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Evaluating Digital Learning Security Model in Higher Education: UTAUT-Based Empirical Study

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Abstract— **This research seeks to enhance privacy and data protection while preserving an effective learning environment by utilizing the UTAUT framework to analyze the adoption of a novel digital security model through protected e-learning. The research model preserves the original UTAUT constructs and items of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI), along with the supplementary constructs of Technological Knowledge (TK), Pedagogical Knowledge (PK), and Technological Pedagogical Knowledge (TPK). Data was gathered from educators, technicians, and administrators of the e-learning management system within Higher Education Institutions. The data is evaluated with SmartPLS 4 employing structural equation modeling. The results indicate that only facilitating environments significantly impact behavioral intention, corroborating the H2 hypothesis. The hypothesis testing results demonstrate that Facilitating Conditions (FC) significantly positively influence Behavioral Intention (BI). This indicates that individuals are more inclined to behave when they perceive enough external resources and support. Furthermore, Performance Expectancy (PE) significantly impacts Behavioral Intention (BI), suggesting a potential influence that requires additional examination.**

Keywords— **UTAUT; digital learning; security; e-learning**

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I. Introduction

The rapid advancement of digital technology has significantly transformed educational practices, leading to a substantial rise in the use of digital learning platforms and e-learning systems. In contemporary education, tools such as Learning Management Systems (LMS) and online courses have become indispensable, facilitating effortless access to learning materials and many functionalities for students and educators. Higher education institutions are progressively adopting digital learning platforms to provide educational services. Global events, notably the COVID-19 pandemic, have accelerated this shift, highlighting the essential need for robust and flexible digital learning systems [1]. Nevertheless, the extensive adoption of these platforms has presented considerable privacy and data protection issues. Notwithstanding existing security precautions, current digital security models frequently fail to adequately address the varied and evolving dangers in digital learning settings.

Studies indicate that adherence to legislation like the General Data Protection Regulation (GDPR) has profoundly impacted worldwide data privacy and cybersecurity practices. This influence underscores the significance of transparency, accountability, and proactive actions [2]. As indicated, the Intelligent Policies Analysis Mechanism (IPAM) emphasizes the imperative of automated and intelligent ways to protect personal information, presenting new data privacy issues [3]. As privacy and cybersecurity roles extend beyond conventional IT services, the necessity for a robust digital security model intensifies, given that insufficient staffing, overwhelming workloads, and misalignment between IT and privacy goals exacerbate vulnerabilities in institutional cybersecurity frameworks [4].

Higher education institutions must adopt more effective and comprehensive digital security frameworks to enhance privacy and data protection while sustaining an efficient learning environment. This research seeks to address these problems by employing the Unified Theory of Adoption and Use of Technology (UTAUT) paradigm, as proposed by [5], to analyze adopting a novel digital security model through secured e-learning. The project employs survey-based data collection and analysis via Partial Least Squares Structural Equation Modelling (PLS-SEM) to identify the primary elements influencing technology acceptance and to develop a model that overcomes current deficiencies in digital learning security.

II. Materials and Method

A. Materials

Understanding technology acceptance theories is crucial to understanding how individuals use digital tools. These theories established frameworks that determine the factors influencing users' decisions to adopt the new technology. Recognizing these theories is essential for enhancing privacy and data protection in higher education institutes, given the increasing reliance on digital learning platforms post-COVID [6]. The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by [5], integrates multiple technology acceptance theories, including the Theory of Reasoned Action (TRA) [7], the Technology Acceptance Model (TAM) [8] and the Theory of Planned Behavior (TPB) [9] to explain user adoption behavior. The model identifies four key constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—moderated by gender, age, experience, and voluntariness of use. Studies have widely applied UTAUT in various domains, including e-learning, healthcare, and digital transformation, demonstrating its effectiveness in predicting technology adoption.

The UTAUT model has become increasingly popular since it was first developed due to rapid technological changes and the need to understand how users accept different technologies. A bibliometric study by [10] analyzed 1,694 research papers and found a steady growth in UTAUT-related studies, particularly in e-learning, healthcare, and e-government sectors. This indicates that UTAUT is versatile and can fit into various research areas. Likewise, [11] looked into how UTAUT is applied in adopting smartphones and wearable technology, showing its significance in responding to the changing needs of users and technology interfaces. Recent research has built upon the UTAUT framework by adding new constructs, showing how it has developed. An updated UTAUT model specifically for mobile learning includes seven new factors like interaction, self-efficacy, and motivation, making it more comprehensive [12]. Meanwhile, UTAUT was used to explore personalized learning systems, proving that it remains effective in educational settings [13].

UTAUT has emerged as a robust and comprehensive paradigm for examining technological acceptance and user behavior. It was selected as the primary model to enhance privacy and data protection in digital learning due to its ability to integrate concepts from other preceding theories and models. The UTAUT model is distinguished by its components, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI). This study will employ supplementary constructs to align with the research setting and objectives. The constructs will be derived from another model, specifically the Technological Pedagogical Content Knowledge (TPACK) framework, initially conceptualized and refined by [14], [15]. The study model will incorporate three more constructs: Technological Knowledge (TK), Pedagogical Knowledge (PK), and Technological Pedagogical Knowledge (TPK). The research proposed model is illustrated in Figure 1 below.

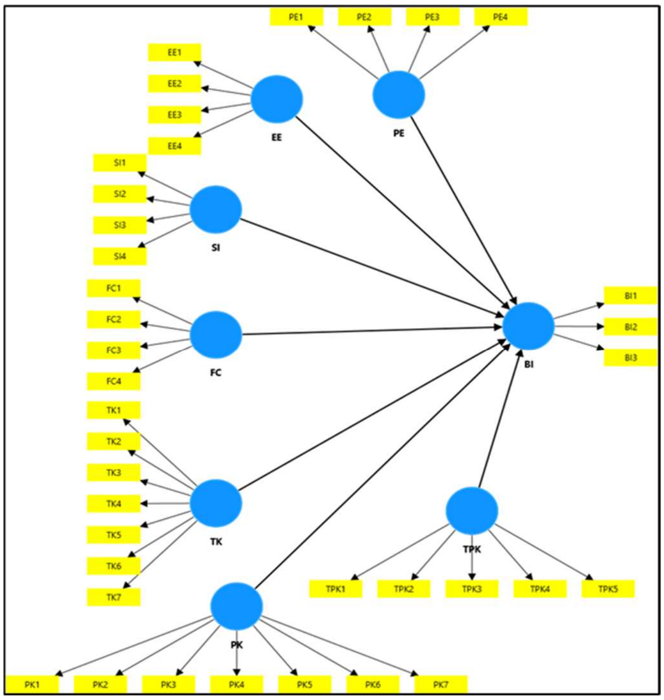

Fig. 1 Research Model of study

1) Behavioral Intention (BI):

Behavioral Intention is a primary construct defined in the original UTAUT conceptual model. It is characterized as a user's inclination or interest in utilizing technology, as articulated by [5]. This construct inherently affects usage behavior. In this model, BI represents users' willingness to adopt and use a secure digital learning platform. The key factors influencing BI can be categorized into:

- Security-Related Factors (Trust in Platform Knowledge - TPK)
- Technology Adoption Factors (Effort Expectancy - EE, Performance Expectancy - PE, Technology Knowledge - TK)
- User Support & Environment (Facilitating Conditions - FC, Social Influence - SI)
- Performance Outcomes (Performance Knowledge - PK)

2) Performance Expectancy (PE):

Performance expectation is a primary construct defined in the original UTAUT model framework. This pertains to the user's anticipation of system or technology efficacy for successful work [16]. Performance expectancy is "the degree to which an individual believes that using the system will assist in achieving improvements in job performance." Performance Expectancy (PE) refers to users' belief that using a secure digital learning platform will enhance their learning experience and outcomes. In other words, it measures whether users perceive the system as useful, efficient, and capable of improving their learning process while ensuring security. A hypothesis is posited:

- H1: PE has a significant influence on BI to use secured e-learning.

3) Effort Expectancy (EE):

Effort expectancy is another main construct established in the original UTAUT model. It is the user's perception of the level of ease in using the system or technology usage, as mentioned by [17]. The study states that the construct as "the degree of ease associated with using the system". Effort Expectancy (EE) refers to how easy users perceive it is to use a secure digital learning platform. It measures whether users believe that interacting with the platform requires minimal effort, is user-friendly, and does not present unnecessary complexity, even with security features in place. The hypothesis is proposed:

- H2: EE significantly influences BI to use secured e-learning.

4) Social Influence (SI):

Social impact constitutes the third of the five primary constructs delineated in the original UTAUT conceptual framework. Social influence refers to the impact of an external group's effect on an individual's decision-making when utilizing a system or technology, as articulated by [18]. In other words, Social Influence (SI) refers to the degree to which users perceive that important people (peers, instructors, colleagues, or organizations) believe they should use a secure digital learning platform. It measures whether external encouragement, recommendations, or pressure impact their intention to adopt secure digital learning. The theory is posited:

- H3: SI has a significant influence on BI to use secured e-learning

5) Facilitating Condition (FC):

Facilitating conditions are the fourth primary construct delineated in the original UTAUT conceptual model. Facilitating Conditions (FC) refers to the resources, infrastructure, and support available to users to help them adopt a secure digital learning platform " [5]. This includes technical support, system reliability, accessibility, and institutional policies that enable or hinder users from using the platform securely. The hypothesis is put forth:

- H4: FC has a significant influence on BI to use secured e-learning

6) Technological Knowledge (TK):

Technological Knowledge is an extra construct incorporated into our UTAUT conceptual paradigm. This concept, derived from the TPACK model, delineates the user's capacity to employ accessible technology, as articulated by effectively [19]. Technological Knowledge (TK) refers to users' understanding and competency in using technology, especially about secure digital learning platforms. It includes their ability to navigate security features, understand risks, and apply best practices for safe digital learning. The hypothesis is put forth:

- H5: TK has a significant influence on BI to use secured e-learning.

7) Pedagogical Knowledge (PK):

Pedagogical Knowledge is an extra construct incorporated into our UTAUT conceptual model. This concept is derived from the TPACK model, defined as the "process and methods of teaching and learning", according to [19]. Pedagogical Knowledge (PK) refers to users' understanding of teaching and learning methodologies, particularly in digital environments. In the context of secure digital learning, PK includes how well users (educators and learners) integrate security-conscious teaching practices into their digital learning experience. The hypothesis is put forth:

- H6: PK has a significant influence on BI to use secured e-learning.

8) Technological Pedagogical Knowledge (TPK)

Technological Pedagogical Knowledge is an extra construct incorporated into our UTAUT conceptual model. Technological Pedagogical Knowledge (TPK) refers to the ability of educators and learners to integrate technology into teaching while considering pedagogical principles effectively [19]. In the context of a secured digital learning platform, TPK also includes how well users balance instructional goals with security best practices, for example, ensuring online assessments are secure, protecting student data, and using digital tools safely. A theory is presented:

- H7: TPK significantly influences BI to use secured e-learning.

B. Methods

The methodology used in this study is presented below.

1) Constructs and Items Expert:

The development of the survey and research model has advanced since before July 2024, retaining the original UTAUT constructs and items of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI) as established by [5], along with the additional constructs of Technological Knowledge (TK), Pedagogical Knowledge (PK), and Technological Pedagogical Knowledge (TPK) introduced by [14] and their original items as detailed by [20]. The research model's components and elements were forwarded to specialists for evaluation to determine their appropriateness for the study. The selected constructs for the study model and the survey items were evaluated and endorsed by specialists across many disciplines. The study consulted six experts to evaluate the structures and items selected for the research. They originate from various organizations, encompassing Higher Education Institutions and the Cybersecurity sector. Their feedback informed the modification of the model and item content.

All consulted specialists had evaluated the constructions and items delineated for the investigation. All have noted that the selected constructions and items were appropriate. However, they also indicated a need for revisions to the items. Upon expert evaluation of the survey items, none were deemed unacceptable. Nonetheless, they share similar observations regarding rephrasing items to enhance respondent comprehension of the survey. The items extracted from the original construct preserved the same quantity as in the initial study, with PE, EE, SI, and FC each comprising four things, BI containing three items, and the supplementary constructs of TK and PK each consisting of seven items, while TPK includes five items.

2) Research Tool:

The survey was created utilizing the Google Form tool to facilitate distribution. This research survey will utilize a scale from 1 (Strongly Disagree) to 6 (Strongly Agree), excluding a Neutral option to guarantee that all respondents provide a definitive answer to the questions, thereby ensuring that their responses can be substantiated as per the findings of [21] and [22] regarding this scale range.

3) Data Acquisition and Respondent

Data was gathered via Google Forms to disseminate the survey to educators, technologists, and administrators of the e-learning management system within the university, serving as the research sample group. Google Forms was selected as the data-collecting method because of its user-friendliness and consistency [23]. A preliminary question regarding the respondent's institution was posed before addressing the primary part of the survey. Following the dissemination of the survey, 39 responses will be gathered and analyzed as our pretest data. The pilot test is anticipated to include more than 150 participants. Table 1 presents the profiles of the respondents.

TABLE I
RESPONDENT PROFILES

Group	Frequency	Percentage
Gender		
Female	23	58.97
Male	16	41.03
Age		
25-30	1	2.56
30-35	10	25.64
40-49	18	46.15
50+	4	10.25
Experience in using e-Learning System		
Less than one year	1	2.56
One to two years	4	10.26
Three to five years	7	17.95
> Five years	27	69.23

III. RESULT AND DISCUSSION

The results from the survey collection is then go through the PLS-SEM tool, which brings the results;

A. Common Method Bias (CMB)

There existed a possibility of Common Method Bias (CMB) due to the same individual responding to both dependent and independent variables, potentially affecting the outcomes. Both procedural and statistical methodologies were utilized to explore the potential for diminishing CMB, incorporating procedural procedures [24] and statistical methods [25].

This strategy involved incorporating unobserved marker variables into the study. The marker variables were considered exogenous inputs utilized to forecast the model's endogenous variables. The incorporation of the marker variable guaranteed the preservation of all effects. This outcome provides scant evidence of Common Method Bias (CMV) impacting the results, indicating that the collected data is improbable to be substantially affected by this bias. In this procedure, all variables are regressed on a common variable, and according to [26], a Variance Inflation Factor (VIF) of less than 3.3 indicates the absence of bias from single-source data. If the VIF exceeds 5 or 10, the variables are modified.

Table II indicates that the VIF exceeds 3.3 but does not go beyond 5. Consequently, the approaches effectively identify CMB. This table displays the comprehensive results of collinearity testing utilizing the Variance Inflation Factor (VIF) for each construct. VIF quantifies multicollinearity, a phenomenon arising when independent variables in a regression model exhibit significant correlation.

TABLE II
FULL-COLLINEARITY TESTING

Construct	BI	EE	FC	PE	PK	SI	TK
VIF	3.820	4.686	4.883	4.666	2.714	2.456	4.727

In this instance, Facilitating Conditions (VIF = 4.883), Technology Knowledge (VIF = 4.727), Performance Expectancy (VIF = 4.666), and Effort Expectancy (VIF = 4.686) are nearing the VIF = 5 threshold, indicating possible collinearity concerns. This indicates that these variables may exhibit substantial correlation, hence distorting regression outcomes and undermining the dependability of individual predictor contributions.

Conversely, Perceived Knowledge (VIF = 2.714) and Social Influence (VIF = 2.456) exhibit lower VIF values, suggesting a diminished worry for multicollinearity. The dependent variable, Behavioral Intention (VIF = 3.820), is categorized within the moderate range. Excessive multicollinearity can inflate standard errors and obscure the true effect of each variable.

B. Measurement Model

This study employs the latest SmartPLS technology [27] for its prediction objectives, and its measurement model assessment evaluated the correlations among items and constructs. The Average Variance Extracted (AVE) considers factor loadings and composite reliability (CR) [28]. In each matrix, both indicators exceeded the evaluation criteria, with CR > 0.7, AVE > 0.5, and factor loadings for the items > 0.5. The findings in Table III indicated that all markers fell within their permissible limits. This table displays construct reliability and validity metrics, encompassing factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct. These metrics evaluate the reliability and validity of the measurement model in structural equation modeling (SEM).

TABLE III
CONVERGENT VALIDITY

Construct	Item	Loading	CR	AVE
BI	BI1	0.967	0.948	0.899
	BI2	0.924		
	BI3	0.952		
EE	EE1	0.912	0.937	0.820
	EE2	0.883		
	EE3	0.925		
	EE4	0.903		
FC	FC1	0.884	0.858	0.692
	FC2	0.792		
	FC3	0.835		
	FC4	0.814		
PE	PE1	0.925	0.947	0.853

Construct	Item	Loading	CR	AVE
	PE2	0.947		
	PE3	0.890		
	PE4	0.931		
PK	PK1	0.943	0.999	0.742
	PK2	0.791		
	PK3	0.920		
	PK4	0.772		
	PK5	0.923		
	PK6	0.722		
	PK7	0.929		
SI	SI1	0.915	0.884	0.703
	SI2	0.804		
	SI3	0.876		
	SI4	0.747		
TK	TK1	0.907	0.940	0.652
	TK2	0.729		
	TK3	0.902		
	TK4	0.653		
	TK5	0.816		
	TK6	0.724		
	TK7	0.881		
TPK	TPK1	0.967	0.971	0.880
	TPK2	0.942		
	TPK3	0.944		
	TPK4	0.901		
	TPK5	0.936		

The findings reveal that all constructs exhibit robust reliability and validity. The factor loadings for each item exceed 0.7, validating that the observed variables accurately assess their corresponding constructs. Nevertheless, certain components, such as PK6 (0.722) and TK4 (0.653), exhibit marginally lower loadings yet remain within an acceptable range. All constructs exhibit Composite Reliability (CR) values over 0.7, signifying substantial internal consistency. Perceived Knowledge (PK) exhibits an exceptionally high CR of 0.999, indicating possible redundancy in its measurement items. The Average Variance Extracted (AVE) values exceed 0.5, confirming sufficient convergent validity, suggesting that each construct accounts for over half of the variance in its items. The minimum AVE is 0.652 for Technology Knowledge (TK), although it still satisfies the validity criterion. The measurement model is both trustworthy and valid; however, certain constructions, such as PK, may require additional examination to remove superfluous components.

Discriminant validity assesses the extent to which one construct is distinct from another, as articulated by [29]. Discriminant validity is assessed using the Heterotrait-Monotrait (HTMT) correlation ratio [30]. An HTMT value less than 0.85 is deemed acceptable, whereas an HTMT value beyond 0.90 indicates that the constructs may be tightly connected and may require modification. The Heterotrait-Monotrait (HTMT) ratio of correlations serves as a more rigorous standard for evaluating discriminant validity in Structural Equation Modelling (SEM). The HTMT ratio assesses the similarity between two constructs, with elevated values signifying a deficiency in distinctiveness.

Table IV indicates that the constructs of Behaviour Intention and Facilitating Condition, represented as Facilitating Condition and Performance Expectancy in the shaded section of the table, exhibit HTMT values over 0.90. Considering these dimensions derive from the UTAUT model, a robust association among behavioral intention, enabling conditions, performance expectancy, and high HTMT aligns with the original study model. Consequently, the research model of the study requires no modifications.

TABLE IV
DISCRIMINATE VALIDITY (HTMT)

Construct	BI	EE	FC	PE	PK	SI	TK	TPK
BI								
EE	0.808							
FC	0.993	0.854						
PE	0.896	0.868	0.914					
PK	0.516	0.646	0.664	0.593				
SI	0.777	0.741	0.725	0.729	0.440			
TK	0.715	0.588	0.676	0.615	0.592	0.687		
TPK	0.596	0.641	0.793	0.655	0.859	0.458	0.487	

The primary worry is the significant correlation of 0.993 between Facilitating Conditions (FC) and Behavioral Intention (BI), indicating that both categories may represent the same notion rather than distinct impacts. Likewise, Performance Expectancy (PE) and FC (0.914) exhibit significant overlap, prompting concerns over their conceptual distinctiveness. Moderate issues with discriminant validity are noted between Effort Expectancy (EE) and Performance Expectancy (PE) (0.868), as well as between EE and Facilitating Conditions (FC) (0.854), suggesting a degree of conceptual repetition. These associations indicate that respondents may view these constructs as closely interconnected, compromising the model's clarity.

Conversely, constructs including Perceived Knowledge (PK), Social Influence (SI), Technology Knowledge (TK), and Technological Pedagogical Knowledge (TPK) demonstrate acceptable HTMT values below 0.85, signifying their distinctiveness from other constructs. To resolve these discriminant validity concerns, it may be essential to reassess the assessment items and conduct exploratory or confirmatory factor analysis (EFA/CFA) to validate item loadings or contemplate the amalgamation of overlapping notions if they are conceptually analogous. Utilizing a higher-order component model or eliminating problematic items may enhance validity if the constructs are logically distinct.

C. *Results*

The hypothesis is considered acceptable if the path coefficient (Beta) has a t-value over 1.165 and a p-value below 0.05 and if the confidence interval lower level (CILL) and upper level (CIUL), do not indicate a NULL value, as articulated by [31]. The study is deemed free of multicollinearity, as the VIF values were less than 5 [28]. Table V presents the results of hypothesis testing for all seven previously stated hypotheses.

TABLE V
HYPOTHESIS TESTING

Hypothesis	Relationship	Beta	Standard Error (SE)	*t*	*p*	CILL	CIUL	VIF	f^2
H1	EE -> BI	0.032	0.165	0.193	0.848	-0.265	0.344	3.820	0.002
H2	FC -> BI	0.609	0.154	3.964	0.000	0.315	0.883	4.686	0.645
H3	PE -> BI	0.253	0.140	1.809	0.073	0.054	0.604	4.883	0.107
H4	PK -> BI	-0.073	0.181	0.406	0.686	-0.357	0.245	4.666	0.009
H5	SI -> BI	0.123	0.140	0.879	0.381	-0.182	0.395	2.714	0.045
H6	TK -> BI	0.150	0.141	1.068	0.288	-0.060	0.444	2.456	0.075
H7	TPK -> BI	-0.111	0.160	0.691	0.491	-0.366	0.077	4.727	0.021

The hypothesis testing results indicate that Facilitating Conditions (FC) are the sole factor significantly affecting

Behavioral Intention (BI), whilst other constructs do not have a statistically significant influence.

1) Significant Correlation: H2: Facilitating Conditions (FC) → Behavioral Intention (BI) ($\beta = 0.609$, $t = 3.964$, $p < 0.001$, $f^2 = 0.645$). FC exerts a significant positive influence on BI, indicating that when individuals recognize adequate external resources and support, their intention to participate in activity escalates. The substantial impact size ($f^2 = 0.645$) validates that FC affects BI.

2) Marginally Significant Correlation: H3: Performance Expectancy (PE) → Behavioral Intention (BI) ($\beta = 0.253$, $t = 1.809$, $p = 0.073$, $f^2 = 0.107$). The influence of PE on BI is not statistically significant at the 0.05 level ($p = 0.073$). Nonetheless, the lower confidence interval (CILL = 0.054) indicates a possible effect that may require additional examination.

3) Insignificant Relationships ($p > 0.05$): H1: Effort Expectancy (EE) → Behavioral Intention (BI) ($\beta = 0.032$, $p = 0.848$, $f^2 = 0.002$) → No significant effect, showing that perceived effort does not influence BI. H4: Perceived Knowledge (PK) → Behavioral Intention (BI) ($\beta = -0.073$, $p = 0.686$, $f^2 = 0.009$) → No significant effect, exhibiting a weak negative influence. H5: Social Influence (SI) → Behavioral Intention (BI) ($\beta = 0.123$, $p = 0.381$, $f^2 = 0.045$) → No significant effect, indicating that social influences do not exert a substantial influence on BI. H6: Technology Knowledge (TK) → Behavioral Intention (BI) ($\beta = 0.150$, $p = 0.288$, $f^2 = 0.075$) → No significant effect, indicating that technological knowledge does not directly influence behavioral intention. H7: Technological Pedagogical Knowledge (TPK) → BI ($\beta = -0.111$, $p = 0.491$, $f^2 = 0.021$) → No significant effect, exhibiting a slight negative correlation.

D. Principal Insights and Consequences

The results indicate that Facilitating Conditions (FC) are the most significant predictor of Behavioral Intention (BI), suggesting that when individuals possess the requisite resources and support, their intention to engage in the action escalates. Performance Expectancy (PE) exhibits a marginal effect that warrants additional investigation, indicating a potential impact on behavioral Intention (BI). Factors such as Effort Expectancy (EE), Perceived Knowledge (PK), Social Influence (SI), Technology Knowledge (TK), and Technological Pedagogical Knowledge (TPK) do not significantly influence Behavioral Intention (BI), indicating that they may not be principal determinants of behavioral intention in this setting.

The elevated VIF values (between 2.456 and 4.883) indicate possible multicollinearity concerns that could compromise the model's stability. The results indicate that only facilitating environments significantly impact behavioral intention, hence corroborating the H2 hypothesis. Based on the PLS-SEM results, the following strategies will help improve the adoption of secure digital learning platforms by addressing key drivers and overcoming weak predictors;

E. Strengthen Facilitating Conditions (FC)

Since Facilitating Conditions (FC) is the strongest predictor of Behavioral Intention (BI), organizations should focus on providing a robust and secure digital infrastructure. To achieve this:

a. Ensure a secure infrastructure by implementing SSL encryption, firewalls, and encrypted databases to protect user data from cyber threats.
b. Provide secure login methods, such as multi-factor authentication (MFA) and biometric verification, to prevent unauthorized access.
c. Offer real-time security support through a dedicated helpdesk, automated threat detection systems, and AI-powered security monitoring to provide immediate assistance in case of security issues.

By reinforcing FC, users will have confidence in the platform's security, increasing their willingness to adopt and use it

F. Enhance Performance Expectancy with Security Features

Since PE is moderately significant, improving security in a way that enhances learning outcomes is key:

a. Secure cloud-based learning that allows remote access while maintaining security.
b. Adaptive security protocols that protect user data while ensuring uninterrupted access.
c. Improve Trust in Security with Visible Protection
d. Since TPK is insignificant, just claiming security is not enough. Instead:
e. Use transparency in security measures (e.g., show "secure connection" indicators).
f. Implement AI-driven security alerts that notify users about potential breaches.

G. Reduce Technical Complexity While Ensuring Security

Since TK is not a major factor, organizations should:

a. Automate security processes (e.g., auto-password generation, single sign-on authentication).
b. Provide in-platform security guidance rather than expecting users to have prior knowledge.

H. Do Not Rely on Social Influence for Adoption

Since SI is not a major predictor, instead of peer recommendations:

a. Leverage regulatory compliance as a security driver (e.g., "This platform meets ISO/IEC 27001 security standards").
b. Use financial and legal incentives (e.g., data protection guarantees and user cybersecurity insurance).

IV. Conclusion

This research intends to improve privacy and data protection while maintaining an efficient learning environment by examining the acceptance of a new digital security model using secured e-learning. To improve behavioral intention (BI) and use secure digital learning platforms, organizations should prioritize facilitating conditions (FC) as the main driver while ensuring that security features enhance learning outcomes rather than create barriers. Technical complexity should be minimized, security measures should be transparent and automated, and trust should be built through compliance and financial incentives rather than social influence. Organizations can drive widespread adoption of secured digital learning platforms by aligning security with usability.

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