Journal of Education and Practice
ISSN 2222-1735 (Paper) ISSN 2222-288X (Online)
Vol.16, No.10, 2025

Does Internet Experience Influence E-Learning Adoption? A Study of Kenyan Undergraduate University Students

Daniel Makini Getuno [1*] Ezra Kiprono Maritim[2] Fred Nyabuti Keraro[3]
1,2,3 Faculty of Education/E-Campus, Egerton University, P.O. BOX 536, Egerton 20115, Kenya
* E-mail of the corresponding author: dmakini@egerton.ac.ke

Abstract
E-learning adoption in Kenya's higher education remains underexplored, particularly regarding student factors influencing its uptake. This is because of a skewed focus on Information and Communication Technology (ICT) infrastructure at these institutions. This study examined the moderating role of internet experience (IXP) on the relationship between performance expectancy (PE) and e-learning adoption (ELA), encompassing both behavioural intention (BI) and actual usage behaviour (UB). By studying new undergraduate students without prior e-learning experience, the research identified key factors affecting initial adoption, readiness, and barriers. A cross-sectional survey, based on a modified Unified Theory of Acceptance and Use of Technology (UTAUT), collected data from 388 students using a Likert-type questionnaire. Partial Least Squares Structural Equation Modelling (PLS-SEM) and PLS-Multi Group Analysis (MGA) revealed that IXP does not moderate PE → BI but does moderate BI → UB. Despite mixed findings, IXP remains a crucial moderating factor in e-learning adoption among undergraduate students in developing countries.
Keywords: Performance Expectancy, Behavioural Intention, Actual Use Behaviour, E-learning Adoption, Moderating Effect, Internet Experience, Higher Education, University

DOI: 10.7176/JEP/16-10-04
Publication date: September 30th 2025

1. Introduction

Universities worldwide have set up e-learning infrastructure and systems and embarked on offering their study programmes through e-learning. However, in developing countries, e-learning is not succeeding the way it is expected, particularly regarding students' intention, actual use of e-learning and by extension, persistence with e-learning. At the same time, the uptake of e-learning in Africa remains low (Namatovu & Arinaitwe, 2024). Although the antecedents of e-learning adoption are known, the moderating effects of internet experience is not. This study therefore sought to confirm the efficacy of the Performance Expectancy (PE) antecedent of e-learning and then determine the moderating effect of Internet Experience (IXP) on two outcomes of e-learning adoption; Behavioural Intention (BI) and Use Behaviour (UB).

1.1 E-learning in Kenya's Universities

There are 78 universities in Kenya, divided into six categories, namely; 35 public chartered, 25 private chartered, eight with letters of interim authority, three constituent colleges of private universities, and two specialized degree awarding institutions. E-learning in Kenyan universities is shaped by national policy shifts and other influences related to internationalization and modernization of education. From a policy perspective, the appointment of the Presidential Working Party on Education Reform (PWPER) in 2022 and the subsequent establishment of the Open University of Kenya (OUK) in 2023 (Naliaka, 2023) lay the foundation for the mainstreaming of e-learning in higher education. From the internationalization perspective, public universities in Kenya have tended to collaborate with international institutions to offer e-learning programmes.

Recent e-learning adoption studies in Kenya collectively highlight the progress, challenges, and strategies associated with e-learning adoption in a broad manner (Richard, 2024; Kirongo et al., 2023; Mmbwanga & Etakwa, 2024). Therefore, the establishment of e-learning in public universities in Kenya appears to be unsupported by specific research focusing on the students' e-learning adoption behaviours.

1.2 Objectives

The objectives of the study were to establish:

i. the relationship between PE and BI to adopt of e-learning
ii. the relationship between BI and UB of e-learning
iii. the moderating effect of IXP on the relationship PE → BI
iv. the moderating effect of IXP on the relationship BI → UB

1.3 Hypotheses

The study tested the null hypotheses; there is no statistically significant:

Ho_1: relationship between PE and BI to adopt of e-learning
Ho_2: relationship between BI and UB of e-learning
Ho_3: moderating effect of IXP on the relationship PE → BI
Ho_4: moderating effect of IXP on the relationship BI → UB

1.4 Assumption

This study was carried out based on the assumption that the differences in the type of e-learning (fully on-line, blended, or use of e-learning as supplementary learning material) does not affect the results of the study.

2. Literature Review

2.1 Internet Experience as Moderator of E-learning Adoption

E-learning in higher education is predominantly internet-based (Allen & Seaman, 2017; Means, et al., 2013; Moore, et al., 2011). Therefore, experience with the internet becomes a pre-requisite for using e-learning with less effort and time (Al-Harbi, 2010). Moreover, learners' success rates in e-learning depend on their competencies in operating computer systems as well as their internet skills (Author & Author, 2018). This means that experience (or lack thereof) with the internet and IT has an influence on e-learning adoption.

2.2 Implementation of E-learning in Kenyan Universities

Teaching and learning at university level in Kenya is receiving unprecedented attention in recent years (Jowi et al., n.d.). This is manifested through prospective learners getting more inquisitive about the nature of study programmes in universities, their duration and fee payable because they see themselves as paying customers (Álvarez-González et al, 2017). Some public universities have implemented e-learning as a repository where class notes and students' assessment records are kept (Barasa & Choti, 2015; Makokha & Mutisya, 2016). In other universities e-learning is implemented in a blended format where the content held in a Learning Management System (LMS) is augmented with tutors actively facilitating learning through online chats and discussion forums (Gikandi & Morrow, 2016; Mwalumbwe & Mtebe, 2017; Vaughan et al., 2013).

2.3 Theoretical Framework

This study used a modified form of the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical framework. The UTAUT was developed through the review, mapping and integration of eight theories and models (Venkatesh et al., 2003). Despite the fact that its use in education appears to be far and wide apart, it is the preferred theory for use in this study because of its explanatory power in technology adoption studies worldwide (Al-Emran et al., 2021; Dwivedi et al., 2020; Venkatesh et al., 2021). The key terms in UTAUT are "acceptance" and "use" of technology. Whereas "use" is applied in its ordinary context in this study, "acceptance" is not. Dillon (2001), defines acceptance of technology as the "demonstrable willingness" to employ information technology in performing a task. In this study, "willingness" is synonymous to "acceptance" and refers to a person's intention to use IT. Taken together, "acceptance" and "use" imply adoption (Al-Maroof et al., 2021; Al-Okaily et al., 2020; Tarhini et al., 2022).

2.4 Conceptual Framework

The conceptual framework of the study is shown in Figure 1.

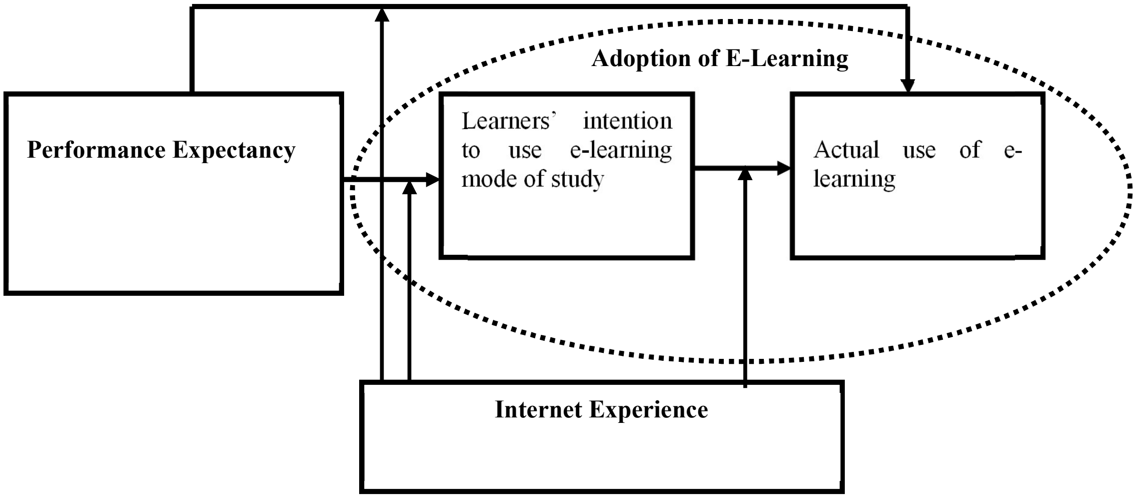

Figure 1: Conceptual Framework

The UTAUT framework identifies four key antecedents influencing technology adoption: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). Among these, PE - the degree to which an individual believes that using e-learning will enhance their academic or professional performance - stands out as the most critical factor driving adoption in higher education. Therefore, our conceptual framework postulates that PE is a determinant of e-learning adoption (ELA), where ELA is represented by both intention and actual use behaviour of e-learning respectively. Further, Higher education institutions must account for varying levels of internet experience among students when implementing e-learning strategies to ensure equitable access and maximize student success. Moreover, internet experience influences both the learners' intention to adopt e-learning as well as the actual use of e-learning. The learners' intention to use e-learning is premised on a future state in which a learner believes that certain conditions will be met, namely; usefulness of e-learning, quick accomplishment of tasks, increased academic productivity and increased chances of getting a high grade.

3. Methodology

A cross-sectional survey research design was used in this study. In this type of survey, data is collected from individuals at once. According to Thomas (2022), the advantages of the cross-sectional survey include: quick and accurate data collection and allows the investigator to gather information from a large population and compare differences between groups.

3.1 Population

We define the general, target and accessible population for this study. The general population of this study comprised of all new undergraduate students registered in all online study programmes in Kenya's public universities. The target population included new undergraduate university students enrolled in any e-learning degree programme, above 18 years of age, male, female, with or without experience in the use of internet. By focusing on new undergraduate students without prior exposure to e-learning, researchers can gain valuable insights into the factors influencing initial adoption, readiness levels, and potential barriers, which are essential for designing effective e-learning strategies. Finally, the accessible population included those in the target population who were available, willing and capable of participating in the study. These were students who were available and could be reached physically in the university at the end of the semester.

3.2 Sampling Procedures and Sample Size

In choosing the sample, three public universities were selected using stratified random sampling. Stratification was based on categorization of the university depending on the number of students; very large (with more than 50,000 students); large (with between 30,000 and 49,999 students) and medium (with between 15,000 and 29,999 students). The universities with below 15,000 students were not considered in this study because most of them were recently established (ROK, 2023) and had not begun offering e-learning courses in a sustainable manner. After selecting one university from each category (stratification), the sample size was determined using the formula specified by Cochran (1963):

$$n = \frac{z^2pq}{e^2}$$

Where,

n = sample size,
p = estimated proportion of the population which has the attribute in question (variance)
q = 1- p,
z = the standard value of z (z-score) associated with the confidence level ($\alpha = 0.10$),
e = the acceptable margin of error (precision).

The study desired a 90 percent confidence level and 5 percent (or 0.05) precision level. The associated z score for this level of precision is 1.65. In addition, since the researcher did not have sufficient and accurate information about the subjects of the study, an assumption was made that half the number of undergraduate students (or 50 percent) have adopted e-learning. Therefore, for a conservative variance of 0.5 (p = 0.5), then the calculated sample is given by:

$$n = \frac{(1.65)^2(0.5)(0.5)}{(0.05)^2}$$
$$= 272$$

During the survey, however, the actual sample was 388 after data cleaning. Table 1 shows the number of copies of the questionnaire issued, returned, and analyzed; and the sample representation per university.

Table 1
Sample Representation Per University

	Copies of Questionnaire Issued	Copies of Questionnaire Returned	Copies of Questionnaire Analyzed	Per Cent of Sample
KU	350	255	245	63.14
EGU	120	57	52	13.40
JKUAT	150	98	91	23.46
Total	520	410	388	100.00

Table 1 shows that 520 copies of the questionnaire were issued, while 410 were returned, and 388 were analyzed. Since it was not possible to estimate beforehand the non-return rate or the number of copies of incomplete questionnaire during the data collection and analysis respectively, a higher estimate was made to compensate for uncertainty arising from incomplete copies of the questionnaire or those containing ambiguous responses. The actual sample in the study was above the required threshold obtained through calculation and was therefore considered appropriate for the study. This is acceptable because a higher sample means better the inference of sample statistics to the population from which the sample is drawn. The implication for using a larger sample is that it leads to a more precise estimation of the population parameters (Asiamah et al., 2017).

The number of copies of questionnaire analyzed per university as a percentage of all the analyzed copies of the questionnaire in the study was computed and is equal to the percentage sample representation per university. Thus, Kenyatta University (KU) had the highest sample representation, then Jomo Kenyatta University of Agriculture and Technology (JKUAT) and lastly, Egerton University (EGU). Interestingly, the sample size representation per university is somewhat proportional to the number of students in each university (Republic of Kenya [ROK], 2023). Table 2 shows the number of undergraduate students in the sampled universities disaggregated by gender from 2019/2020 to 2022/2023 academic years.

Table 2
Undergraduate Students in the Sampled Universities

Academic Year	University	Number of Undergraduate Students			Percent
		Male	Female	Total	%
2019/2020	KU	47,222	25,727	72,949	58.9
	JKUAT	19,554	14,616	34,170	27.5
	EGU	9,710	7,136	16,846	13.6
2020/2021	KU	38,425	31,227	69,652	56.0
	JKUAT	21,740	15,004	36,744	29.5
	EGU	10,340	7,649	17,989	14.5
2021/2022	KU	38,357	31,866	70,223	58.1
	JKUAT	18,243	13,469	31,712	26.2
	EGU	10,967	7,982	18,949	15.7
2022/2023*	KU	37,889	30,016	67,905	55.8
	JKUAT	19,856	14,664	34,520	28.4
	EGU	11,130	8,132	19,262	15.8

Source: R.O.K. (2023, p.339-340)
* Projected

3.3 Instrumentation
The Students' E-Learning Adoption Questionnaire (SeLAQ) was used for data collection. It was pilot-tested with 38 first-year e-learning students in JKUAT at the end of the semester. The SeLAQ had two sections; A and B in which the items in section A sought demographic information relating to the students, namely; the university where the student was registered, gender, age, internet experience, and academic programme. Section B consisted of seven-point Likert type statements with a score range from 1 to 7, where, 1: Strongly Disagree, 2: Disagree, 3: Somewhat disagree, 4: Neither agree nor disagree, 5: Somewhat agree, 6: Agree; and 7: Strongly Agree. The items in section B of the SeLAQ covered constructs representing antecedents of BI and UB.

3.4 Validity and Reliability
The validity of a data collection instrument is the degree of its "trustworthiness" in measuring a particular construct. The SmartPLS software for Windows was used to estimate the reliability of SeLAQ and returned a reliability coefficient of 0.78. A reliability coefficient above 0.7 is considered acceptable for the instrument (Santos & Reynaldo, 1999), and therefore suitable for use in the study. According to UCLA (2016), the Cronbach's alpha coefficient is a measure of internal consistency, or how closely related a set of items are as a group. It is a function of the number of scale or test items and the average inter-correlation among the items. Thus, a high value of Cronbach – alpha implies that the average inter-item correlation is also high.

3.5 Data Analysis
Although we collected demographic data, some of it was not used in the analysis. In this case, with the exception of internet experience, the rest of the data on the university where the student was registered, gender, age, and academic programme were not included in the analysis. This is because, collecting demographic data without using it in analysis is a valuable practice that enhances research credibility, ensures sample representation, supports ethical transparency, and allows for future analysis. While the data may not be immediately relevant to statistical findings, its presence strengthens the study's overall rigor and applicability.

The hypotheses of the study were tested using inferential statistics employing the Partial Least Squares, Structural Equation Modelling (PLS-SEM) technique as proposed by Ringle et al. (2005), Wong (2010), and Wong (2013). The software used to run the analysis was the SmartPLS (Version 3.2 for Windows). This technique was preferred because it is suitable for small samples (below 500). This is despite the fact that the most common method used is usually Linear Structural Relations (LISREL) and Analysis of Moment Structures (AMOS) on the Statistical Package for Social Scientists (SPSS). The later requires a minimum sample of 500 (Wong, 2010) in order to generate stable estimation of the prediction parameters. Similarly, the data set for use in both cases has to be normally distributed, or else standard errors must be used with care when the assumptions of multivariate normality are not met. In this study, the data set was normally distributed and the assumptions of multivariate normality were met. This approach has gained prominence in recent years given that Tarhini et al. (2014), Tarhini et al. (2017), and; Samsudeen and Mohamed (2019) used the PLS-SEM approach to analyse data on factors influencing university students' adoption of e-learning in England, the United Kingdom (UK) and Sri Lanka respectively. Further analysis of the effect of the moderators on e-learning adoption was done using PLS-Multigroup analysis. In order to successfully analyze the data using PLS-SEM, it is imperative to understand the model structure.

According to Wong (2013), SEM has two sub-models, namely; the inner model (known as the structural model) and the outer model (known as the measurement model). Figure 2 shows the inner model represented by the constructs PE, BI and UB while the outer model shows their respective indicators.

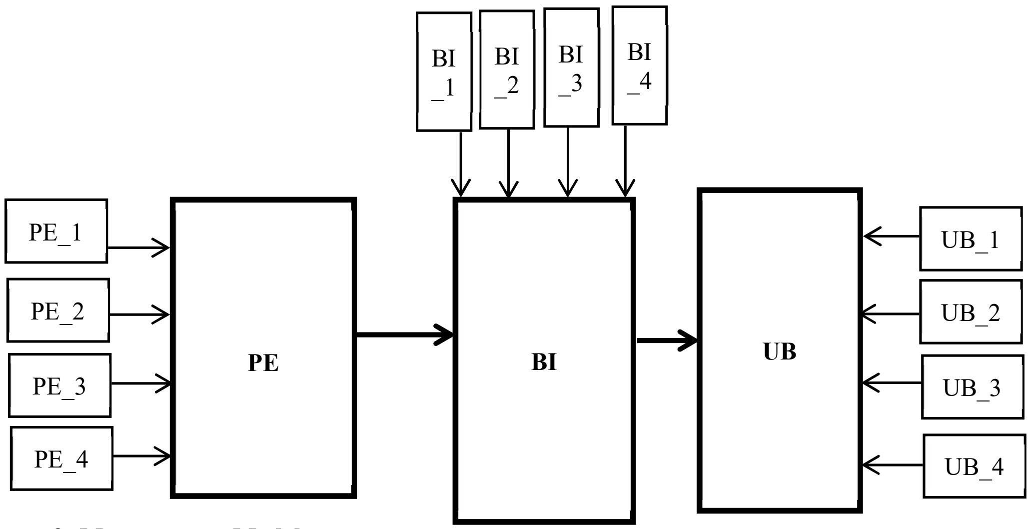

Figure 2: Measurement Model

Figure 2 shows that the exogeneous variable, PE is represented by four indicators, PE_1, PE_2, PE_3 and PE_4. The variable BI, which is both exogeneous (on account of being influenced by PE) and endogenous (on account of influencing UB) is represented by four indicators, BI_1, BI_2, BI_3 and BI_4. Lastly, the endogenous variable, UB is represented by four indicators, UB_1, UB_2, UB_3 and UB_4. Table 3 shows the latent variables and their corresponding indicators and labels that were used for analysis.

Table 3

Latent Variables, Indicators and their Explanation

Latent Variable	Label	Indicators	Explanation
Performance Expectancy	PE		
	PE_1	Usefulness of e-learning	The e-learning mode of study is useful for the degree programme
	PE_2	Quick accomplishment of tasks	The e-learning mode of study enables accomplishment tasks more quickly.
	PE_3	Increased academic productivity	The e-learning mode of study has contributed to increased academic productivity.
	PE_4	Increased chances of getting a high grade	The e-learning mode of study has increased the chances of getting a high grade
Behavioural Intention	BI		
	BI_1	Improved academic productivity	The intention to use the e-learning mode of study in future if it will improve my academic productivity.
	BI_2	Ease of use	Intention to use the e-learning mode of study in future if it would be easy to use.
	BI_3	Approval by role models	The intention to use the e-learning mode of study in future if my role models approve of it.
	BI_4	Availability of assistance	The intention to use the e-learning mode of study in future if someone is available to assist with any difficulties with e-learning
Actual Use Behaviour	UB		
	UB_1	Login	Frequency of login onto the e-learning platform

Latent Variable	Label	Indicators	Explanation
			since admission into university
	UB_2	Reading	Frequency of reading the online learning materials since admission into university
	UB_3	Downloading	Frequency of downloading the online learning materials since admission into university
	UB_4	Printing	Frequency of printing the online learning materials since admission into university

4. Findings

Before testing the hypotheses, the Discriminant Validity (DV) test was carried out to verify whether the data used in the study are reliable and valid for testing the hypotheses. The assessment of DV is a mandatory requirement in any research that involves latent variables for the prevention of multicollinearity issues (Hamid et al., 2017). In this study, DV was assessed using the Cross Loadings Test criterion. After this confirmatory test, the results of testing the hypotheses as well as the moderating effect of internet experience on the relationship between PE and ELA is presented.

Table 4
Cross Loading Test for Predictor and Outcome Constructs

Indicators	PE	BI	UB
PE_1	**(0.77)**	0.10	-0.05
PE_2	**(0.77)**	0.05	-0.08
PE_3	**(0.75)**	-0.15	-0.16
PE_4	**(0.72)**	-0.00	0.29
BI_1	0.11	**(0.87)**	-0.17
BI_2	-0.13	**(0.81)**	-0.04
BI_4	0.01	**(0.69)**	0.26
UB_1	0.29	-0.03	**(0.66)**
UB_2	0.17	0.17	**(0.78)**
UB_3	-0.21	-0.06	**(0.80)**
UB_4	-0.20	-0.09	**(0.76)**

Note. Values in bold and parentheses show the intersection of indicators and the construct

The results in Table 4 indicate that all the values of the cross loadings (shown in bold) exceeded the suggested threshold of 0.50 (Hair et al., 2017). Thus, the data used in the study are reliable and valid to prove the hypotheses and contributed satisfactorily to the indicators of the PE construct. In addition, the individual constructs' indicator's outer loadings were higher than all its cross-loadings with other constructs, indicating that DV was achieved (Henseler et al., 2015). However, the Table shows that the indicators BI_3 (approval by role models) has been dropped from the resulting model and therefore has no role in determining the measurement model. This means that the ensuing measurement model has three indicators for the latent variable BI while the other latent variables (PE, and UB) have all their four indicators retained in the measurement model.

4.1 The Relationship Between PE and BI

Descriptive statistics for the indicators of PE are presented in Table 5. It shows the mean (*m*), standard deviation (*SD*) and the percentage scores of each indicator on a scale of 1 - 7.

Table 5
Descriptive Statistics for PE

Items	Mean	S.D.	Percent Scores						
			1	2	3	4	5	6	7
1. The e-learning mode of study is useful for the degree programme I am pursuing.	6.45	1.11	1.00	0.00	3.10	3.10	6.20	14.40	72.20
2. Using the e-learning mode of study enables me to accomplish tasks more quickly.	5.89	1.61	4.10	3.10	2.10	5.20	14.40	18.60	52.60
3. Using the e-learning mode of study has increased my academic productivity.	5.80	1.52	4.10	0.00	4.10	7.20	18.60	19.60	46.40
4. Using the e-learning mode of study has increased my chances of getting a high grade.	5.65	1.61	4.10	0.00	8.20	9.30	13.40	22.70	42.30

n = 388

The tests of significance were performed above the 90% level of confidence ($p < 0.10$). Table 6 shows the effect sizes, standard errors (S.E), t-values, p-values and the decision for the path relationship, PE→BI, emanating from the interpretation of these values.

Table 6
Path Coefficients and Structural Model Assessment for PE → BI

Path Relationship/Hypothesis	Effect Size	SE	t-values	p-values	Decision
PE→BI	0.15	0.05	3.16	.002*	Supported

Note. SE denotes standard error of mean
* $p \leq .10$

The results in Table 6 indicate that there was a significant positive relationship between PE and BI ($\beta = .15$, $t = 3.16$, $p = .002$) above the 90% level of confidence ($p<0.01$). Therefore, according to this study, PE is a significant predictor of BI and the hypothesis that 'there is no statistically significant relationship between PE and BI', was rejected; thus, supporting the significance of the relationship, PE→BI.

4.2 The Relationship Between BI and UB

The descriptive statistics for the indicators of BI are presented in Table 7. It shows the mean (*m*), standard deviation (*SD*) and the percentage scores of each indicator on a scale of 1 - 7.

Table 7
Descriptive Statistics for BI

Item	Mean	S.D.	Percent Scores						
			1	2	3	4	5	6	7
1. I intend to use the e-learning mode of study in the next three months if it will improve my academic productivity.	6.47	0.91	1.00	0.00	0.00	13.40	0.00	12.40	70.10
2. I intend to use the e-learning mode of study in the next three months if it would be easy to use.	6.34	1.24	2.10	1.00	0.00	6.20	5.20	19.60	66.00
3. I intend to use the e-learning mode of study in the next three months if my role models approve of it.	5.38	2.15	14.40	2.10	2.10	6.20	12.40	13.40	49.50
4. I intend to use the e-learning mode of study in the next three months if someone is available to assist me with any difficulties with e-learning	6.38	1.32	3.10	1.00	1.00	3.10	3.10	18.60	70.10

n = 388

The tests of significance were performed above the 90% level of confidence ($p < 0.10$). Table 8 shows the path relationships, effect sizes, standard errors (S.E), t-values, p-values and the decision (supported or not supported) emanating from the interpretation of these values.

Table 8
Path Coefficients and Structural Model Assessment for BI→UB

Path Relationship/Hypothesis	Effect Size	SE	t-values	p-values	Decision
BI→UB	0.08	0.04	1.83	.067*	Supported

Note. SE denotes standard error of mean
* $p \leq .10$

The results in Table 8 show a significant positive relationship between BI and UB ($\beta = 0.083$, $t = 1.83$, $p = .067$*) above the 90% level of confidence ($p<0.01$). Therefore, according to this study, BI is a significant predictor of UB. Thus, the hypothesis that 'there is no statistically significant relationship between BI and UB' was rejected; thus, supporting the significance of the relationship BI →UB.

4.3 Descriptive Statistics for UB

Since UB is the ultimate outcome of this study, it was not possible to determine its relationship with some other subsequent outcome as was done in the previous sections. Therefore, the only way to study UB was to determine the relative contribution of its indicators to the latent variable. This is important so that the full picture of the variables can be presented Table 9 presents the descriptive statistics for the indicators of UB. It shows the mean (*m*), standard deviation (*SD*) and the percentage scores of each indicator on a scale of 1 - 7.

Table 9
Descriptive Statistics for UB

Items	Mean	S.D.	Percent Scores						
			1	2	3	4	5	6	7
1. I have logged onto the e-learning platform a lot since my admission into this university	6.01	1.60	4.10	3.10	1.00	5.20	13.40	12.40	60.80
2. I have read the online learning materials a lot since my admission into this university	5.64	1.66	5.20	1.00	5.20	7.20	21.60	14.40	45.40
3. I have downloaded the online learning materials a lot since my admission into this university	5.09	2.02	9.30	6.20	7.20	10.30	15.50	13.40	38.10
4. I have printed the online learning materials a lot since my admission into this university	4.20	2.20	20.6	7.20	9.30	14.40	13.40	13.40	21.60

(n = 388)

4.4 The Moderating Effect of IXP on the Relationship PE → BI
Table 10 shows the results of the moderating effect of internet experience on the relationship between PE and BI using MGA. It shows the path coefficients and p-values for each category as well as the t- and p- values for the total effects.

Table 10
Moderation Effects of Internet Experience on the Relationship: PE→BI

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
IXP	Inexp	Exp	Inexp	Exp	Inexp + Exp	Inexp + Exp
	0.44	0.06	.001*	.211	1.26	.105

* $p \leq .10$

The results in Table 10 show that IXP is not a significant moderator of the relationship between PE and BI (p = 0.105). The moderation effect is however, significant in favour of inexperienced internet users compared to the experienced internet users (p = 0.001* for inexperienced internet users and p = 0.211 for experienced internet users). Thus, while the relationship between PE and BI is not significantly moderated by IXP, the moderating effect is stronger for inexperienced internet users than it is for experienced internet users.

4.5 The Moderating Effect of IXP on the Relationship BI → UB
Table 11 shows the results of the moderating effect of IXP on the relationship between BI and UB using MGA. It shows the path coefficients and p-values for each category as well as the t- and p- values for the total effects.

Table 11
Moderation Effects of Internet Experience on the Relationship: BI→UB

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
IXP	Inexp	Exp	Inexp	Exp	Inexp + Exp	Inexp + Exp
	0.32	-0.33	.001*	.001*	2.11	.017*

* $p \leq .10$

The results in Table 11 show that IXP is a significant moderator of the relationship between BI and UB (p = 0.017*).

The moderation effects are significant, but not different for both inexperienced and experienced internet users (p = 0.001*). Thus, the relationship between BI and UB is moderated by IXP; the moderating effect being equally strong for students at all levels of IXP (experienced and inexperienced).

5. Discussion

The study results indicate that PE is a key predictor of e-learning adoption, where the influence of PE on the variance of BI at 15.2% is stronger compared to the influence of BI on,UB at 8.3%. While IXP moderates the relationship BI → UB it does not moderate the relationship PE → BI. At the same time, the moderation effect for the relationship BI → UB is the same for both experienced and inexperienced internet users. These findings align with Abbad (2021) and Bellaaj et al. (2015), who found that BI positively influences the use of e-learning systems in developing countries and that internet experience strengthens the effect of PE on BI. However, the widely held notion of a strong direct relationship between intention and actual behavior (Ajzen & Madden, 1986; Davis, 1989; Marandu et al., 2019) is challenged because, for intention to result into actual behaviour, the influence of IXP as a moderator becomes imperative.

6. Conclusion

This study uncovers a paradox in e-learning adoption: the two core elements—intention and actual use—are shaped differently by students' internet experience (IXP). While IXP does not affect students' intention to use e-learning, it does influence their actual use, regardless of how long they have been online. This means Kenyan university students are confident in trying e-learning systems even with limited hands-on experience. To boost adoption, universities should go beyond infrastructure—strengthening ICT training, providing resources, and offering comprehensive learner support. The findings shift the focus from building technological infrastructure for learning to understanding and influencing learner behaviour.

References

Abbad, M.M.M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and Information Technologies, 26,* 7205 - 7224. https://doi.org/10.1007/s10639-021-10573-5

Ajzen, I., & Madden, T. J. (1986). Prediction of goal-directed behaviour: Attitudes, intentions, and perceived behavioural control. *Journal of Experimental Social Psychology, 22*(5), 453–474. https://doi.org/10.1016/0022-1031(86)90045-4

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2021). Technology acceptance model in M-learning context: A systematic review. *Computers & Education, 160*, 104052. https://doi.org/10.1016/j.compedu.2020.104052

Al-Harbi, K.R.A. (2010). *Investigating factors influencing the adoption of e-learning: Saudi students' perspective.* [Doctoral dissertation]. University of Leicester, UK.

Allen, I. E., & Seaman, J. (2017). Digital learning compass: Distance education enrollment report 2017. Babson Survey Research Group. https://eric.ed.gov/?id=ED580868

Al-Maroof, R. A. S., Al-Qaysi, N. M., & Salloum, S. A. (2021). The acceptance and use of Google Classroom during COVID-19 pandemic: A multiple country study. *International Journal of Educational Management, 35*(6), 1216–1233. https://doi.org/10.1108/IJEM-09-2020-0588

Al-Okaily, M., Alqudah, H., Matar, A., Lutfi, A., & Taamneh, A. (2020). Assessing the relationship between digital transformation and technology acceptance model: Mediating effect of e-learning quality during COVID-19. *Sustainability, 12*(21), 8765. https://doi.org/10.3390/su12218765

Álvarez-González, P., López-Miguens, M.J. and Caballero, G. (2017). Perceived employability in university students: developing an integrated model. *Career Development International*, *22* (3), 280-299. https://doi.org/10.1108/CDI-08-2016-0135

Asiamah, N., Mensah, H. K., & Oteng-Abayie, E. F. (2017). Do larger samples really lead to more precise estimates? A simulation study. *American Journal of Educational Research, 5*(1), 9-17. doi: 10.12691/education-5-1-2

Author, & Author. (2018). Deleted for Peer Review

Barasa, J. M., & Choti, T. (2015). Adoption of e-learning in Kenyan universities: The case of Jomo Kenyatta University of Agriculture and Technology. *Journal of Education and Practice, 6*(18), 53–60. Retrieved from https://www.iiste.org/Journals/index.php/JEP/article/view/24347

Bellaaj, M., Zekri, I., & Albugami, M. (2015). The continued use of e-learning system: An empirical investigation using UTAUT model at the University of Tabuk. *Journal of Theoretical and Applied Information Technology, 72*(2), 464-474.

Chao, C. (2019). Factors determining the behavioral intention to use mobile learning: an application and extension of the UTAUT model. *Frontiers in Psychology, 10*, Article1652. https://doi.org.10.3389/fpsyg.2019.01652

Cochran, W.G. (1963). *Sampling Technique.* (2nd ed.). John Wiley and Sons Inc., New York.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly*, *13*(3), 319 -340. doi:10.2307/249008

Dillon, A. (2001). *User Acceptance of Information Technology. Encyclopaedia of Human Factors and Ergonomics.* Taylor and Francis.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2020). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers, 22*(3), 719-734. https://doi.org/10.1007/s10796-019-09978-1

Gikandi, J. W., & Morrow, D. (2016). Towards learner-centred pedagogies in open, distance, and e-learning environments: The case of interactive online learning designs in Kenyan universities. *International Review of Research in Open and Distributed Learning, 17*(2), 167–190. https://doi.org/10.19173/irrodl.v17i2.2170

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.

Hamid, A. Sami, W., & Sidek, M. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker Criterion versus HTMT Criterion. *Journal of Physics: Conference Series, 890,* Article ID: 012163. https://doi.org/10.1088/1742-6596/890/1/012163

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Academy of Marketing Science,43,*115-135. https://doi.org/10.1007/s11747-014-0403-8

Jowi, J. O., Obamba, M., Sehoole, C., Barifaijo, M., Oanda, O., & Alabi, G. (n.d.). *Governance of higher education, research and innovation in Ghana, Kenya and Uganda.* OECD.

Kirongo, A. C., Bundi, D., & Kitaria, D. T. (2023). Use of EdTech in support of remote learning during COVID-19 pandemic in Kenya. *Journal of the Kenya National Commission for UNESCO*, 2(1). Retrieved from https://journals.unesco.go.ke/index.php/jknatcom/article/view/14

Makokha, G. L., & Mutisya, D. N. (2016). Status of e-learning in public universities in Kenya. *The International Review of Research in Open and Distributed Learning, 17*(3), 341–359. https://doi.org/10.19173/irrodl.v17i3.2234

Marandu, E., Makudza, F., & Ngwenya, S. (2019). Predicting students' intention and actual use of e-learning using the Technology Acceptance Model: A case from Zimbabwe. *International Journal of Learning, Teaching and Educational Research*. *18*(1),110-127. https://doi.org.10.26803/ijlter.18.6.7

Means, B., Toyama, Y., Murphy, R., & Bakia, M. (2013). The effectiveness of online and blended learning: A meta-analysis of the empirical literature. *Teachers College Record, 115*(3), 1-47. https://doi.org/10.1177/016146811311500307

Mmbwanga, F., & Etakwa, E. (2024). The reality of eLearning in Kenyan universities. *Journal of the Kenya National Commission for UNESCO*, 5(1).

Moore, J. L., Dickson-Deane, C., & Galyen, K. (2011). e-Learning, online learning, and distance learning environments: Are they the same? *The Internet and Higher Education, 14*(2), 129-135. https://doi.org/10.1016/j.iheduc.2010.10.001

Mwalumbwe, I., & Mtebe, J. S. (2017). Using learning analytics to predict students' performance in Moodle learning management system: A case of Kenyatta University, Kenya. *The Electronic Journal of Information Systems in Developing Countries, 79*(1), 1–13. https://doi.org/10.1002/j.1681-4835.2017.tb00577.x

Naliaka, F. (2023, August 3). President Ruto Awards Charter to Open University of Kenya. *Citizen Digital.* https://www.citizen.digital/news/president-ruto-awards-charter-to-open-university-of-kenya-n324825

Namatovu, H. K., & Arinaitwe, I. (2024). Student adoption of e-learning at Makerere university during COVID-19: A structural equation modelling based on the unified theory of acceptance and use of technology. *E-Learning and Digital Media,* 0(0). https://doi.org/10.1177/20427530241254537

Republic of Kenya, ROK (2023). *The Economic Survey 2023: Providing, Managing and Promoting Quality Statistics.* Kenya National Bureau of Statistics.

Richard, M. O. (2024). Designing, implementing, and managing e-learning in Kenya: Issues, challenges, and solutions.

Ringle, C., Wende, S., & Will, A. (2005). *SmartPLS 2.0 (Beta).* www.smartpls.de

Samsudeen, S.N., & Mohamed, R. (2019). University students' intention to use e-learning systems: A study of higher educational institutions in Sri Lanka. *Interactive Technology and Smart Education, 16(3),* 219-238. www.emeraldinsight.com/1741-5659.htm

Survey Response Rates: Tips on How to increase your survey response rates (n.d.). *People Pulse.* https://peoplepulse.com/resources/useful-articles/survey-response-rates/
Tarhini, A., Hone, K., & Liu, X. (2014). Measuring the moderating effect of gender and age on e-learning acceptance in England: A structural equation modelling approach for an extended technology acceptance model. *Journal of Educational Computing Research, 51*(2),163-184. https://doi.org/10.2190/EC.51.2.b
Tarhini, A., Hone, K., & Liu, X. (2022). Applying the unified theory of acceptance and use of technology to understand students' behavioral intention to use e-learning: Evidence from the Arab world. *Education and Information Technologies, 27*(4), 5499–5521. https://doi.org/10.1007/s10639-021-10791-9
Tarhini, A., Masa'deh, R.E., Al-Busaidi, K.A., Mohammed, A.B., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: A structural equation modelling approach. *Journal of International Education in Business, 10*(2), 164-182. https://doi.org/10.1108/JIEB-09-2016-0032
Thomas, L. (2022, July 21). Cross-sectional study: Definition, uses and examples. *Scribbr.* https://www.scribbr.com/methodology/cross-sectional-study/
UCLA. (2016). Introduction to SAS. UCLA: Statistical Consulting Group. [Web page]. https://stats.idre.ucla.edu/sas/modules/sas-learning-moduleintroduction-to-the-features-of-sas/
Vaughan, N.D., Cleveland-Innes, M., & Garrison, D.R. (2013). *Teaching in blended learning environments: Creating and sustaining communities of inquiry.* [E-Book]. https://archive.org/details/TeachingInBlendedLearningEnvironments/page/n19/mode/2up?view=theater
Venkatesh, V., Morris, M. G., Davis, B. D., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425 - 478.
Venkatesh, V., Thong, J. Y. L., & Xu, X. (2021). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems, 21*(4), 328-375. https://doi.org/10.17705/1jais.00657
Wong, K. K. (2010). Handling small survey sample size and skewed dataset with partial least square path modelling. *Vue: The Magazine of the Marketing Research and Intelligence Association*, November, p. 20-23.
Wong, K. K. (2013). Partial Least Squares Structural Equation Modelling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin,* 24, Technical Note 1. http://marketing-bulletin.massey.ac.nz

Daniel Makini Getuno (MEd) is a PhD candidate and Lecturer of Educational Technology and Physics Teaching Methods at the Department of Curriculum, Instruction and Educational Management, Egerton university. He is also the Head of Learner/Tutor Support at the E-Campus of Egerton University.

Fred Nyabuti Keraro (PhD) is Professor of Science Education and Director of the School of Distance Learning and at Egerton University. Prof. Keraro holds a PhD in Science Education of Egerton university and teaches Biology Education at the Department of Curriculum, Instruction and Educational Management of Egerton University.

Prof. Ezra Kiprono Maritim (D. Ed) is the Chair of Council of the Open University of Kenya. He is the immediate former Director of the School of Distance Learning at Egerton University. He earned his Doctorate degree in human Development from Havard University in 1979 and until recently, he has been teaching Educational Psychology at the Department of Psychology and Educational Foundations of Egerton University.