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EMPIRICAL ANALYSIS OF A UTAUT-BASED DIGITAL LEARNING SECURITY MODEL IN HIGHER EDUCATION

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Abstract:

To improve privacy and data protection while maintaining an efficient learning environment, this research aims to tackle these challenges by applying the UTAUT framework to examine the acceptance of a new digital security model by using secured e-learning. The research model maintains the original UTAUT constructs and items of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC) and Behavioural Intention (BI) and the additional construct of Technological Knowledge (TK), Pedagogical Knowledge (PK) and Technological Pedagogical Knowledge (TPK). Data was collected among Higher Education Institutions educator, technician and administrator of the e-Learning management system. The data is analysed using SmartPLS 4 using structural equation modelling. The finding shows that only facilitating conditions significantly influence behavioural intention, which supports the H2 hypothesis. The hypothesis testing results indicate that Facilitating Conditions

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(FC) have a significant positive effect on BI, suggesting that individuals are more likely to engage in a behaviour when they perceive sufficient external resources and support. Additionally, Performance Expectancy (PE) exhibits a marginally significant effect on BI, indicating a potential influence that warrants further investigation.

Keywords:

UTAUT, Digital Learning, Security, E-Learning

Introduction

The fast growth of digital technology has really changed how education works, resulting in a big increase in the use of digital learning platforms and e-learning systems. Tools like Learning Management Systems (LMS) and online courses are now essential in today's education, allowing both students and educators to easily access learning materials and use different features for teaching and studying. Higher education institutions increasingly turn to digital learning platforms to deliver educational services. This transformation has been expedited by global events, particularly the COVID-19 pandemic, which emphasized the critical requirement for strong and adaptable digital learning systems (Zawacki-Richter, 2021). However, the broad implementation of these platforms has brought forth significant challenges concerning privacy and data protection. Despite the presence of existing security measures, the current digital security models often fall short of effectively addressing the diverse and evolving threats encountered in digital learning environments.

Research has shown that compliance with regulations such as the General Data Protection Regulation (GDPR) has significantly influenced global data privacy and cybersecurity practices. This influence highlights the importance of transparency, accountability, and proactive measures, as articulated by (Olukunle Oladipupo Amoo et al., 2024). In addition, the Intelligent Policies Analysis Mechanism (IPAM) highlights the necessity for automated and intelligent strategies to safeguard personal information, as noted by (Demertzis et al., 2020) bringing new challenges regarding data privacy. As privacy and cybersecurity roles continue to expand beyond traditional IT services, the need for a secured digital security model becomes increasingly critical as limited staffing, excessive workloads, and a lack of alignment between IT and privacy objectives contribute to vulnerabilities in institutional cybersecurity frameworks (Muscanell, 2023).

Higher education institutions must embrace more effective and all-encompassing digital security models to improve privacy and data protection while maintaining an efficient learning environment. This research aims to tackle these challenges by applying the Unified Theory of Acceptance and Use of Technology (UTAUT) framework by (Venkatesh et al., 2003) to examine the acceptance of a new digital security model by using secured e-learning. Through survey-based data collection and analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM), the study seeks to identify the main factors that impact technology acceptance and to create a model that addresses the existing gaps in digital learning security.

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Literature Review

UTAUT has become a strong and thorough framework for studying how people accept technology and behave as users. It was chosen as the main model to improve privacy and data protection in digital learning because it can combine ideas from several earlier theories and models. The UTAUT model is notable for featuring constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC) and Behavioural Intention (BI). This research will use additional constructs to suit the context and target of research. The constructs are to be taken from a construct from another model, and in this study, it will be using the construct from a model called Technological Pedagogical Content Knowledge (TPACK), which was first conceptualised by (Mishra & Koehler, 2006) and further developed by (Koehler et al., 2014). There will be an additional three constructs for the research model which are Technological Knowledge (TK), Pedagogical Knowledge (PK) and Technological Pedagogical Knowledge (TPK). The research model is shown in Figure 1 below.

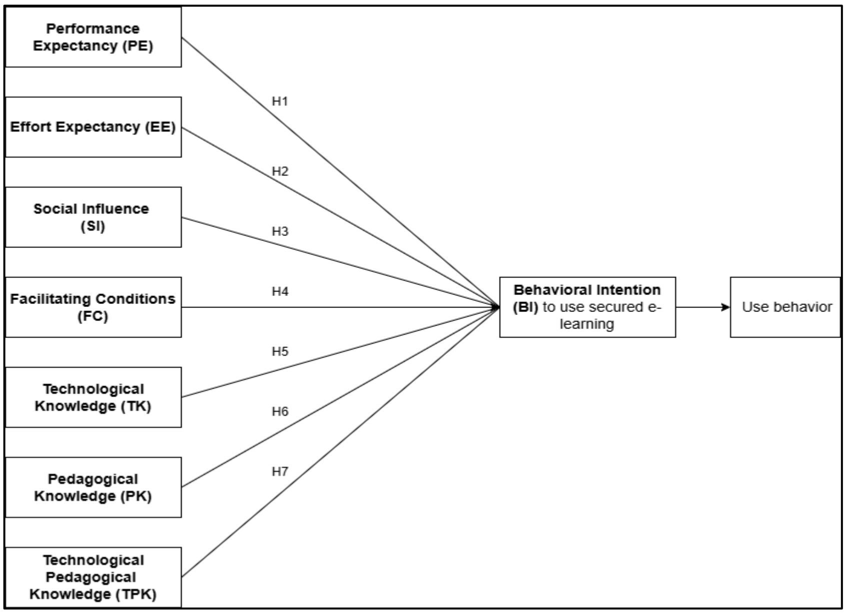

Figure 1: Research Model

Performance Expectancy (PE)

Performance expectancy is one of the main constructs established in the original UTAUT model framework. It refers to the user's expectation of system or technology performance to succeed in their work (Hasan et al., 2023) They defined performance expectancy as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance". The performance expectancy for this study is to understand the security measures in an e-learning platform to protect user's privacy and data. The hypothesis is proposed:

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

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

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(Ajibade & Zaidi, 2023). They stated the construct as "the degree of ease associated with using the system". In the context of our study, we want to understand how easy it is to navigate an e-learning system's security measures. The hypothesis is proposed:

H2: EE has a significant influence on BI to use secured e-learning

Social Influence (SI)

Social influence is the third of five main constructs established in the original UTAUT concept model. Social influence is where the perception of an outsider group's influence on a user's decision when using a system or technology, as stated by (Alqahtani et al., 2022). (Venkatesh et al., 2003) defined the construct as 'the degree to which an individual perceived that others. In the context of our study, it is how user manage their privacy and data protection when there are influence from outsider such as social norms or organizational culture. The hypothesis is proposed:

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

Facilitating Condition (FC)

Facilitating conditions are the fourth main constructs established in the original UTAUT concept model. It is the user's perception of the availability of resources and support to facilitate or disable the usage of a technology or "the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system", as stated by (Venkatesh et al., 2003). In our study, this factor is to explore the user's organisation available support in utilising their secured e-learning platform. The hypothesis is proposed:

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

Behavioural Intention (BI)

Behavioural Intention is one of the main constructs established in the original UTAUT concept model. It is defined as a user's desire or interest to use a technology stated by (Venkatesh et al., 2003). This construct naturally has an influence on use behaviour.

Technological Knowledge (TK)

Technological Knowledge is an additional construct that we added to our UTAUT concept model. It is a construct taken from the TPACK model that describes the user's ability to utilise available technology efficiently as stated in (Lim et al., 2022). The hypothesis is proposed:

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

Pedagogical Knowledge (PK)

Pedagogical Knowledge is an additional construct that we added to our UTAUT concept model. It is a construct taken from the TPACK model where it is a "process and the methods of teaching and learning" as stated in (Lim et al., 2022). It includes the ability to manage and facilitate teaching and learning activities. In the context of our study, we analyse the user's perception of PK when using the security measures of the e-learning they use to protect their privacy and data protection. The hypothesis is proposed:

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

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Technological Pedagogical Knowledge (TPK)

Technological Pedagogical Knowledge is an additional construct that we added to our UTAUT concept model. It is a construct taken from the TPACK model where it is the user's ability to implement technology utilisation into their teaching and learning practices as described by (Lim et al., 2022). The hypothesis is proposed:

H7: TPK has a significant influence on BI to use secured e-learning

Methodology

Constructs And Items Expert

The creation of the survey and research model has been progressed since before July 2024 with the research model maintaining the original UTAUT constructs and items of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC) and Behavioural Intention (BI) from (Venkatesh et al., 2003) and the additional construct of Technological Knowledge (TK), Pedagogical Knowledge (PK) and Technological Pedagogical Knowledge (TPK) by (Koehler et al., 2014) and its original items in (Schmidt et al., 2009). The research model's constructs and items were then emailed to experts to review to see if the chosen constructs and items were appropriate for the research.

The chosen constructs for the research model, as well as the items for the survey, were analysed and approved by experts in various fields. The research reached out to six experts to analyse the constructs and the items chosen for the research. They are from different organizations, including Higher Education Institutions and the Cybersecurity industry. Adjustments to the model and item content were based on their comments.

All experts referred to had reviewed the constructs and items listed for the research. All have commented that the constructs and items chosen were suitable but also remarked on needing correction with the items. After experts reviewed the survey's items, none of the items listed were rejected. Still, they have common remarks in rewording the items for the respondent to be able to understand the survey more easily. As the items were taken from its original construct, it maintained the same number of items from its original study, with PE, EE, SI, and FC having four items each, the BI only having three, and the additional construct of TK and PK both have seven items while TPK has five items.

Research Instrument

The survey was developed using the Google Form application to distribute the survey more easily. This research survey will be measured based on a scale ranging from 1 (Strongly Disagree) to 6 (Strongly Agree); the Neutral value is exempt from the scale to ensure all respondents will have an answer to the questions and to ensure respondent will give a respond which can be justified by (Guy & Norvell, 1977; Nowlis et al., 2002) in using this range of scale.

Table 1: Respondent Profiles

Group	Frequency	Percentage
Gender		
Female	23	58.97
Male	16	41.03

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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

Data Collection and Respondent

Data was collected using Google Forms to distribute the survey to educators, technicians and administrators of the e-learning management system in an institution as the research sample group. Google Forms was chosen as the data collection method due to its ease of use and uniformity (Regmi et al., 2017). A screening question of the respondent's institute was also mentioned before answering the main section of the survey. After sharing the survey, 39 respondents to be collected and processed as our pretest data. The pilot test is expected to have over 150 respondents. Table 1 above shows the respondent profiles.

Data Analysis

Common Method Bias (CMB)

There was a potential for Common Method Bias (CMB) where the same person answered both dependent and independent variables, which could influence the results. Both procedural and statistical approaches were employed to address the possibility of reducing CMB, and procedural techniques (Podsakoff et al., 2012) and statistical methods (Kock, 2015) were used.

This method entailed the integration of unobserved marker variables into the analysis. These marker variables were regarded as exogenous factors and used to predict the model's endogenous variables. The inclusion of the marker variable ensured that all effects were preserved. This result offers minimal evidence of Common Method Bias (CMV) affecting the results, suggesting that the gathered data is unlikely to be significantly influenced by this bias. All the variables are regressed against a common variable in this method, and according (Franke & Sarstedt, 2019) to the Variance Inflation Factor (VIF) < 3.3, there is no bias from the single-source data. If the VIF > 5 or 10 is considered problematic, the variables are adjusted.

Table 2 shows that VIF is over 3.3 but is not over 5. Therefore, the methods succeed in the identification of CMB. This table presents the full collinearity testing results using each construct's Variance Inflation Factor (VIF). VIF measures multicollinearity, which occurs when independent variables in a regression model are highly correlated.

Table 2: 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

Source: SmartPLS 4

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In this case, Facilitating Conditions (VIF = 4.883), Technology Knowledge (VIF = 4.727), Performance Expectancy (VIF = 4.666), and Effort Expectancy (VIF = 4.686) are approaching the VIF = 5 threshold, suggesting potential collinearity issues. This means these variables might be strongly correlated, distorting regression results and affecting individual predictor contributions' reliability.

Meanwhile, Perceived Knowledge (VIF = 2.714) and Social Influence (VIF = 2.456) have lower VIF values, indicating less concern for multicollinearity. The dependent variable, Behavioral Intention (VIF = 3.820), also falls within the moderate range. If multicollinearity is too high, it may inflate standard errors and make it difficult to determine the true impact of each variable.

Measurement Model

The latest SmartPLS tool (Ringle et al., 2024) is used for this study due to the predictive purpose, and the correlations between items and constructs were tested using its measurement model assessment. The Average Variance Extracted (AVE) considers factor loadings and composite reliability (CR) (Hair, Matthews, et al., 2017). For each matrix, both indicators surpassed the assessment standards, where the CR > 0.7, the AVE > 0.5, and factor loadings for the items were > 0.5. The results in Table 3 suggested that all indicators were within their acceptable range. This table presents construct reliability and validity measures, including factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct. These metrics assess the reliability and validity of the measurement model in structural equation modeling (SEM).

Table 3: 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
	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		

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	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		

Source: SmartPLS 4

The results indicate that all constructs demonstrate strong reliability and validity. The factor loadings for each item are above 0.7, confirming that the observed variables effectively measure their respective constructs. However, a few items, such as PK6 (0.722) and TK4 (0.653), have slightly lower loadings, though still within an acceptable range. All constructs' Composite Reliability (CR) values exceed 0.7, indicating high internal consistency. Notably, Perceived Knowledge (PK) has an unusually high CR of 0.999, which suggests potential redundancy in its measurement items. The Average Variance Extracted (AVE) values are all above 0.5, ensuring adequate convergent validity—meaning that each construct explains more than half of the variance in its items. The lowest AVE is 0.652 for Technology Knowledge (TK), but this still meets the validity threshold. The measurement model is reliable and valid, but some constructs, such as PK, may need further review to eliminate redundant items.

The discriminant validity measures the magnitude to which one construct differs from another as explained by (Hair, Sarstedt, et al., 2017). The discriminant validity is measured using the Hetrotrait-Monotrait (HTMT) correlation ratio (Henseler et al., 2015), where if the HTMT < 0.85 are considered acceptable and HTMT > 0.90, the constructs may be closely related and may need adjustment. The Heterotrait-Monotrait (HTMT) ratio of correlations is a stricter criterion for assessing discriminant validity in Structural Equation Modeling (SEM). The HTMT ratio measures how similar two constructs are, with high values indicating a lack of distinctiveness.

Table 4 shows that the Behaviour Intention and Facilitating Condition constructs as Facilitating Condition and Performance Expectancy pair, as shown in the shaded area in the table, have HTMT > 0.90. Given that these constructs are from the UTAUT model, a strong interrelationship between behaviour intention, facilitating condition, and performance expectancy and the high HTMT is consistent with the original research model. Therefore, no change is needed for the study's research model.

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Table 4: 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	

Source: SmartPLS 4

The highest concern is the high correlation between Facilitating Conditions (FC) and Behavioral Intention (BI) at 0.993, suggesting that these constructs may measure the same concept rather than separate influences. Similarly, Performance Expectancy (PE) and FC (0.914) show a high degree of overlap, raising concerns about their conceptual distinctiveness. Moderate discriminant validity concerns are also observed between Effort Expectancy (EE) and PE (0.868), as well as EE and FC (0.854), which indicates some degree of conceptual redundancy. These correlations suggest that respondents might perceive these constructs as highly related, potentially affecting the clarity of the model.

On the other hand, constructs such as Perceived Knowledge (PK), Social Influence (SI), Technology Knowledge (TK), and Technological Pedagogical Knowledge (TPK) exhibit acceptable HTMT values below 0.85, indicating that they remain distinct from other constructs. To address these discriminant validity issues, it may be necessary to re-examine the measurement items, perform exploratory or confirmatory factor analysis (EFA/CFA) to verify item loadings, or consider merging overlapping constructs if they are conceptually similar. Applying a higher-order factor model or removing problematic items could improve validity if the constructs are theoretically distinct.

Discussion and Conclusion

The hypothesis is deemed acceptable if the path coefficient (Beta) value with a *t*-value > 1.165 and a *p*-value < 0.05 and if the confidence internal lower level and upper level (CILL and CIUL, respectively) do not demonstrate NULL value as stated by (Hair, Tomas, et al., 2017). The study is considered multi-collinearity free as the VIF values were < 5 (Hair, Matthews, et al., 2017). Table 5 shows the hypothesis testing result for all 7 hypotheses mentioned before.

Table 5: 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

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H7	TPK -> BI	-0.111	0.160	0.691	0.491	-0.366	0.077	4.727	0.021

The hypothesis testing results reveal that Facilitating Conditions (FC) are the only factor significantly influencing Behavioral Intention (BI), while other constructs do not show a statistically significant impact.

1. Significant Relationship:
   - H2: Facilitating Conditions (FC) → BI ($\beta = 0.609$, $t = 3.964$, $p < 0.001$, $f^2 = 0.645$)
     - FC has a strong positive effect on BI, meaning that when individuals perceive sufficient external resources and support, their intention to engage in behaviour increases.
     - The large effect size ($f^2 = 0.645$) confirms that FC influences BI.
2. Marginally Significant Relationship:
   - H3: Performance Expectancy (PE) → BI ($\beta = 0.253$, $t = 1.809$, $p = 0.073$, $f^2 = 0.107$)
     - The positive effect of PE on BI is not statistically significant at the 0.05 level ($p = 0.073$).
     - However, the lower confidence interval (CILL = 0.054) suggests a potential effect, which may warrant further investigation.
3. Non-Significant Relationships ($p > 0.05$):
   - H1: Effort Expectancy (EE) → BI ($\beta = 0.032$, $p = 0.848$, $f^2 = 0.002$) → No significant effect, indicating that perceived effort does not impact BI.
   - H4: Perceived Knowledge (PK) → BI ($\beta = -0.073$, $p = 0.686$, $f^2 = 0.009$) → No significant effect, with a weak negative influence.
   - H5: Social Influence (SI) → BI ($\beta = 0.123$, $p = 0.381$, $f^2 = 0.045$) → No significant effect, suggesting that social factors do not strongly influence BI.
   - H6: Technology Knowledge (TK) → BI ($\beta = 0.150$, $p = 0.288$, $f^2 = 0.075$) → No significant effect, implying that knowledge of technology does not directly shape BI.
   - H7: Technological Pedagogical Knowledge (TPK) → BI ($\beta = -0.111$, $p = 0.491$, $f^2 = 0.021$) → No significant effect, with a weak negative relationship.

Key Insights & Implications:

- The findings suggest that Facilitating Conditions (FC) are the strongest predictor of Behavioral Intention (BI), indicating that when individuals have access to necessary resources and support, their intention to engage in behaviour increases.
- Performance Expectancy (PE) shows a borderline effect that could be explored further, as it suggests a possible influence on BI.
- Other factors such as Effort Expectancy (EE), Perceived Knowledge (PK), Social Influence (SI), Technology Knowledge (TK), and Technological Pedagogical Knowledge (TPK) do not significantly impact BI, suggesting that they may not be key drivers of behavioral intention in this context.
- The high VIF values (ranging from 2.456 to 4.883) suggest potential multicollinearity issues, which may affect the stability of the model.

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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 by using secured e-learning. The finding shows that only facilitating conditions significantly influence behavioural intention, which supports the H2 hypothesis.

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