatibility reflects how well BBCV aligns with existing certificate verification processes, organisational values, and regulatory requirements within HEIs. By focusing on these two DOI attributes, the framework addresses the most salient internal barriers likely to influence early-stage adoption of BBCV.

Furthermore, the framework introduces resistance to change, as a moderating variable. Resistance to change reflects individuals' psychological and behavioural opposition to new systems that threaten established routines, professional autonomy, or institutional stability. In the context of BBCV, resistance to change is expected to condition the strength of the relationships between TRI and DOI factors and intention to adopt. Specifically, high resistance to change may weaken the positive effects of innovativeness, optimism, and compatibility, while amplifying the negative effects of discomfort, insecurity, and perceived complexity.

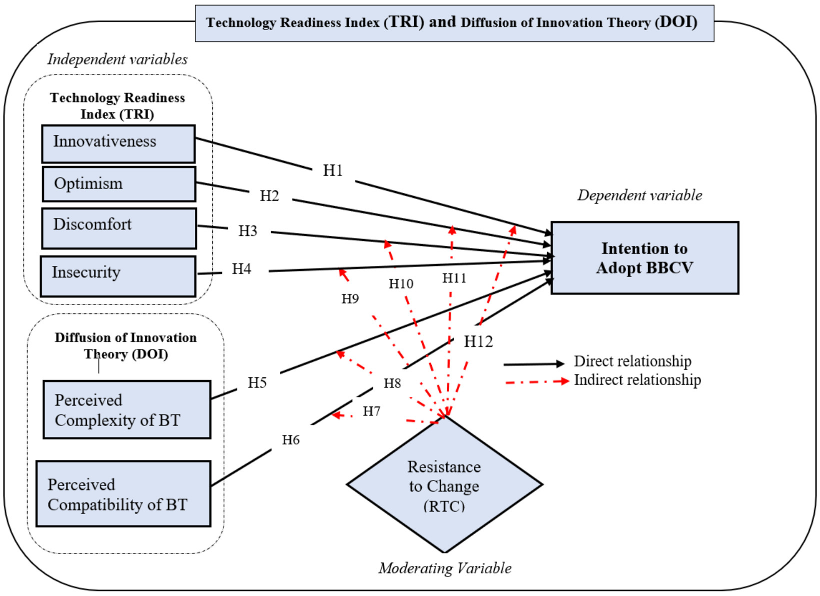

Fig. 1. *Research model.*

IV. RESEARCH METHODOLOGY

A. DATA COLLECTION

Data for this study were collected through a structured questionnaire links distributed via email to staff members working in student records offices at public and private universities across 15 states in Iraq. The data collection took place during the summer of 2025. Specifically, the data collection took three months May, June and July. The questionnaire targeted respondents directly involved in student records management and certificate verification processes. To enhance the response rate, several follow-up strategies were implemented. These included reminder phone calls, SMS notifications, group reminder emails, and notices posted on institutional boards for participants who had not responded within one month. A total of 700 questionnaires were distributed during the data collection period. As a result of the follow-up efforts, 608 completed questionnaires were returned, representing a response rate of 86.86%. Of the returned questionnaires, 22 were excluded from further analysis due to the presence of univariate and multivariate outliers. Consequently, 586 questionnaires were deemed valid and usable for statistical analysis, yielding an effective response rate of 83.71%. This high response rate exceeds the minimum threshold recommended for survey-based studies and provides a robust dataset for subsequent analysis. The measurement and structural models were evaluated using PLS-SEM, enabling rigorous assessment of construct validity, reliability, and the hypothesized relationships among the study variables.

Table 1: Demographic profile of the 586 respondents

Demographics	Frequency	Percentage (%)
Gender		
Male	347	59.2
Female	239	40.8
Age		
20–29 years	114	19.5
30-39 years	222	37.9
40-49 years	166	28.3
50 years and above	84	14.3
Education Level		
High School	12	2.0
Bachelors	272	46.4
Masters	193	32.9
PhD	109	18.6
Experience in Certificate Verification		
Less than one year	143	24.4
1 - 5 Years	236	40.3
6 - 10 Years	83	14.2
11 Years and above	124	21.2
Type of University		
Public	498	85.0
Private	88	15.0
Names of the States of Iraq		
Al-Anbar	73	12.5
Al-Muthana	29	4.9
Al-Qadisiyyah	33	5.6
Babil	20	3.4
Baghdad	105	17.9
Basrah	35	6.0
Dhi Qar	28	4.8
Diyala	37	6.3
Karbala	26	4.4

Kirkuk	29	4.9
Misan	23	3.9
Mosul	28	4.8
Najaf	40	6.8
Salah El-Din	42	7.2
Wasit	38	6.5

B. STUDY INSTRUMENT

The study employed a 41-item questionnaire to validate the research model and hypotheses because it evaluated the 8 survey constructs. The questions used in the present study questionnaires were derived from existing studies but were modified to fit the study objectives. Specifically, the adjustment was necessary to tailor the question based on the present study's needs and improve the generalization of the study findings.

C. COMMON METHOD BIAS (CMB)

Common Method Bias (CMB) was assessed to determine whether the data collected from a single questionnaire introduced systematic measurement bias. Harman's single-factor test was applied to all measurement constructs. The results indicated that no single factor accounted for the majority of the variance, suggesting that CMB is not a serious concern in this study. In addition, a full collinearity assessment was conducted using variance inflation factor (VIF) values. All VIF values ranged between 1.699 and 3.046, which are below the recommended threshold of 3.3. This further confirms the absence of common method bias in the dataset. Overall, the results from both Harman's single-factor test and the VIF analysis demonstrate that common method bias does not significantly affect the data. Therefore, the relationships among the study constructs can be interpreted with confidence, and the findings of this study are not threatened by CMB.

V. FINDINGS AND DISCUSSION

A. CONVERGENT VALIDITY

Construct reliability and validity are essential criteria for evaluating the adequacy of the measurement model. In line with prior studies, construct reliability was assessed using Cronbach's Alpha (CA), composite reliability (CR), and Dijkstra–Henseler's rho (ρA), while convergent validity was examined through indicator loadings and average variance extracted (AVE) [85],[86]. As presented in Table 2, the CA values range from 0.602 to 0.876, indicating acceptable to strong internal consistency and exceeding the recommended threshold of 0.70 for most constructs [87]. Similarly, composite reliability coefficients (CR-C) range between 0.772 and 0.910, which are well above the minimum acceptable value of 0.70, thereby confirming satisfactory construct reliability. In addition, the CR-A (ρA) values for all constructs exceed 0.70, meeting the recommended criteria for exploratory and advanced research phases [88].

Table 2: Measuring the construct reliability and convergent validity

Variable	Items	Loadings	CA	CR-A	CR-C	AVE
Discomfort	DCFT1	0.634	0.602	0.669	0.772	0.534
	DCFT2	0.710				
	DCFT4	0.834				
Innovativeness	INNV1	0.862	0.784	0.800	0.874	0.698
	INNV2	0.869				
	INNV3	0.773				
Insecurity	INSC1	0.791	0.832	1.086	0.868	0.627
	INSC2	0.808				
	INSC3	0.931				
	INSC7	0.600				
Intention to Adopt BBCV	INT1	0.839	0.863	0.863	0.907	0.709
	INT2	0.847				
	INT3	0.826				
	INT4	0.855				
Optimism	OPTM1	0.699	0.865	0.869	0.903	0.652
	OPTM2	0.855				
	OPTM3	0.811				
	OPTM4	0.842				
	OPTM5	0.821				
Perceived Compatibility	PCOM1	0.797	0.876	0.876	0.910	0.668
	PCOM2	0.817				
	PCOM3	0.836				
	PCOM4	0.828				
	PCOM5	0.808				
Perceived Complexity	PCXT3	0.815	0.789	0.797	0.863	0.613
	PCXT4	0.742				
	PCXT5	0.831				
	PCXT6	0.740				
Resistance to Change	RTC1	0.762	0.847	0.913	0.894	0.678
	RTC2	0.871				
	RTC4	0.800				
	RTC5	0.857				

Convergent validity was assessed using indicator factor loadings and AVE values. Factor loadings for all retained items exceed the recommended threshold of 0.70, indicating that the indicators adequately represent their respective latent constructs [85]. Items with low loadings were removed to improve measurement quality, as noted in Table 2. Furthermore, the AVE values range from 0.534 to 0.709, exceeding the minimum threshold of 0.50, which suggests that each construct explains more than half of the variance of its indicators [86], [89]. Overall, the results demonstrate that the measurement model satisfies the requirements for construct reliability and convergent validity. The high factor loadings, acceptable reliability coefficients, and AVE values above the recommended thresholds provide strong empirical support for the adequacy and robustness of the constructs used in this study.

B. DISCRIMINANT VALIDITY

A construct is said to have discriminant validity if it can be evaluated based on the extent to which it can be distinguished from other constructs [87]. The term "discriminant validity" refers to the degree to which one variable possesses distinguishable qualities in comparison to those of the others [90]. The present research employed a variety of reliable methods to evaluate the discriminant validity of the variables under consideration. Moreover, discriminant validity was established by employing the criteria proposed by [91], which involved comparing item loadings with those of other items in a cross-loadings analysis Table 3. Cross-loadings, which refer to item-level discriminant validity, are considered one of the key criteria for evaluating the extent to which a measurement instrument adequately discriminates across different constructs.

Table 3: Fornell and Larcker Criterion

Constructs	DCFT	INNV	INSC	INT	OPTM	PCOM	PCXT	RTC
DCFT	0.731							
INNV	0.422	0.835						
INSC	0.196	-0.075	0.792					
INT	0.418	0.763	-0.165	0.842				
OPTM	0.455	0.734	-0.080	0.732	0.807			
PCOM	0.440	0.647	-0.044	0.665	0.662	0.818		
PCXT	0.384	0.471	0.079	0.510	0.540	0.672	0.783	
RTC	0.118	-0.143	0.600	-0.220	-0.125	-0.127	-0.037	0.824

The above criterion is particularly significant for indicating discriminant validity [92]. [93] asserted that discriminant validity is established when each item has low correlations with all other constructs, except for the construct with which it is theoretically associated. The current study used cross-loadings to provide empirical support for discriminant validity.

C. MODEL FIT

Model fit in this study was assessed using Smart PLS through multiple goodness-of-fit indices to evaluate the adequacy of the proposed PLS-SEM model. Following prior PLS-SEM literature, the standardised root mean square residual (SRMR) was used as the primary global fit measure [94]. SRMR reflects the difference between the observed correlation matrix and the model-implied correlation matrix, where values below 0.08 indicate a good model fit [95]. As shown in Table 4, the SRMR values for both the saturated model (0.037) and the estimated model (0.039) are well below the recommended threshold, confirming an acceptable overall model fit.

Table 4: Model fit

Indices	Saturated model	Estimated model
SRMR	0.037	0.039
d_ULS	1.144	1.269
d_G	0.369	0.374
Chi-square	1157.246	1174.224
NFI	0.909	0.907

In addition to SRMR, the normed fit index (NFI) was examined. NFI compares the chi-square value of the proposed model with that of a null or benchmark model, with values exceeding 0.90 indicating a good fit [96]. The NFI values of 0.909 for the saturated model and 0.907 for the estimated model exceed the recommended cutoff, further supporting the adequacy of the model. Other fit indices, including the squared Euclidean distance (d_ULS) and the geodesic distance (d_G), were also assessed. These indices evaluate the discrepancy between the empirical covariance matrix and the model-implied covariance matrix [97]. The d_ULS values (1.144 for the saturated model and 1.269 for the estimated model) and d_G values (0.369 and 0.374, respectively) indicate only minor differences between observed and predicted correlations. Moreover, the chi-square values for the saturated (1157.246) and estimated (1174.224) models show minimal deviation, suggesting consistency between model specification and data. Overall, the results across SRMR, NFI, d_ULS, d_G, and chi-square indices demonstrate that the proposed PLS-SEM model exhibits a satisfactory fit to the data. Consistent with recommendations by [98], the model evaluation relies on a combination of fit measures rather than a single index, thereby strengthening confidence in the robustness and validity of the structural model.

D. HYPOTHESES TESTING USING PLS-SEM

Structural Equation Modeling (SEM) using Smart PLS was employed to examine the relationships among the theoretical constructs and to test the study hypotheses. The structural model assessment focused on the significance of the path coefficients using bootstrapping procedures, with t-values and p-values used to determine hypothesis support. The results of the hypothesis testing are presented in Table 5. The findings indicate that several direct relationships with INT are statistically significant. Specifically, INNV → INT (H1) shows a strong positive effect ($t = 9.521$, $p < 0.001$), indicating that innovation significantly influences INT. Similarly, OPTM → INT (H2) is significant ($t = 5.263$, $p < 0.001$), as well as DCFT → INT (H3) ($t = 2.302$, $p = 0.011$) and INSC → INT (H4) ($t = 3.056$, $p = 0.001$). Furthermore, PCOM → INT (H6) demonstrates a significant positive relationship ($t = 3.846$, $p < 0.001$). These results confirm that INNV, OPTM, DCFT, INSC, and PCOM are important predictors of INT.

However, PCXT → INT (H5) is not significant ($t = 0.987$, $p = 0.163$), indicating that PCXT does not directly influence INT in this model. Regarding the moderation effects of RTC, most interaction terms were not significant. The moderating effects of RTC × PCOM (H7) ($t = 1.305$, $p = 0.097$), RTC × PCXT (H8) ($t = 0.241$, $p = 0.405$), RTC × INSC (H9) ($t = 0.063$, $p = 0.475$), and RTC × OPTM (H11) ($t = 0.951$, $p = 0.171$) were not supported. In contrast, RTC × DCFT → INT (H10) shows a significant moderating effect ($t = 2.305$, $p = 0.011$), indicating that RTC strengthens the relationship between DCFT and INT. Additionally, RTC × INNV → INT (H12) is significant ($t = 1.741$, $p = 0.042$), suggesting that RTC also moderates the relationship between INNV and INT.

In sum, out of twelve hypotheses, seven were supported (H1, H2, H3, H4, H6, H10, H12), while five were not supported (H5, H7, H8, H9, H11). The findings highlight that several direct predictors significantly influence INT, while RTC exhibits selective moderating effects rather than a uniform moderating role across all relationships.

Table 5: Hypotheses-testing of the research model (significant at p** <= 0.01, p* < 0.05)

Hypothesis	Relationship	t-values	p-values	Decision
H1	INNV -> INT	9.521	0.000	Supported
H2	OPTM -> INT	5.263	0.000	Supported
H3	DCFT -> INT	2.302	0.011	Supported
H4	INSC -> INT	3.056	0.001	Supported
H5	PCXT -> INT	0.987	0.163	Not-Supported
H6	PCOM -> INT	3.846	0.000	Supported
H7	RTC x PCOM -> INT	1.305	0.097	Not-Supported
H8	RTC x PCXT -> INT	0.241	0.405	Not-Supported
H9	RTC x INSC -> INT	0.063	0.475	Not-Supported
H10	RTC x DCFT -> INT	2.305	0.011	Supported
H11	RTC x OPTM -> INT	0.951	0.171	Not-Supported
H12	RTC x INNV -> INT	1.741	0.042	Supported

The measurement model assessment (see Fig. 2) demonstrates that the reflective constructs exhibit generally strong indicator reliability. Most item loadings exceed the recommended threshold of 0.70, indicating that the indicators share a high proportion of variance with their respective latent constructs. For example, INNV indicators load between 0.773 and 0.869, OPTM between 0.699 and 0.855, PCOM between 0.797 and 0.882, PCXT between 0.740 and 0.831, and RTC between 0.762 and 0.871. INT also shows high loadings ranging from 0.826 to 0.855, suggesting that its indicators are highly representative of the construct. Although a few items such as DCFT1 (0.634) and INSC7 (0.600) fall slightly below the ideal 0.70 level, they remain acceptable in exploratory and behavioral research, particularly where overall construct reliability is adequate.

In terms of construct reliability and convergent validity, the consistently high loadings across most indicators suggest that composite reliability (CR) and Average Variance Extracted (AVE) are likely above recommended thresholds (CR > 0.70, AVE > 0.50). This indicates that each construct explains more than half of the variance of its indicators and that internal consistency is satisfactory.

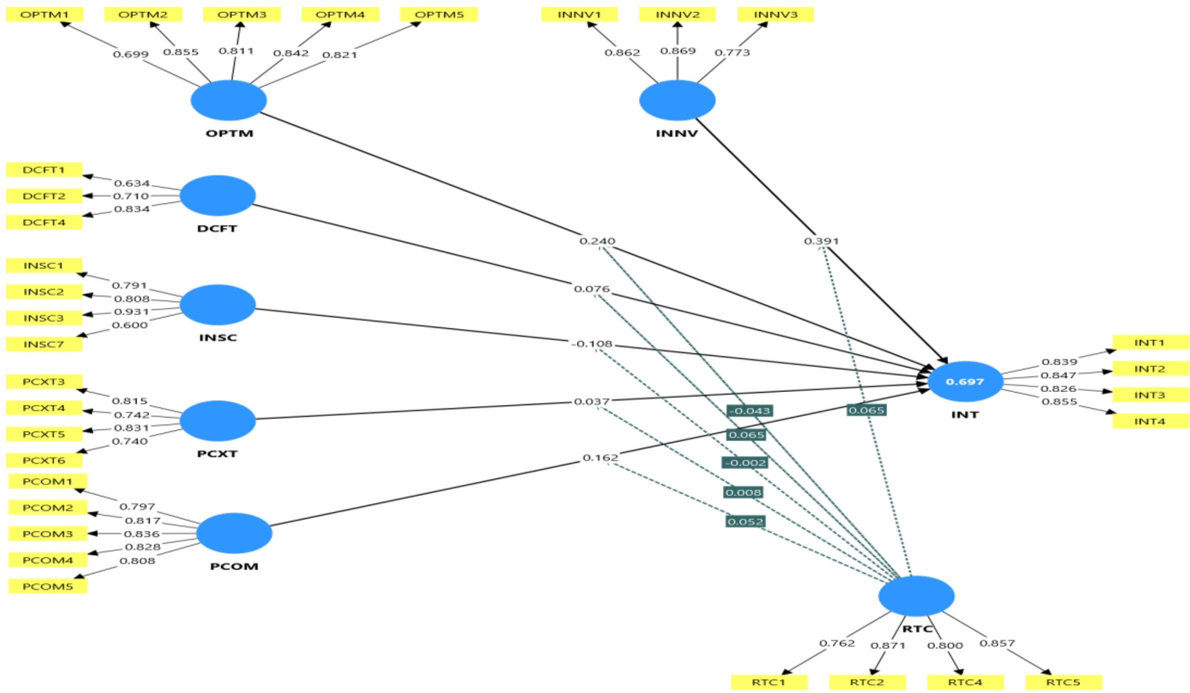

Fig. 2 *Measurement model*

The measurement model therefore demonstrates good convergent validity, as indicators of the same construct strongly converge. Combined with the previously established discriminant validity, the results confirm that the measurement model in Fig. 2 is robust and suitable for evaluating the structural relationships in the PLS-SEM analysis.

Figure 3 presents the structural model results obtained from the PLS-SEM analysis. The model explains a substantial proportion of variance in INT, with an R^2 value of 0.697, indicating strong predictive power. This means that approximately 69.7% of the variance in INT is explained jointly by INNV, OPTM, DCFT, INSC, PCXT, PCOM, and the interaction terms involving RTC. Such an R^2 value suggests that the model has high explanatory capability in predicting INT within the study context.

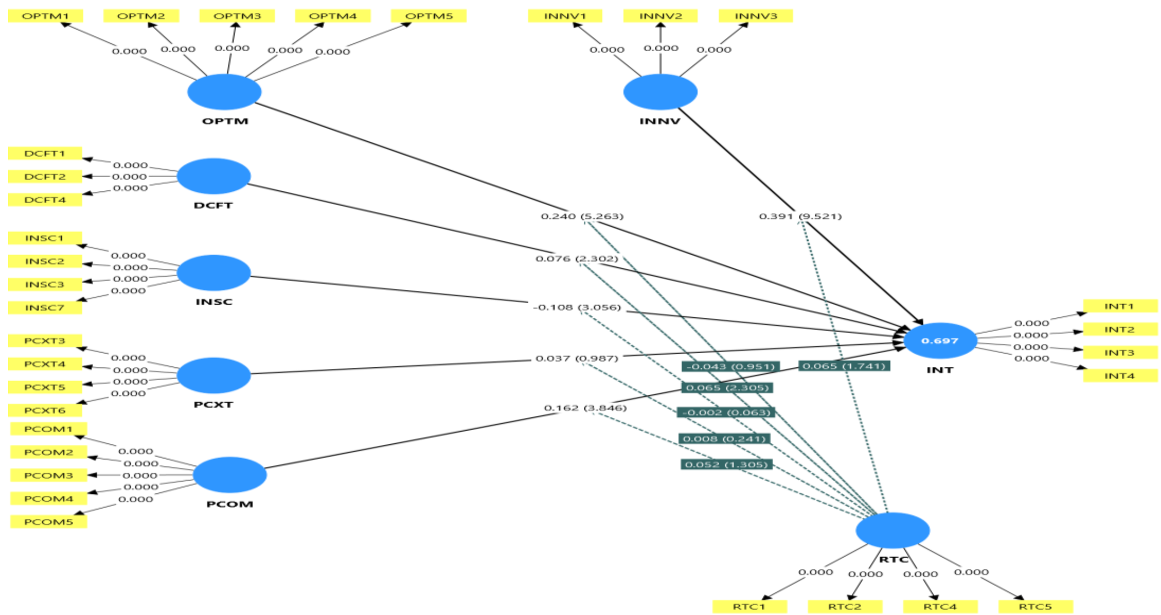

Fig. 3 *Structural model*

Regarding the direct effects, several constructs show significant positive relationships with INT. INNV → INT ($\beta = 0.391$, $t = 9.521$) represents the strongest effect, followed by OPTM → INT ($\beta = 0.240$, $t = 5.263$) and PCOM → INT ($\beta = 0.162$, $t = 3.846$). DCFT → INT ($\beta = 0.076$, $t = 2.302$) and INSC → INT ($\beta = 0.108$, $t = 3.056$) also demonstrate significant contributions, though with smaller effect sizes. In contrast, PCXT → INT ($\beta = 0.037$, $t = 0.987$) is not significant, indicating that this construct does not meaningfully influence INT in the presence of other predictors. The moderating role of RTC is selective rather than universal. The interaction RTC × DCFT → INT ($\beta = 0.065$, $t = 2.305$) and RTC × INNV → INT ($\beta = 0.065$, $t = 1.741$) are significant, suggesting that RTC strengthens the effects of DCFT and INNV on INT. However, moderation effects for RTC × PCOM, RTC × PCXT, RTC × INSC, and RTC × OPTM are not significant, as their t-values fall below the recommended threshold. This implies that RTC does not consistently condition all predictor INT relationships, but rather enhances specific ones.

VI. DISCUSSION

A. THEORETICAL AND PRACTICAL IMPLICATIONS

Firstly, this study advances the growing body of knowledge on blockchain technology adoption in educational and certification contexts, an area that remains underexplored compared with financial and supply-chain applications. While prior blockchain adoption studies largely emphasize technical architecture or general technology acceptance, limited research systematically investigates behavioral drivers of intention to adopt blockchain-based certificate verification systems. This study addresses that gap by empirically identifying the key psychological and contextual determinants of INT, thereby extending technology adoption research into the academic credential verification domain. The findings demonstrate that INNV is the strongest predictor of INT, highlighting the theoretical importance of individual innovativeness in emerging decentralized technologies. This supports innovation diffusion perspectives, suggesting that individuals who are open to new technologies are more inclined to accept blockchain-based verification mechanisms.

Additionally, OPTM and PCOM significantly influence adoption intention, reinforcing the relevance of positive technology beliefs and information exchange in shaping behavioral outcomes. The significant effects of DCFT and INSC further extend technology acceptance literature by emphasizing the role of user capability and organizational readiness in blockchain adoption. Secondly, this study contributes theoretically by examining the moderating role of RTC. The results reveal that RTC does not uniformly hinder adoption; instead, it selectively moderates relationships such as INNV → INT and DCFT → INT. This finding refines resistance theory by demonstrating that resistance can condition how personal and skill-based factors translate into behavioral intention, rather than acting solely as a direct barrier. The model explains a substantial proportion of variance in INT ($R^2 = 0.697$), indicating strong explanatory power and validating the integrative framework used in this study. From a practical standpoint, the study provides evidence-based insights into which factors most strongly drive adoption intention, allowing policymakers and educational technology planners to prioritize interventions that foster innovation readiness, digital competence, and effective communication strategies.

B. LIMITATIONS AND SUGGESTIONS FOR FUTURE STUDIES

Despite its contributions, this study has several limitations. First, the model focuses on selected technological, psychological, and institutional factors; other relevant determinants such as perceived risk, trust, regulatory environment, or cost considerations were not included. Future research could integrate these variables to develop a more comprehensive adoption framework.

Second, the study relies on cross-sectional survey data, which limits the ability to draw definitive causal inferences. Longitudinal studies could provide deeper insight into how adoption intention evolves as users gain more experience with blockchain-based verification systems. Third, the research context may limit generalizability. Cultural, institutional, and technological readiness differences across regions or countries could influence adoption behavior. Future studies should conduct cross-country comparisons to validate and extend these findings. Finally, future research could employ mixed methods or complementary analytical techniques to capture non-linear and configurational effects among adoption factors, thereby enriching understanding beyond linear SEM relationships.

VII. CONCLUSION

This study examined the determinants of intention to adopt blockchain-based certificate verification using a PLS-SEM approach. The findings reveal that the proposed model demonstrates strong explanatory power, accounting for a substantial proportion of variance in adoption intention. Among the predictors, innovation emerged as the most influential factor, followed by optimism, perceived communication, institutional support, and digital competence. These results underscore that both individual dispositions toward technology and enabling organizational conditions play critical roles in fostering acceptance of blockchain-enabled verification systems. The study further contributes by highlighting the conditional role of resistance to change. Rather than acting as a uniform barrier, resistance selectively moderates specific relationships, particularly those involving innovation and digital competence. This suggests that user resistance shapes how personal and skill-related factors translate into adoption intention, offering a more nuanced understanding of behavioral responses to emerging technologies.

Overall, the study extends technology adoption research into the domain of blockchain applications in educational credential verification and provides empirical evidence on the key drivers of user intention. By identifying the most influential factors, the research offers valuable insights for institutions and technology providers seeking to implement secure, transparent, and efficient certificate verification systems. Future research can build on these findings by incorporating additional contextual variables, longitudinal designs, and cross-regional comparisons to further refine understanding of blockchain adoption behavior.

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فهم دوافع نية تبني التحقق من الشهادات القائم على تقنية Blockchain: تحليل PLS-SEM

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الخلاصة:

لا تزال مؤسسات التعليم العالي في الدول النامية تواجه صعوبات في التحقق من صحة الشهادات بسبب قصور أنظمة التحقق المركزية. ورغم أن التحقق من الشهادات باستخدام تقنية البلوكشين يوفر بديلاً آمناً وشفافاً، إلا أن نية تبني هذه التقنية لا تزال منخفضة لعدم فهم العوامل السلوكية المؤثرة فيها بشكل كافٍ. تهدف هذه الدراسة إلى تطوير واختبار نموذج متكامل يجمع بين أبعاد مؤشر الجاهزية التكنولوجية، وعوامل انتشار الابتكار، والتعقيد المُدرك، والتوافق، ومقاومة التغيير، وذلك لتفسير نية تبني التحقق من الشهادات باستخدام تقنية البلوكشين. جُمعت بيانات استبيان من 586 مسؤولاً عن سجلات الطلاب في 64 جامعة عراقية، وحُللت باستخدام نمذجة المعادلات الهيكلية الجزئية (PLS-SEM). تشير النتائج إلى أن الابتكار والتفاؤل وعدم الارتياح وانعدام الأمان والتوافق المُدرك تؤثر بشكل كبير على نية التبني، بينما لا يُعد التعقيد المُدرك عاملاً مؤثراً. وتُعد مقاومة التغيير عاملاً مُعدِّلاً بشكل انتقائي لتأثير الابتكار وعدم الارتياح دون غيرهما من العوامل المؤثرة. يُظهر النموذج قدرة تفسيرية عالية، مؤكداً على الدور المهيمن للجاهزية النفسية ومقاومة التغيير على حساب الاعتبارات التقنية البحتة. تُوسّع هذه الدراسة نطاق الأدبيات المتعلقة بتبني تقنية البلوكشين من خلال دمج وجهات نظر نظرية متعددة في سياق تعليمي، وتقدم إرشادات عملية لبناء القدرات والتدريب وإدارة التغيير لدعم تطبيق تقنية البلوكشين في تطوير أنظمة التعليم العالي.