E-Learning Adoption and Use in Higher Education: Evidence from Zimbabwe

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Abstract
E-Learning adoption and use by university students have become prevalent worldwide, but developing nations still need to catch up. This study aims to establish critical paths amongst determinants of "behavioural Intention" and "use behaviour" in eLearning use and adoption in Higher Education in Zimbabwe using the modified Unified Theory of Acceptance and Use of Technology. The PLS-SEM method was used to evaluate the modified unified theory of acceptance and use of technology path model. A sample of 520 university students was used to collect data using an online survey created on Google Forms. The findings show that "Habit" had the most influence (0.804) on "Behavioural Intention," followed by "Performance Expectancy" (0.319) and "Effort Expectancy" (0.270). Behavioural Intention had a significant influence (0.831) on "Use Behaviour." The path model explains 88.8% of "Behavioural Intention" and 76.1% of "Use Behaviour" variances. Though limited, this study is significant to students in higher Education, policymakers and researchers, given the importance of technology in the education sector.

Key words: e-learning; online learning; e-learning platforms; ODeL; higher education

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Résumé: L'adoption et l'utilisation de l'apprentissage en ligne par les étudiants sont devenues courantes dans le monde entier, mais les pays en développement doivent encore rattraper leur avance. Cette étude vise à établir des chemins critiques entre les déterminants de « l'intention comportementale » et du « comportement d'utilisation » dans l'utilisation et l'adoption de l'eLearning dans l'enseignement supérieur au Zimbabwe en utilisant la théorie unifiée modifiée de l'acceptation et de l'utilisation de la technologie. La méthode PLS-SEM a été utilisée pour évaluer la théorie unifiée modifiée de l'acceptation et de l'utilisation de la technologie. Un échantillon de 520 étudiants universitaires a été utilisé pour collecter des données à l'aide d'une enquête en ligne créée sur Google Forms. Les résultats montrent que l'« habitude » a la plus grande influence (0,804) sur l'« intention comportementale », suivie de l'« attente de performance » (0,319) et de l'« attente d'effort » (0,270). L'intention comportementale a une influence significative (0,831) sur le « comportement d'utilisation ». Le modèle de cheminement explique 88,8 % de la variance des « intentions comportementales » et 76,1 % de la variance des « comportements d'utilisation ». Bien que limitée, cette étude est importante pour les étudiants, les décideurs politiques et les chercheurs, étant donné l'importance de la technologie dans l'enseignement superieur.

Mots clés: e-learning ; apprentissage en ligne ; plateformes d'apprentissage en ligne ; ODeL ; enseignement supérieur

Introduction

Integrating e-learning in education has become a crucial focus point, with universities positioned as a significant ground globally after COVID-19. COVID-19 revolutionised the education sector through technology, though historical traces of technological use in education date back to the 1960s (Weizenbaum, 1966; Faqih & Jaradat, 2021; Cukurova et al., 2023; Williamson et al., 2023; Gill et al., 2024; Bashir & Lapshun, 2025; Sherif & Amudha, 2025). Technology adoption and use in education date back to chatbot development (Weizenbaum, 1966; Cukurova et al., 2023; Bashir & Lapshun, 2025; Sherif & Amudha, 2025). However, eLearning became prevalent during and after COVID-19, especially in developed countries, but developing countries still need to catch up due to financial and infrastructural challenges. Adopting and using technology in education has seriously improved human capital development and higher education learning (Maune, 2023). Maune (2016), Qazi et al. (2020), Williamson et al. (2023) and Bashir and Lapshun (2024) argue that technology has become a crucial element in human capital development due to a significant increase in demand for novel skills. Higher Education today has become a conduit through which technologies are developed and unveiled. Universities must adapt and exploit these new technologies, impacting human capital development and meeting the demands of the 21st century. Artificial intelligence applications such as ChatGPT have significantly transformed educational landscapes, with educators and learners leveraging their capabilities to augment their learning experiences through dynamic feedback (Cukurova et al., 2023).

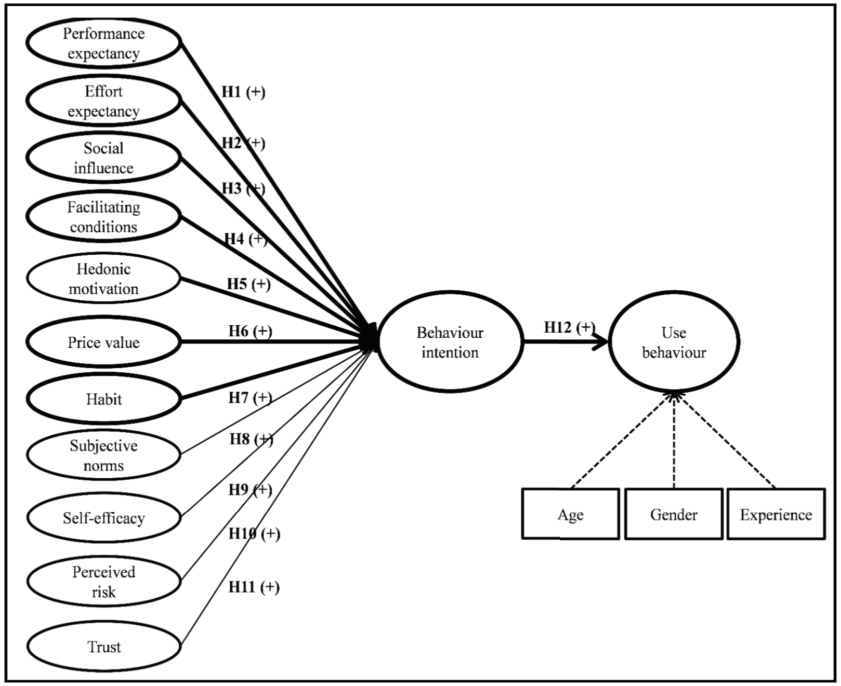
Adopting and using e-learning technologies in universities is challenging (Strzelecki, 2023). Such challenges, particularly in Africa, have been influenced by socioeconomic classes dating back to the colonial era (Maune, 2023). The colonial era left a divide that is prevalent up to today. Irrespective of these challenges, the following eLearning platforms are being used in universities in Zimbabwe: Microsoft Teams, Wiseup, Moodle, and ChatGPT. Although eLearning adoption and use have gained popularity in Zimbabwe recently, research into factors influencing behaviour intention and use behaviour among university students still needs to be explored. This gap is particularly significant as it aids in informed policy development and implementation. Moreover, understanding the factors influencing student behaviour in e-learning use and adoption in higher education is crucial and needed. In closing this research gap, a clear perspective of the factors influencing the adoption and use of eLearning helps the educational system through tailor-made approaches that address students' concerns.

Since the construction of the UTAUT and its modification into UTAUT2, literature has shown an increasing interest in adopting and using technology in higher education (Venkatesh et al., 2003; Venkatesh et al., 2012). The impact of COVID-19 has also seen an increase in the use of e-learning technologies by university students worldwide. However, developing countries still need to catch up due to several financial and infrastructure constraints. Despite all these challenges, studies have shown a spike in university students' uptake of eLearning platforms (Akbari et al., 2022; Shams et al., 2022; Cojocariu et al., 2014; Wang et al.,, 2010; Maune, 2023; Ahmad et al. 2023). More research has also been conducted on the impact of AI applications on academic integrity (Cotton & Cotton, 2023; Tlili et al., 2023; Williamson et al., 2023).

Maune (2023) argues that several factors influence university students' behaviour intention and use of e-learning platforms. Kempson and Whyley (1999), Ellis et al. (2010) and Beck et al., (2009) argue that factors such as literacy, information, involuntary or voluntary, cost, trust, socioeconomic, eligibility, and documentation are among the top most influencers of eLearning technologies adoption and use in universities by students. These factors must, however, precede behaviour intentions and use behaviour (Shneor & Munim, 2019).

Various theories such as Theory of Reasoned Action - TRA (Fishbein & Ajzen, 1975), Theory of Planned Behaviour - TPB (Ajzen, 1991), UTAUT (Venkatesh et al., 2003), and UTAUT2 (Venkatesh et al., 2012) and later modifications by various researchers, form the bases for this study. An extended model (Maune, 2021) developed in a prior study by the same author was examined using SEM to distinguish factors that impact eLearning technologies adoption and use by students in universities in Zimbabwe. Figure 1 provides the research model adopted for this study.

Figure 1: Path Analysis Model (Maune, 2021).



Hypothesis Development

The hypotheses below were formulated from a prior research model (Maune, 2021) developed by the same author, as shown in Figure 1. These hypotheses validated and tested the proposed path analysis model shown above. Table 1 shows the proposed research hypothesis.

Table 1: Proposed Research Hypothesis

Proposed Hypothesis
H_1 "Performance expectancy will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_2 "Effort expectancy will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_3 "Social influence will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_4 "Facilitating conditions will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_5 "Hedonic motivation will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_6 "Price value will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_7 "Habit will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_8 "Subjective norms will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_9 "Self-efficacy will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_{10} "Perceived risk will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H_{11} "Trust will have a direct positive influence on the behavioural intention to use eLearning platforms in universities by students."
H12 "Behavioural intention to use will have a direct positive influence on the eLearning platform use behaviour in universities by students."

This article seeks to close this research gap by examining the factors influencing e-learning technologies in higher education using the SmartPLS-SEM approach in Zimbabwe. An extended Unified Theory of Acceptance and Use of Technology (UTAUT2) by Venkatesh et al. (2012) and Maune (2021) informed the study by examining the factors influencing behaviour intention and use behaviour of e-learning technologies by university students in Zimbabwe.

The article first explains the extended model by Maune (2021) on eLearning adoption and use in Zimbabwe. A measurement scale tailor-made to suit this framework is also presented. After that, the results of the analysis using Smart PLS-SEM are shared. This is followed by a deep discussion of the research findings showcasing significant contributions of the study. The study will conclude with theoretical and practical implications, limitations, and future research direction.

Material and Methods

This study examined the use and adoption of eLearning in Zimbabwe's higher education. The role of behavioural intention was also examined. The study used a quantitative method to gain an in-depth appreciation of the relationships between the variables. We collected data from students in their second year (2.2) and fourth year (4.2) from two universities (one state-owned and one privately owned) using Google Forms online survey. A total number of 1680 commerce students were invited to participate in the survey from June to November 2023. Students were promised confidentiality, anonymity of responses, and voluntary participation to avoid biases. The survey was sent through a link generated from the Google Forms platform. At least ten minutes were needed to complete the survey. A pilot survey was distributed to 10 university students and lecturers to identify conspicuous characteristics and confusing, complex, and poorly worded questions. These adjustments were then incorporated into the primary survey that was distributed.

Limitations

This study uses a PLS-SEM algorithm to analyse the data to examine eLearning adoption and use by students in Zimbabwe universities. A path model in Figure 1 was evaluated to establish significant relationships between indicators. Sample size limited this study as a more significant sample could have improved the findings. This study could have used more universities, but only two were targeted. The study was also limited to students in the Faculty of Commerce and levels 2.2 and 4.2. Financial resources also limited the study as this study was self-funded. Given funding, the researcher could have improved the sample size by targeting students in different faculties and programs. The study was also limited to a single methodology.

Mixed methods will improve the research findings as studies have shown that mixed methods are better than mono-methods. Mixing qualitative and quantitative research methods is critical in dealing with biases associated with using one method. By using mixed methods, the researcher can answer a broader and more complete range of research questions because the researcher is not confined to a single method or approach. The researcher will be able to use the strengths of an additional method to overcome the weaknesses of another method by using both methods in a research study. Despite all this, the researcher forged ahead with the approach that worked for this study since truth is a 'normative concept.'

Respondents and Procedure

Completed surveys were automatically received from 525 respondents (31.25%). Observations with supposed unengaged respondents and missing data were deleted, and data from 520 respondents with complete data were utilised (30.95% response rate). Marcoulides and Saunders` (2006) investigation guided the sample size utilised in this article. The minimum sample size necessary must be determined by the maximum number of arrows pointing to the latent variable in the model (Marcoulides & Saunders, 2006). Prior scholars (Hoyle, 1995) also influenced the work, arguing that a modest sample size is usually an excellent place to start when performing path modelling. In this study, unengaged respondents reported the same response for all successive items (for example, a five across all observable variables). Descriptive demographic statistics are shown in Table 2.

Table 2: Demographic Statistics

Variable	Category	Occurrence	%age
Sex	Female	198	38%
	Male	322	62%
Age	<20	15	3%
	21 – 30	385	74%
	31 – 40	120	23%
Marital Status	Single	463	89%
	Married	52	10%
	Divorced	5	1%
Education	Level Two (2)	182	35%
	Level Four (4)	338	65%

Source: Compilation by author

Measurement

The students were invited to complete an online survey in Google Forms to measure the latent variables presented in the modified UTAUT model (Maune, 2021). These latent variables are self-efficacy, habit, hedonic motivation, performance expectancy, price value, effort expectancy, perceived risk, social influence, trust, facilitating conditions, subjective norms, behaviour intention, and use behaviour. The latent constructs scales in the model were adapted and modified from prior studies (Shneor & Munimb, 2019; Venkatesh et al., 2003; Groß, 2015; Venkatesh et al., 2012; and Abrahão et al., 2016). Wong (2013) explains that SEM has two measurement scales: reflective and formative. The indicators are firmly connected and interchangeable, implying that reliability and validity tests were conducted in agreement with previous research (Shneor & Munimb, 2019; Petter et al., 2007; Hair et al., 2013). A 5-point Likert scale was utilised, with 1 indicating complete disagreement and 5 indicating complete agreement. Table 3 shows measurement items, factor loadings, and sources.

Table 3. Latent Variables, Measurement Items, Factor Loadings, and Sources

Latent variable	Measurement items	Factor loadings	Source
Performance Expectancy (PE)	1. "I find eLearning useful in my daily learning." 2. "Using eLearning increases my chances of achieving my learning goals." 3."Using eLearning helps me accomplish my studies/learning more quickly." 4. "Using eLearning increases my productivity."	0.933 Deleted 0.942 Deleted	'Venkatesh et al. (2003) & Venkatesh et al. (2012).'
Effort expectancy (EE)	1. "Learning how to use eLearning is easy for me." 2. "My interaction with eLearning is clear and understandable." 3. "I find eLearning easy to use." 4. "It is easy for me to become skillfull at using eLearning."	1.000 Deleted Deleted Deleted	'Venkatesh et al. (2003) & Venkatesh et al. (2012).'
Social influence (SI)	1. "People who are important to me think that I should use eLearning." 2. "People who influence my behaviour think that I should use eLearning." 3. "People whose opinions I value prefer that I use eLearning."	0.894 0.877 Deleted	'Venkatesh et al. (2012) & Venkatesh et al. (2003).'
Facilitating conditions (FC)	1. "I have the resources necessary to use eLearning." 2. "I have the knowledge necessary to use eLearning." 3. "ELearning platforms are compatible with other technologies I use." 4. "I can get help from others when I have difficulties using eLearning."	1.000 Deleted Deleted Deleted	'Venkatesh et al. (2003) & Venkatesh et al. (2012).'

Hedonic motivation (HM)	1. "Using eLearning is fun." 2. "Using eLearning is enjoyable." 3. "Using eLearning is very entertaining."	0.815 0.943 0.920	Venkatesh et al. (2012).
Price value (PV)	1. "ELearning is reasonably priced." 2. "ELearning is a good value for the money." 3. "At the current price, eLearning provide good value."	0.676 0.859 0.898	Venkatesh et al. (2012).
Habit (HT)	1. "The use of eLearning has become a habit for me." 2. "I am addicted to using eLearning." 3. "I must use eLearning." 4. "Using eLearning has become natural to me."	0.910 0.656 0.841 0.888	Venkatesh et al. (2012).
Perceived risk (PR)	1. "I would not feel completely safe to provide personal information through eLearning platforms." 2. "I am worried about the future use of eLearning platforms because other people might be able to access my data." 3. "I do not feel protected when sending confidential information via eLearning platforms." 4. "The likelihood that something wrong will happen with the use of eLearning platforms is high."	0.588 Deleted 0.943 0.710	Abrahao et al., 2016.
Trust (TT)	1. "I think they are honest." 2. "I think they are trustworthy." 3. "I think they provide good services to users." 4. "I think they care about their users and take their concerns seriously." 5. "I think they keep users' security and privacy in mind."	Deleted Deleted 0.956 Deleted 0.663	Groß (2015).

Subjective norms (SN)	1. "People who are important to me think that I should use eLearning platforms in learning." 2. "People who influence my behaviour encourage me to use eLearning platforms in learning." 3. "My colleagues think that I should use eLearning platforms in learning." 4. "My friends think that I should use eLearning platforms in learning."	0.876 0.637 0.867 Deleted	Shneor & Munimb (2019).
Self-efficacy (SE)	1. "I have confidence in my ability to use eLearning platforms in learning." 2. "I have the expertise needed to use eLearning platforms." 3. "I am confident in my ability to navigate and use eLearning platforms in learning." 4. "I am confident in my ability to use eLearning platforms in learning."	0.836 Deleted Deleted 0.999	Shneor & M u n i m b (2019).
Behavioural intention (BI)	1. "I intend to continue using eLearning platforms in learning in the future." 2. "I will always try to use eLearning platforms in learning." 3. "I plan to continue to use eLearning platforms in learning frequently."	0.924 Deleted 0.919	'Venkatesh et al. (2003) & Venkatesh et al. (2012).'
Use behaviour (UB)	1. "I frequently use eLearning platforms in learning." 2. "I spend much effort in using eLearning platforms in learning."	0.925 0.811	Shneor & Munimb (2019).

Source: Authors' compilation

Structural Equation Modelling Approach

This study utilised SmartPLS3 for data analysis, following previous methods in SEM (Maune et al., 2021). This approach was preferred due to predictive accuracy and its applicability in dealing with small sample sizes. Despite the limitations associated with the approach (Wong, 2013), it has become more prevalent in applied research projects. Moreover, Maune et al. (2021) argue that the approach has been applied in management information systems, marketing, organisation, business strategy, and behavioural sciences, among other fields. Data was first cleaned before being uploaded into SmartPLS 3 software for analysis.

Analysis

Figure 3 shows the partial least square path model estimations for this study. The results of the path analysis model are as follows:

Reflective Measurement Scale

There are two types of measurement scales in SEM: formative and reflective. A reflective measurement scale was adopted in this study because the indicators were highly correlated and interchangeable (Haenlein & Kaplan, 2004; Petter et al., 2007; Hair et al., 2013). Therefore, the study thoroughly examined the reliability and validity of the indicators. Maune et al. (2021) argue that each reflective indicator is related to a specific latent variable or construct using a simple regression analysis.

During the evaluation of the measurement model, 17 items were removed because of low factor loadings (<0.600) and high cross-loading (Gefen & Straub, 2005). Cronbach's alpha and composite reliability (CR) tests were used to test the reliability of the constructs (Table 4). All the constructs in the study met the required CRs threshold (0.700) in accordance with Hair et al., (2017). The Cronbach's alpha was above the threshold of 0.700 for each construct. Convergent validity was acceptable since the AVE exceeded 0.500 (Bagozzi & Yi, 1988). Table 4 shows the reliability, validity and factor loadings output. The Fornell-Larcker criterion was used to assess discriminant validity, and the output is shown in Table 5. The results in Table 5 align with Fornell and Larcker (1981), showing a more significant square root of AVE than the inter-construct correlation for all the constructs. The Heterotrait-Monotrait ratio was also used to assess the discriminant validity of correlations (Henseler et al., 2015). The output shows all values below the 0.900 threshold, establishing discriminant validity (Table 6).

Table 4. Factor Loadings, VIF, Composite Reliability, Convergent Validity

Indicators	Loadings	VIF	Cronbach's Alpha	Composite Reliability	AVE
PE1	0.933	4.384	0.935	0.935	0.879
PE3	0.942	4.384			
EE1	1.000	1.000	1.000	1.000	1.000
SI1	0.894	2.596	0.879	0.879	0.784
SI2	0.877	2.596			
FC1	1.000	1.000	1.000	1.000	1.000
HM1	0.815	3.354	0.923	0.923	0.801
HM2	0.943	3.308			
HM3	0.920	3.763			
PV1	0.676	1.946	0.854	0.855	0.667
PV2	0.859	2.404			
PV3	0.898	2.122			
HT1	0.910	2.910	0.896	0.897	0.689
HT2	0.656	2.044			
HT3	0.841	2.566			
HT4	0.888	3.070			
PR1	0.588	1.741	0.794	0.799	0.580
PR3	0.943	1.872			
PR4	0.710	1.544			
TT3	0.956	1.673	0.776	0.802	0.677
TT5	0.663	1.673			
SN1	0.876	1.634	0.844	0.841	0.642
SN2	0.637	2.510			
SN3	0.867	2.668			
SE1	0.836	3.297	0.910	0.917	0.848
SE4	0.999	3.297			
BI1	0.924	3.576	0.918	0.918	0.849
BI3	0.919	3.576			
UB1	0.925	2.292	0.858	0.861	0.757
UB2	0.811	2.292			

Table 5. Fornell-Larcker Criterion

	BI	**EE**	**FC**	**HM**	**HT**	**PE**	**PR**	**PV**	**SE**	**SI**	**SN**	**TT**	**UB**
BI	0.921												
EE	0.832	1.000											
FC	0.788	0.811	1.000										
HM	0.859	0.829	0.772	0.895									
HT	0.897	0.781	0.741	0.889	0.830								
PE	0.872	0.847	0.837	0.898	0.862	0.937							
PR	-0.102	-0.043	-0.108	-0.107	-0.098	-0.068	0.761						
PV	0.699	0.718	0.649	0.731	0.835	0.781	-0.066	0.817					
SE	0.072	0.161	0.098	0.078	0.052	0.077	-0.230	0.146	0.921				
SI	0.847	0.810	0.803	0.858	0.887	0.871	0.102	0.714	0.012	0.886			
SN	0.020	0.120	0.071	0.061	-0.028	0.042	-0.417	0.051	0.691	-0.060	0.801		
TT	0.123	0.052	0.023	0.072	0.081	0.044	-0.387	0.013	0.154	0.041	0.444	0.823	
UB	0.869	0.715	0.716	0.796	0.846	0.833	-0.101	0.725	0.078	0.773	0.069	-0.029	0.870

Table 6. Heterotrait-Monotrait Ratio (HTMT)

	BI	EE	FC	HM	HT	PE	PR	PV	SE	SI	SN	TT	UB
BI	-												
EE	0.832												
FC	0.788	0.811											
HM	0.857	0.828	0.771										
HT	0.892	0.777	0.737	0.887									
PE	0.872	0.847	0.837	0.896	0.861								
PR	0.160	0.110	0.146	0.163	0.148	0.119							
PV	0.695	0.715	0.642	0.730	0.835	0.775	0.089						
SE	0.082	0.159	0.094	0.098	0.088	0.086	0.305	0.148					
SI	0.846	0.810	0.803	0.857	0.889	0.871	0.138	0.711	0.048				
SN	0.055	0.114	0.070	0.079	0.057	0.071	0.433	0.054	0.680	0.073			
TT	0.130	0.082	0.080	0.086	0.103	0.089	0.384	0.089	0.155	0.092	0.504		
UB	0.868	0.717	0.716	0.797	0.855	0.836	0.141	0.734	0.078	0.775	0.084	0.064	-

Structural Model

The path analysis model was evaluated once the reliability and validity of variables were established. The theoretical model below is evaluated to give empirical evidence of the path model using SmartPLS (Avkiran, 2018; Tenenhaus et al., 2005).

$$\xi_j = \beta_{jo} + \sum_i \beta_{ji} \xi_j + \nu_j$$

Where: ξ_j is the endogenous construct and ξ_i represents the exogenous constructs, while β_{jo} is the constant term in this (multiple) regression model, β_{ij} are the regression coefficients, and v_j is the error term; the predictor specification condition applies.

The PLS-SEM path analysis model output in Figure 2 shows the hypothesised results of the path analysis model in Figure 1. The path analysis model was evaluated using the significance of paths Q2 and R2. The strength of each structural path determined (R2 value for the dependent variable) the goodness fit of the model. Falk and Miller (1992) argue that the value for R2 should be equal to or over 0.1. The output in Table 7 shows all R2 values for the study, which were above 0.1. The study, therefore, established the predictive capability of the model. Wong (2013) argues that Q2 establishes the predictive relevance of endogenous variables. Therefore, the study established a Q2 above zero (0), denoting predictive relevance. The study output in Table 7 denotes the significance of the prediction by the constructs.

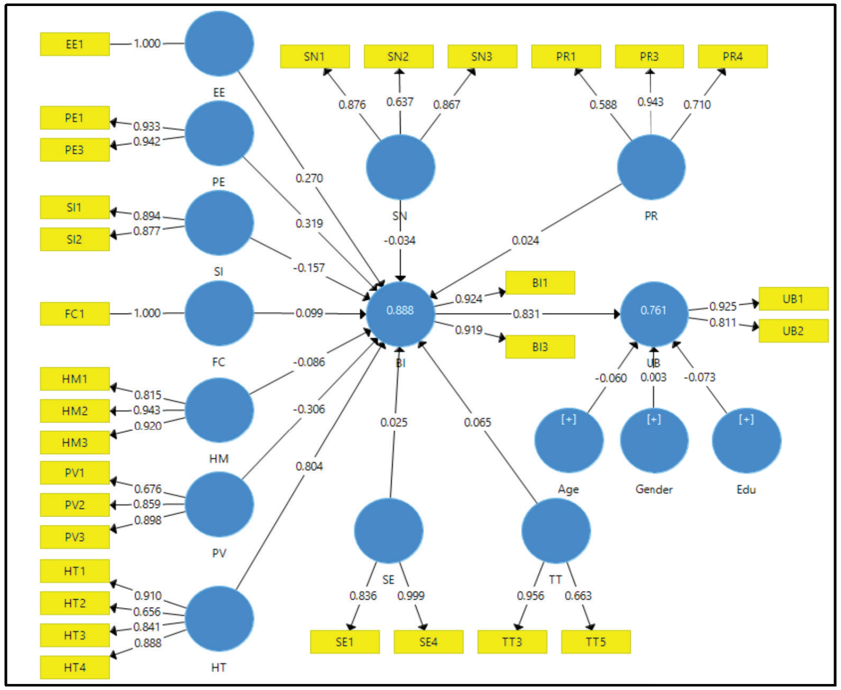
The collinearity of constructs was assessed by examining the outer VIF values of the model. Table 4 shows the output of VIF values for all exogenous and related endogenous variables groupings. The VIF output values were below the threshold of 5, denoting the non-existence of collinearity among indicators in the model. Hence, collinearity was not an issue in the model. Further examination of the output was carried out, and the results are shown in Table 7. The outputs verify the hypotheses and the significance testing for the path coefficients within the path analysis model.

Table 7. Path Coefficients, Confidence Intervals, R2, R2 Adjusted, and Q2

Hypothesis	Relationship	β	STDEV	T Statistics	P Values	2.50%	97.50%
H1	PE - > BI	0.319	0.172	1.074	0.283	-0.173	0.499
H2	EE - > BI	0.270	0.141	1.652	0.099	-0.025	0.528
H3	SI - > BI	-0.157	0.100	0.577	0.564	-0.116	0.288
H4	FC - > BI	0.099	0.094	1.005	0.315	-0.092	0.286
H5	HM - > BI	-0.086	0.114	0.537	0.592	-0.155	0.290
H6	PV - > BI	-0.306	0.070	1.299	0.194	-0.244	0.037
H7	HT - > BI	0.804	0.109	3.650	0.000	0.197	0.623
H8	SN - > BI	0.025	0.084	0.511	0.610	-0.064	0.278
H9	SE - > BI	-0.034	0.075	0.632	0.528	-0.253	0.066

H10	PR - > BI	0.024	0.071	0.647	0.517	-0.217	0.071
H11	TT - > BI	0.065	0.070	0.665	0.506	-0.111	0.175
H12	BI - > UB	0.831	0.074	9.604	0.000	0.546	0.838
		R2	R^2 Adjusted	Q2			
	BI	0.888	0.874	0.657			
	UB	0.761	0.751	0.515			

Figure 2: PLS-SEM Path Model Output

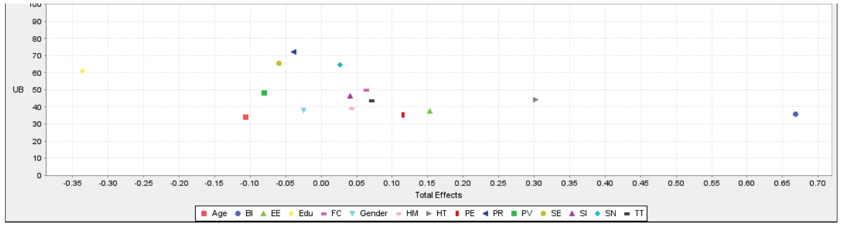


Goodness of fit: SRM, Saturated Model – 0.064, and estimated Model – 0.066.

Importance-Performance Map Analysis (IPMA)

IPMA was extracted to establish the importance and performance of model path variables. Performance shows the magnitude of each latent construct score, while importance shows the total effect on the targeted construct in the PLS-SEM path model. The output of the IPMA is critical in prioritising management action. As a matter of priority, management should focus more on addressing the performance of indicators that show immense importance in explaining certain targeted constructs, nonetheless having low performance.

Figure 3: Importance-Performance Map Analysis



The study considered an indicator important when its total effect on "Use Behaviour" (UB) was high (Y-axis). Therefore, in this study, "Habit" (HT) (0.302) has greater absolute importance on UB outside BI (0.668) (Figure 3 and Table 8). Moreover, an indicator performs better when it has a higher score. This score reflects robust measurement of paths as shown by the X-axis. In this study, "Perceived Risk" (PR) (72.155) shows more excellent performance than any other indicators (Table 8 and Figure 3).

Discussion

This study examines eLearning adoption and use in higher Education in Zimbabwe. A PLS-SEM approach was used to analyse data collected through an online survey targeting students at two Zimbabwe universities. A modified UTAUT2 model (Figure 1) was examined. The study placed more emphasis on BI and UB's psychological reasoning. Behaviour intention and use of eLearning in higher education by students is considered planned behaviour. A path analysis framework modified from UTAUT2 in Figure 1 was examined using the PLS-SEM algorithm to establish significant model paths and associations. The output extracts are shown in Table 2 to Table 7.

Of importance, however, was the relationship between "Habit" and "Behaviour Intention" (HT -> BI), which is significant at a 95% confidence level with a p-value of < 0.05 (0.000) and a T-Statistic of 3.650. Another noteworthy relationship was BI -> UB, which was significant at a 95% confidence level with a p-value of <0.05 (0.000) and a T-Statistic of 9.604. The observation reveals that HT has the most noticeable influence (0.804) on BI, followed by PE (0.319), then EE (0.270) and FC (0.099). BI has a significant influence (0.831) on UB, accounting for 76.1% of the UD variance. All the latent variables account for 88.8% of the BI variance, as indicated by R2. The variances explained by previous researchers were higher than those of previous researchers (Strzelecki, 2023; Maican et al., 2019; Hoi, 2020). The (HT -> BI) findings are consistent with previous studies (Strzelecki, 2023; Sitar-Taut & Mican, 2021; Alotumi, 2022; Jakkaew & Hemrungrote, 2017; Kumar & Bervell, 2019). However, some of the findings needed to be more consistent with other prior studies (Twum et al., 2022; Ain et al., 2016), which found no direct effect of HT on BI.

During the evaluation of the paths, 17 items (indicators) were omitted because of low-factor loadings or high-cross loadings, as supported by Gefen and Straub (2005). Data did not support these paths. Most of these omitted indicators were from EE and FC despite previous findings that showed their significant influence on the latent variables (Venkatesh et al., 2003; Venkatesh et al., 2012; Limayem et al., 2007). These findings were inconsistent with findings from other previous studies (Arain et al., 2019; Azizi et al., 2020; Nikolopoulou et al., 2020; Raman & Don, 2013; Raffaghelli et al., 2022; Mehta et al., 2019) who found a strong correlation between the variables.

All latent variables except HT were insignificant towards BI at a 95% confidence level, as shown by their p-values and t-statistics. This was so despite prior findings (Venkatesh et al., 2003; Groß, 2015; Shneor & Munimb, 2019; Venkatesh et al., 2012; Abrahão et al., 2016; Roy, 2017). The study results, however, confirm previous researchers` findings (Khurana & Jain, 2019; Barua et al., 2018; Chao, 2019; Liu & Tai, 2016; Tarhini et al., 2019; Gharaibeh et al., 2020). The following model paths were established: HT -> BI and BI -> UB with significant p-values and t-statistics.

Our findings showed that HM has an insignificant negative impact on BI. The finding is inconsistent with prior studies (Azizi et al., 2020; Hu et al., 2020; Faqih & Jaradat, 2021) while consistent with findings by Ain et al. (2016) and Raza et al. (2022). The findings on SI align with those by Alotumi (2022) and Kumar and Bervell (2019), who found the insignificant influence of SI on BI. PV has an insignificant negative influence on BI, consistent with prior findings (Strzelecki, 2023; Nikolopoulou et al., 2020; Osei et al., 2022). However, this was inconsistent with findings by Farooq et al. (2017) and Azizi et al. (2020). Furthermore, our findings regarding FC aligned with prior studies (Strzelecki, 2023; Alotumi, 2022; Kumar & Bervell, 2019; Dajani & Abu Hegleh, 2019). This was contrary to findings by Faqih & Jaradat (2021) and Yu et al. (2021).

The significance of paths Q2 and R2 were used to assess the path analysis model's goodness of fit, as denoted in Table 7. Predictive relevance was

established for constructs in line with prior studies (Falk & Miller, 1992; Briones-Penalver et al., 2018).

The most important finding for students' eLearning adoption and use in higher education relates to the IPMA, which identifies significant focus areas. These are the areas of focus that generate targeted constructs within the PLS-SEM path analysis diagram. In this study, "Habit" (HT) (0.302) had the most significant absolute importance on UB outside BI (0.668) (Figure 3 and Table 8). The same was "Perceived Risk" (PR) (72.155), which showed the most outstanding performance of any other indicator in the study (Table 8 and Figure 3). Ceteris paribus, a unit rise in HT performance will result in a 0.302 rise in UB (Figure 3 and Table 8).

Table 8. Importance-Performance Analysis

Variable	Performance	Total effect
BI	35.763	0.668
EE	37.750	0.153
FC	49.750	0.064
HM	38.961	0.043
HT	44.244	0.302
PE	35.349	0.115
PR	72.155	-0.039
PV	48.170	-0.080
SE	65.341	-0.060
SI	46.613	0.041
SN	64.692	0.026
TT	43.345	0.071
UB	40.614	-

Conclusion and Implications

Conclusion

This study uses a PLS-SEM algorithm to analyse the data to examine eLearning adoption and use by students in Zimbabwe universities. A path model in Figure 1 was evaluated to establish significant relationships between indicators. This path model was a modification of the UTAUT2 that incorporated other latent variables selected from other theories of technology adoption and use (Maune, 2023). This study confirmed "Habit"'s significant influence on BI and eLearning use in Zimbabwe's higher education. The adoption and use of eLearning is still in its infancy in Zimbabwe, with different universities at different levels of adoption and use. Therefore, there is a need for more research studies to be carried out in the field. This study can provide the basis or foundation for further future studies.

Implications for Research

This study uses a PLS-SEM algorithm to analyse the data to examine eLearning adoption and use by students in Zimbabwe universities. A path model in Figure 1 was evaluated to establish significant relationships between indicators. This path model was a modification of the UTAUT2 that incorporated other latent variables selected from other technology adoption and use theories. The application and replication of the path analysis model are critical for ODeL experts and other practitioners in higher education, given how technological developments are impacting higher education. The role of technology has become more critical than ever before, especially with the impact of AI. The findings of this study are critical to the development of higher education in developing countries, particularly Zimbabwe. The findings of this study will hopefully guide future research.

Although UTAUT2 is an essential theory in evaluating relationships between constructs in the use of technology, modifications and expansion of the theory have proved vital in different fields, with different results being realised. This is critical in research since there is no one solution to a given problem. Researchers should, therefore, forge ahead with what works since truth is a normative concept – the truth is what works.

The proposed path analysis model was evaluated empirically using PLS-SEM to establish critical relationships in eLearning adoption and use in higher education. This approach adopted a cognitive psychological human behaviour in decision making. The results of this study show an insignificant relationship among all the constructs except for HT and BI, which had significant paths, as shown by their p-values and t-statistics. Habit was identified as a critical determinant in adopting and using eLearning in higher education in Zimbabwe. This confirms the findings by Strzelecki (2023).

Overall, results showed that behavioural intention significantly influences use behaviour in eLearning use in universities in Zimbabwe. To further authenticate these findings, there is a need to analyse this data using different analytical software such as AMOS, R and Stata. A more significant sample might be considered in this endeavour. Further modifications may be required to this framework. This study was critical in addressing the research gap exposed by prior research (Maune, 2023). The study (Maune, 2023) reviewed relevant literature in developing the extended path model that was evaluated by this study. This study provides the starting point for further future research in the field. Critical dimensions have been identified that will help in future research. The path model was informed by literature (Maune, 2023).

Furthermore, by expanding the path model, we hypothesised that social influence, habit, performance expectancy, facilitating conditions, effort expectancy, subjective norm, self-efficacy, hedonic motivation, price value, trust, and perceived risk were critical determinants in adopting and using online learning applications by university students in Zimbabwe. However, data needed to support more indicators for facilitating conditions and effort expectancy; hence, they were omitted in the final model. However, the results in this study align well with those from prior studies (Khurana & Jain, 2019; Shneor & Munimb, 2019; Chao, 2019; Tarhini et al., 2019; Gharaibeh et al., 2020).

Implications for Practice

Technology has proven a key factor in higher education, especially during and after the COVID-19 pandemic. Globally, technology has become prevalent in higher education, especially AI-related applications such as ChatGPT. Gill et al. (2024) argue that "AI applications are becoming crucial for colleges and universities, whether personalised learning, computerised assessment, smart educational systems, or supporting teaching staff. They offer support that results in reduced expenses and enhanced learning results." However, although the use of technology in higher education has become popular, it comes with its risks and difficulties. To this end, Gill et al. (2024) state that "there are concerns regarding the potential misuse of [technology], as it could be employed to generate academic tests and assignments for students and provide tailored responses to coursework questions and assessments. As a result, several institutions have forbidden students from using [certain technologies], including a ban within an entire country."

The path analysis model explained and predicted various relationships, as shown in the Figures and Tables above. This has practical implications in recommending factors driving 'Behavioural Intention' and 'Use Behaviour' in the use of online learning applications by university students. The path analysis model has essential inferences that are critical for higher education. The most essential discovery was that Habit (HT) plays a critical role in eLearning adoption and use in universities in Zimbabwe.

Furthermore, the IPMA has also proven to be critical in decision-making. In this case, "Habit" (HT) (0.302) had the most significant absolute importance on UB outside BI (0.668) (Figure 3 and Table 8). The same was "Perceived Risk" (PR) (72.155), which showed the most outstanding performance of any other indicator in the study (Table 8 and Figure 3). IPMA clearly shows critical areas for managerial focus and prioritisation. For example, management should focus on higher-importance and low-performance constructs. These constructs have higher chances for improvement. This is critical for management since it is illogical to focus on constructs of low importance, as this will have no impact on improving the targeted construct.

References

Abrahão, R. S., Moriguchi, S. N., & Andrade, D. F. (2016). Intention of adoption of mobile payment: An analysis in the light of the Unified Theory of Acceptance and Use of Technology (UTAUT). *RAI Revista de Administração e Inovação*, 13, 221–230.

Ahmad, S., Mohd Noor, A. S., Alwan, A. A., Gulzar, Y., Khan, W. Z., & Reegu, F. A. (2023). E-learning acceptance and adoption challenges in higher education. *Sustainability, 6*, 1-16. https://doi. org/10.3390/su15076190

Ain, N., Kaur, K., & Waheed, M. (2016). The influence of learning value on learning management system use. *Information Development, 32*(5), 1306–1321. https://doi.org/10.1177/0266666915597546

Ajzen, I. (1991). The theory of planned behaviour. *Organisational Behavior and Human Decision Process, 50*(2), 179–211. https://doi.org/10.10 80/08870446.2011.613995

Akbari, M., Danesh, M., Rezvani, A., Javadi, N., Banihashem, S. K., & Noroozi, O. (2022). The role of students' relational identity and autotelic experience for their innovative and continuous use of e-learning. *Education and Information Technologies*, 28, 1911 – 1934. https://doi.org/10.1007/s10639-022-11272-5

Alotumi, M. (2022). Factors influencing graduate students' behavioural intention to use Google Classroom: Case study-mixed methods research. *Education and Information Technologies, 27*(7), 10035–10063. https://doi.org/10.1007/s10639-022-11051-2

Arain, A. A., Hussain, Z., Rizvi, W. H., & Vighio, M. S. (2019). Extending UTAUT2 toward acceptance of mobile learning in the context of higher education. *Universal Access in the Information Society, 18*(3), 659–673. https://doi.org/10.1007/s10209-019-00685-8

Avkiran, N. K. (2018). Rise of the Partial Least Squares Structural Equation Modeling: An application in banking. In N. K. Avkiran and C. M. Ringle (Eds.), Partial Least Squares Structural Equation Modeling, *International Series in Operations Research & Management Science* (pp. 1-29). https://doi.org/10.1007/978-3-319-71691-6_1

Azizi, S. M., Roozbahani, N., & Khatony, A. (2020). Factors affecting the acceptance of blended learning in medical education: Application of UTAUT2 model. *BMC Medical Education, 20*(1), 1-9. https://doi. org/10.1186/s12909-020-02302-2.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science, 16*(1), 74–94.

Barua, Z., Alam, M. Z., & Hu, W. (2018). Using the UTAUT model to determine factors affecting acceptance and use of Mobile Health (mHealth) services in Bangladesh. *Journal of Studies in Social Sciences, 17*(2), 137-172.

Bashir, S., & Lapshun, A. L. (2025). E-learning future trends in highereducation in the 2020s and beyond. *Cogent Education, 12*(1), 1-15. DOI: 10.1080/2331186X.2024.2445331

Beck, T., Demirgüç-Kunt, A., & Honohan, P. (2009). Access to financial services: Measurement, impact, and policies. T*he World Bank Research Observer, 24*(1), 119-145.

Briones-Penalver, A. J., Bernal-Conesa, J. A., & Nieves-Nieto, C. (2018). Analysis of corporate social responsibility in Spanish agribusiness and its influence on innovation and performance. *Corporate Social Responsibility and Environmental Management, 25*(2), 182-193.

Chao, C.-M. (2019). Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model. *Frontiers in Psychology*, 10, 1-14. https://doi.org/10.3389/fpsyg.2019.01652

Cojocariu, V.-M., Lazar, I. Nedeff, V., & Lazar, G. (2014). SWOT analysis of e-learning educational services from the perspective of their beneficiaries. *Procedia - Social Behavioral Sciences*, 116, 1999–2003. https://doi:10.1016/j.sbspro.2014.01.510

Cotton, D. R. E., & Cotton, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International, 61*(2), 228-239. https://doi.org/10.108 0/14703297.2023.2190148

Cukurova, M., Miao, X., & Brooker, R. (2023). Adoption of artificial intelligence in schools: Unveiling factors influencing teachers' engagement. In N. Wang, G. Rebolledo-Mendez, N. Matsuda, O. C. Santos, V. Dimitrova (Eds.), *Artificial Intelligence in Education* (pp. 151–163). https://doi.org/10.1007/ 978-3- 031- 36272-9_13

Dajani, D., & Abu Hegleh, A. S. (2019). Behaviour intention of animation usage among university students, Heliyon. 5(10), 1-10. https://doi. org/10.1016/j.heliyon.2019.e02536

Ellis, K., Lemma, A., & Rud, J.-P. (2010). *Investigating the impact of access to*

financial services on household investment. Overseas Development Institute.
Falk, R. F., & Miller, N. B. (1992). A primer for soft modelling. Universityof Akron Press.
Faqih, K. M. S., & Jaradat, M.-I. R. M. (2021). Integrating TTF and UTAUT2 theories to investigate the adoption of augmented reality technology in education: Perspective from a developing country. *Technology in Society, 67*(2): 101787. https://doi.org/10.1016/j.techsoc.2021.101787
Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies. *Interactive Technology and Smart Education, 14*(4), 329–348. https://doi.org/10.1108/ITSE-06-2016-0015
Fishbein, M. & Ajzen, I. (1975). *Belief, attitude, intention and behavior: an introduction to theory and research*. Addison-Wesley.
Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. J*ournal of Marketing Research, 18*(1), 39-50.
Gefen, D., & Straub, D. (2005). A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. *Communications of the Association for Information Systems, 16*(1), 91-109.
Gharaibeh, N., Gharaibeh, M. K., Gharaibeh, O., & Bdour, W. (2020). Exploring intention to adopt mobile commerce: Integrating UTAUT2 with social media. *International Journal of Scientific and Technology Research, 9*(3), 3826-3833.
Gill, S. S., Xu, M., Patros, P., Wu, H., Kaur, R., Kaur, K., Fuller, S., Singh, M., Arora, P., Parlikad, A. K., Stankovski, V., Abraham, A., Ghosh, S. K., Lutfiyya, H., Kanhere, S. S., Bahsoon, R., Rana, O., Dustdar, S., Sakellariou, R., … Buyya, R. (2024). Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots. *Internet of Things and Cyber-Physical Systems*, 4, 19–23. https://doi.org/10.1016/j.iotcps.2023.06.002
Groß, M. (2015). Exploring the acceptance of technology for mobile shopping: An empirical investigation among smartphone users. *The International Review of Retail, Distribution and Consumer Research, 25*(3), 215–235.
Haenlein, M., & Kaplan, A. M. (2004). A beginner's guide to partial least squares analysis. *Understanding Statistics, 3*(4), 283–297.
Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2013). *A primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage.
Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd Ed.). Sage.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science, 43* (1), 115–135.
Hoi, V. N. (2020). Understanding higher education learners' acceptance and use of mobile devices for language learning: A Rasch-based path modelling approach. *Computers & Education, 146*(1):103761. https://doi.org/10.1016/j.compedu.2019.103761.
Hoyle, R. H. (ed.). (1995). *Structural equation modeling.* SAGE Publications.
Hu, S., Laxman, K., & Lee, K. (2020). Exploring factors affecting academics' adoption of emerging mobile technologies: An extended UTAUT perspective. *Education and Information Technologies, 25*(5), 4615–4635. https://doi.org/10.1007/s10639-020-10171-x
Jakkaew, P., & Hemrungrote, S. (2017). The use of UTAUT2 model for understanding student perceptions using Google Classroom: A case study of introduction to information technology course. I*nternational Conference on Digital Arts, Media and Technology* (pp. 205–209). https://doi.org/10.1109/ICDAMT.2017.79049 62
Kempson, E., & Whyley, C. (1999). *Kept out or opted out: Understanding and combating financial inclusion*. Policy Press.
Khurana, S., & Jain, D. (2019). Applying and extending UTAUT2 model of adoption of new technology in the context of M-Shopping fashion apps. *International Journal of Innovative Technology and Exploring Engineering, 8*(9S), 752-759. https://doi.org/10.35940/ ijitee.I1122.0789S19
Kumar, J. A., & Bervell, B. (2019). Google Classroom for mobile learning in higher education: Modelling the initial perceptions of students. *Education and Information Technologies, 24*(2), 1793–1817. https://doi.org/10.1007/s10639-018-09858-z
Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *MIS Quarterly, 31*(4), 705–737.
Liu, G. -S., & Tai, P. T. (2016). A study of factors affecting the intention to use mobile payment services in Vietnam. *Economics World, 4*(6), 249-273. https://doi.org/10.17265/2328-7144/2016.06.001
Maican, C. I., Cazan, A. -M., Lixandroiu, R. C., & Dovleac, L. (2019). A study on academic staff personality and technology acceptance: The case of communication and collaboration applications. *Computers & Education, 128*(1), 113–131. https://doi.org/10.1016/j.compedu.2018.09.010.
Marcoulides, G. A., & Saunders, C. (2006). Editor's comments – PLS: A

silver bullet? *MIS Quarterly, 30*(2), iii-ix.
Maune, A. (2016). Human capital intelligence and economic development. *Journal of Problems and Perspectives Management, 14*(3), 120–130.
Maune, A. (2021). Intention to use mobile applications in competitive intelligence: An extended conceptual framework. *Journal of Intelligence Studies in Business, 11*(2), 6–29.
Maune, A. (2023). Adoption and use of eLearning platforms by universities in developing countries: Evidence from Zimbabwe. *Cogent Education, 10*(2), 1–13. https://doi.org/10.1080/233118 6X.2023.2287905
Maune, A., Matanda, E., & Mundonde, J. (2021). Financial inclusion as an intentional behaviour in Zimbabwe. *Acta Universitatis Danubius OEconomica, 17*(4), 177-211.
Mehta, A., Morris, N. P., Swinnerton, B., & Homer, M. (2019). The influence of values on e-learning adoption. *Computers & Education, 141*, 1-16. https://doi.org/10.1016/j.compedu.2019.103617
Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2020). Acceptance of mobile phone by university students for their studies: An investigation applying UTAUT2 model. *Education and Information Technologies, 25*(5), 4139–4155. https://doi.org/10.1007/s10639-020-10157-9
Osei, H. V., Kwateng, K. O., & Boateng, K. A. (2022). Integration of personality trait, motivation and UTAUT 2 to understand e-learning adoption in the era of the COVID-19 pandemic. *Education and Information Technologies, 27*(8), 10705–10730. https://doi.org/10.1007/s10639-022-11047-y
Petter, S., Straub, D., & Rai, A. (2007). Specifying formative constructs in information systems research. *MIS Quarterly, 31*(4), 623-656.
Qazi, W., Raza, S. A., Khan, K. A., & Salam, J. (2020). Adoption of e-learning system in higher education environments: Evidence from modified UTAUT model. ASR: CMU Journal of Social *Sciences and Humanities,* 7(1), 1-19. https://doi.org/10.12982/CMUJASR.2020.003
Raffaghelli, J. E., Rodriguez, M. E., Guerrero-Roldan, A. -E., & Baneres, D. (2022). Applying the UTAUT model to explain the students' acceptance of an early warning system in higher education. *Computers & Education, 182*(5), 1-14. https://doi.org/10.1016/j.compedu.2022.104468
Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies, 6*(7), 157–164. https://doi.org/10.5539/ies.v6n7p157
Raza, S. A., Qazi, Z., Qazi, W., & Ahmed, M. (2022). E-learning in higher education during COVID-19: Evidence from blackboard learning system. *Journal of Applied Research in Higher Education, 14*(4),

1603–1622. https://doi.org/10.1108/JARHE-02-2021-0054
Roy, S. (2017). App adoption and switching behavior: Applying the extended tam in smartphone app usage. *Journal of Information Systems and Technology Management, 14*(2), 239–261. https://doi. org/10.4301/S1807-17752017000200006
Shams, M. S., Niazi, M. M., Gul, H., Mei, T. S., & Khan, K. U. (2022). E-learning adoption in higher education institutions during the COVID-19 pandemic: A multigroup analysis. *Front. Educ.*, 6, 1-16. https://doi:10.3389/feduc.2021.783087
Sherif, J. P. M. N., & Amudha, R. (2025). Effectiveness of e-learning among higher education students: A literature review. *International Journal of Research in Management, 7*(1), 129-135. https://doi.org/10.33545/26648792.2025.v7.i1b.274
Shneor, R., & Munimb, Z. H. (2019). Reward crowdfunding contribution as planned behaviour: An extended framework. *Journal of Business Research, 103*, 56–70.
Sitar-Taut, D. A., & Mican, D. (2021). Mobile learning acceptance and use in higher education during social distancing circumstances: An expansion and customisation of UTAUT2. *Online Information Review, 45*(5), 1000–1019. https://doi.org/10.1108/OIR-01-2021-0017
Strzelecki, A. (2023). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education, 49*(2), 1-23. https://doi.org/10.1007/s10755-023-09686-1
Tarhini, A., Alalwan, A. A., Shammout, A. B., & Al-Badi, A. (2019). An analysis of the factors affecting mobile commerce adoption in developing countries: Towards an integrated model. *Review of International Business and Strategy, 29*(3), 157-179.
Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics and Data Analysis*. *48*(1), 159–205.
Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments, 10*(1), 15. https://doi.org/10.1186/ s40561-023-00237-x
Twum, K. K., Ofori, D., Keney, G., & Korang-Yeboah, B. (2022). Using the UTAUT, personal innovativeness and perceived financial cost to examine student's intention to use E-learning. *Journal of Science and Technology Policy Management, 13*(3), 713–737. https://doi.org/10.1108/JSTPM-12-2020-0168
Venkatesh, V., Thong, J., & Xu, X. (2012). Consumer acceptance and

use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478.

Wang, M., Ran, W., Liao, J., & Yang, S. J. H. (2010). A performance-oriented approach to E-Learning in the workplace. *Educational Technology & Society, 13*(4), 167–179. https://www.jstor.org/stable/jeductechsoci.13.4.167

Weizenbaum, J. (1966). ELIZA—a computer program for the study of natural language communication between man and machine. *Communications of the ACM, 9*(1), 36–45. https:// doi.org/10.1145/365153.365168

Williamson, B., Macgilchrist, F., & Potter, J. (2023). Re-examining AI, automation and datafication in Education. *Learning, Media and Technology, 48*(1), 1–5. https://doi.org/10. 1080/17439884.2023.2167830

Wong, K. K.-K. (2013). Partial Least Squares Structural Equation Modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin, 24*(1), 1–33. http://marketing-bulletin.massey.ac.nz

Yu, C.-W., Chao, C.-M., Chang, C.-F., Chen, R.-J., Chen, P.-C., & Liu, Y.-X. (2021). Exploring behavioral intention to use a mobile health education website: An extension of the UTAUT 2 model. SAGE Open, 11(4), 1–12. https://doi.org/10.1177/21582440211055721