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Modelling E-learning Adoption: The Relationship Between Performance Expectancy and Behavioural Intention

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ABSTRACT

This study advances an e-learning adoption model by exploring the link between Performance Expectancy (PE) and Behavioural Intention (BI) to adopt e-learning among undergraduate students in Kenya's public universities. Using the Unified Theory of Acceptance and Use of Technology (UTAUT), data were collected from a sample of 388 respondents through a questionnaire. Analysis was conducted using Partial Least Squares Structural Equation Modelling (PLS-SEM) and Multi-Group Analysis (MGA). Findings indicate that PE significantly predicts e-learning adoption, with this effect moderated by gender, showing equal strength for both male and female students. The study recommends incorporating PE as a key predictor of BI in e-learning adoption models for higher education.

Keywords: *model; e-learning adoption; performance expectancy; behavioural intention; higher education*

INTRODUCTION

According to the Commission for University Education (CUE, 2014), e-learning refers to the use of technology to improve distance education, promote open learning, and make learning more flexible and accessible. According to Rodrigues et al. (2019), e-learning is a personalized, interactive online educational experience that uses digital resources. E-learning adoption begins when an individual or an organization starts to use e-learning technology (Carr, 1999). While there are arguments suggesting a difficulty in finding a commonly agreed upon definition of e-learning, and by extension, e-learning adoption (Arkorful & Abaidoo, 2015; Sener, 2015), it is our position that researchers should be free to provide their own contextual definitions of e-learning. University students hold expectations about e-learning including those about their performance, referred to as Performance Expectancy (PE). Venkatesh et al. (2003) originally defined PE as the degree to which an individual perceives that using a new technological system will enhance their job performance. This definition has received various modifications that are context-specific. For example, Sewandono et al. (2022) defined PE as the degree to which faculty believe that using e-learning will positively impact their research productivity. This study defines PE as the extent to which the e-learning mode of study will help students excel in their academic performance.

To contextualize it further, e-learning can benefit students by allowing them to complete tasks more efficiently, increase their academic output, and improve their chances of achieving higher grades in their courses. According to Venkatesh et al., (2003), PE is theorized to influence the behavioural intention (BI) to adopt e-learning. In this study, BI is characterized by; increased academic productivity, ease of use of e-learning technology, approval by role models, and availability of assistance with e-learning. In this context, the research investigated whether PE is a predictor of BI.

However, according to Kasanjara & Maguya (2024), e-learning is not as successful as anticipated, particularly in terms of students' intention, actual use, and continued use of the e-learning mode of study. Although a number of e-learning adoption models have been developed globally, most of them often fail to adequately explain the adoption of e-learning, particularly in HEIs in developing countries. Given the limitations of existing e-learning models, it is crucial to develop a new model to address these gaps. The partial model developed in this study will contribute to the promotion of e-learning adoption in Kenya's universities.

Objectives

i) To establish the relationship between PE and the BI;
ii) To determine the moderating effect of gender (GND), age (AGE), and internet experience (IXP) on the relationship between the PE and BI.

Hypotheses

H_{01}: There is no statistically significant relationship between PE and BI to adopt e-learning.

H_{02}: There is no statistically significant moderating effect of gender (GND), age (AGE), and internet experience (IXP) on the relationship between the PE and BI.

Assumptions

- the difference in the type of e-learning (fully on-line, blended, e-learning as supplementary learning material) offerings by public universities in Kenya, did not affect the study findings.
- the lecturers teaching online programmes at public universities in Kenya had some basic level of proficiency in delivering online programmes at the undergraduate level.
- public universities with student populations below 15,000 had not matured enough to start offering e-learning in a meaningful manner and therefore could not be included in the study.

Limitations

This study used students' self-reported measures about their intentions to adopt e-learning. This is because, measuring e-learning adoption, particularly in terms of BI is quite a complicated process. For instance, it would be simplistic to measure e-learning adoption through finding the number of hits or logins by students in the university's e-learning platform.

LITERATURE REVIEW

Online Learning in Kenya's Universities

The literature indicates that universities worldwide have embarked on offering their courses electronically through e-learning in order to modernize their programme delivery and cater for the increased demand for university education. In Kenya, the University of Nairobi (UoN) pioneered e-learning in 2004 (Tarus, et al., 2015). This was followed by Kenyatta University in 2005; Jomo Kenyatta University of Agriculture and Technology in 2006; Moi University in 2007, and: Egerton University in 2014. The introduction of e-learning into the academic arena in Kenya is viewed as a disruption of how universities were operating in the past. Furthermore, e-learning has permeated all facets of society in such speed and to an extent that it could be considered the “new-normal”.

Similarly, teaching and learning at the university level in Kenya has been subjected to unprecedented scrutiny in recent years (Jowi et al., n.d.). This is due to an increase in student numbers arising from a quest for further education among the population. Further, Jowi, et.al. (n.d.) argued that Kenya's recent focus on knowledge-based development and the Science-Technology-Innovation model creates the scene for critical evaluation of the existing e-learning infrastructure, identifying its strengths, weaknesses, and areas for improvement. Holmes (2020) identified six types of e-learning: fixed, adaptive, asynchronous, interactive, individual, and collaborative. Fixed e-learning offers the same content to all learners, while adaptive e-learning tailors content to individual preferences. Asynchronous and interactive e-learning allow for flexible learning, while individual and collaborative e-learning focus on independent and group study, respectively.

Public universities in Kenya offer a mix of all the six types and have implemented online learning in different ways. Some have implemented it as a repository where class notes and students’ assessment records are kept. Others have implemented e-learning by means of an active learning platform where content is held in a Learning Management System (LMS), with tutors actively facilitating learning by engaging with students in various ways through online chats and discussion forums.

Performance Expectancy as a Predictor of E-learning adoption

When students join university, they have expectations about the grades they would obtain or the competencies they expect to acquire at the end of their studies. They gauge the worth or usefulness of their academic pursuit from the lens of the grades they can achieve. At the very least they expect to graduate with a “good” grade. This expectation is what is referred to as PE in this study and is defined as the degree to which a student believes that using the e-learning mode of study will help them attain higher grades. This definition was derived from Venkatesh et al. (2003) while referring to e-learning adoption at the workplace. They defined PE as ‘the degree to which an individual believes that the e-learning system use will yield gain in work performance’ (p.447). Further, Venkatesh et al. argued that PE is the strongest predictor of BI, an assertion that will be tested in this study. According to Venkatesh et al. (2003), there are five constructs from the different models and theories that form the UTAUT that pertain to PE. These are: perceived usefulness (from TAM/TAM2 and C-TAM-TPB), extrinsic motivation (from MM), job-fit (from MPCU), relative advantage (from DOI), and outcome expectations (from SCT). Therefore, PE was included in this study as a predictor of undergraduate students’ BI to adopt the e-learning mode of study.

Behavioural Intention as an Outcome

Behavioural Intention, as an outcome of e-learning, has been chosen from a general assumption in human behaviour that action precedes intention. For instance, we assume that students’ intention to engage in e-learning results in them actually preferring and therefore using the e-learning mode of study. However, the theory behind the assertion that behaviour or action is preceded by intention is that humans act rationally and not emotionally – a form of behavioural control (Ajzen, 1991). Tzeng et al. (2022) argued that the relationship between intention and behaviour cannot be predicted directly but is affected by other variables that modify this relationship.

Moderating the Relationship between Predictors and Outcomes

A moderator of e-learning adoption is a characteristic, or an attribute of an individual learner that strengthens or weakens the relationship between a predictor and an individual learner’s adoption of e-learning. The study of moderating effects is important because it helps avoid generalizing the results of a study in two ways: first, to the extent of obscuring differences in the various causal effects, and secondly, treating the population as though it were homogeneous in all respects. Venkatesh et al. (2003) established that the relationship between the predictors of e-learning adoption and the intention to adopt new technology is moderated by gender, age, voluntariness, and experience. In this study, GND, AGE and IXP were presumed to have a moderating effect on the relationship between PE and BI. While a student's academic programme was thought to have a moderating effect on e-learning adoption, there was insufficient support of this presumption from the literature. The next sub-sections provide a description of each of the moderators.

Age as a Moderator of E-learning Adoption

Age is a significant factor to consider in human learning and development. A person's age is likely to dictate his or her disposition to take one course of action and not another – in this case, to adopt e-learning or not. The effect of age in moderating e-learning adoption has been studied in several contexts and has yielded mixed results. For instance, a study by Fleming et al. (2017) found that age does not significantly affect employees' acceptance, satisfaction, or future use of e-learning. Instead, low complexity, authenticity, and technical support are key predictors of future use intentions. In contrast, they found three variables to be useful predictors of intention for future use of organisational e-learning; low complexity, authenticity and technical support. On the contrary, Venkatesh et.al. (2003), found that, age was a significant moderating factor in e-learning adoption.

From the foregoing arguments, we note that age tends to affect e-learning adoption differently depending on the age of the learner. Research by Plude & Hoyer (1985), suggested that as people age, they may find it more challenging to process complex information and allocate attention to job-related tasks. Further, Morris & Venkatesh (2000), argued that age differences are applicable in technology adoption contexts. On a different note, Levy (2016), interestingly proposed that studies of gender differences can be misleading without reference to age. Therefore, in order to confirm the role of age in moderating the relationship between predictors and the learners' BI to adopt e-learning, the study included age as a moderating factor.

Gender as a Moderator of E-learning Adoption

The term "gender" refers to whether an individual is genetically and biologically male or female (Wilson, 2002). Some research studies in technology adoption include gender as a consideration in disaggregating research results (Shaouf & Altaqqi, 2018). In a study comprising 302 Computer Science undergraduate students in one of the public universities in Iraq, Al-Azawei (2019) investigated gender as a moderator of the relationship between e-learning self-efficacy and BI towards adoption of Learning Management Systems (LMS). The findings revealed that gender differences had a slight moderating influence on the relationship between e-learning self-efficacy and LMS acceptance. Specifically, self-efficacy had a more significant impact on the intention to use LMSs among men compared to women

Other studies suggest that women tend to be more sensitive to others' opinions regarding their intention to use new technology (Venkatesh et al., 2000; Venkatesh & Morris 2000). On the other hand, research on gender differences indicated that men tend to be highly task-oriented (Alfaro, 2023; Garvin, 2012) regarding the adoption of new technology. Therefore, PE, which focuses on task accomplishment, is likely to be especially salient to men than women. These studies tend to support the view that gender differences do indeed have an effect on technology adoption. Levy (2016) suggested that studies of gender differences can be misleading without reference to age. Thus, gender effects are driven by psychological phenomena embodied within socially constructed gender roles (Garvin, 2012). As a result, this study explored gender as a moderating variable in e-learning adoption.

Internet Experience as a Moderator of E-learning Adoption

As e-learning offering in higher education is predominantly Internet-based, experience with the Internet affords the learner some knowledge on how to use e-learning with less effort and time (Al-Harbi, 2010). Learners' ability to succeed in e-learning is influenced by their technical skills in computer operation and Internet navigation, as well as their understanding of the substantive subject matter (Kerka, 1999). Furthermore, a study by Morss (1999), cited by Abbad et al. (2009), found that students with greater experience using technology were more likely to utilize a learning management system compared to those with less IT experience.

Moreover, Venkatesh (2003), showed that the relationships among the constructs appearing in the combined Theory of Planned Behaviour and Technology Adoption Model (C-TPB-TAM) were moderated only by user experience. Thus, in designing e-learning systems the user's level of experience with the use of the Internet should be taken into account because less experienced users will tend to rely on different factors compared to experienced ones. This means that experience with the use of the Internet has an influence on e-learning adoption. On this account, this study investigated Internet experience as a moderator of e-learning adoption among undergraduate university students.

Conceptual Framework

The conceptual framework used for this study is shown in Figure1 below. It is derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et.al., 2003). The UTAUT was preferred because of its explanatory power in technology adoption studies worldwide (Al-Harbi, 2010; AlAwadhi & Morris, 2008; Mtebe & Raisamo, 2014, Kolog, 2015; Khater, 2016; Al-Mamary et al.., 2016; Williams et al.,2015; Maldonado et al., 2011).

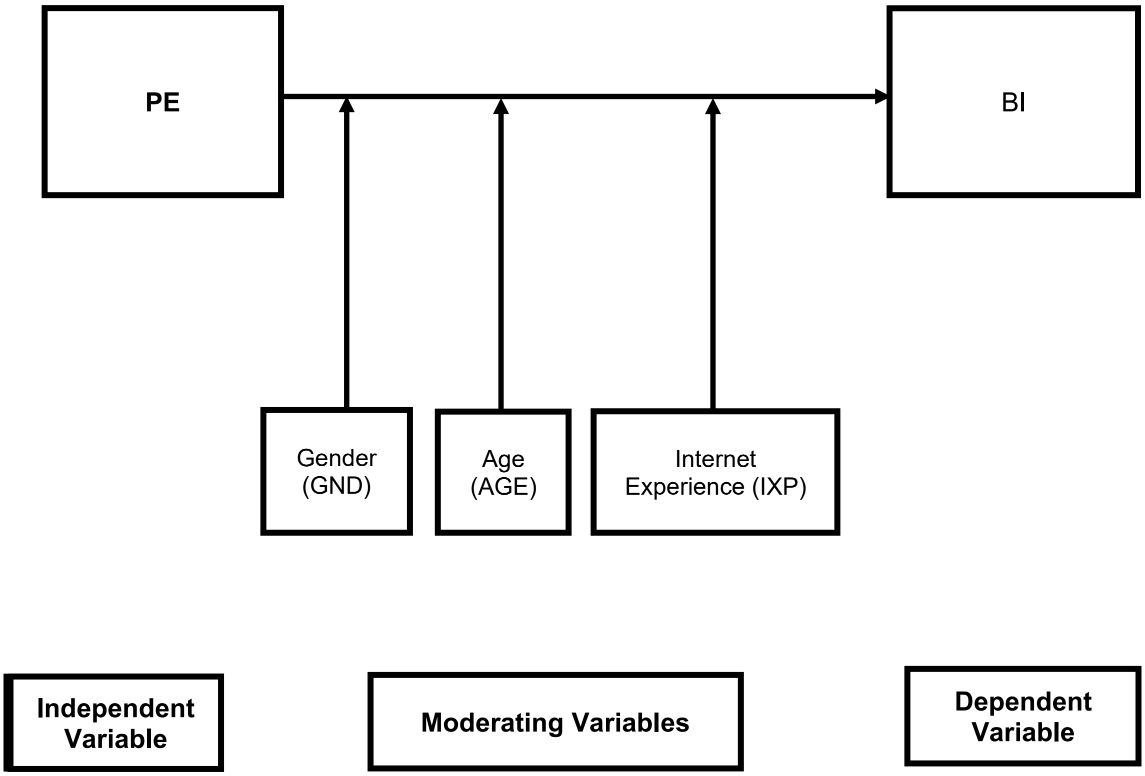

Figure 1: Conceptual Framework

STUDY DESIGN AND METHODS

This study was conducted in three universities in Kenya, namely; Kenyatta University (KU), Egerton University (EGU), and Jomo Kenyatta University of Agriculture and Technology (JKUAT). It adopted a cross-sectional survey research design. The data were collected from individuals at a single point in time. According to Thomas (2022), some of the advantages of the cross-sectional survey include; affording the researcher the ability to collect the data quickly and accurately, especially if the data collection instrument has already been pilot-tested. However, Thomas lists the following disadvantages of the cross-sectional survey research design; it cannot establish a cause-effect relationship among the variables under study; it cannot be used to analyse behaviour over a period of time or to establish long-term trends. Additionally, the data snapshot may not accurately reflect the behaviour of the entire group. In the context of this study, the advantages outweighed the disadvantages and therefore paved the way for the use of the cross-sectional survey design.

The general population of the study comprised new undergraduate students registered in e-learning programmes in all public universities in Kenya. Registration, in the context of e-learning is synonymous to admission to the university and has nothing to do with learning. This population could thus be described as those students who use various combinations of pure online and face-to-face study modes, commonly referred to as blended learning. On the other hand, the target population included new university students enrolled in any e-learning undergraduate degree programme, above 18 years of age, male or female and with or without experience with the Internet. Finally, the population accessible for the study comprised those students in the target population who were available, willing and capable of participating in the study. These were students who were available during orientation and could be reached physically or electronically (via e-mail or phone call) before and during the study.

Sampling Procedures and Sample Size

The sample size was determined based on the formula provided by Cochran (1963):

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

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 (α = 0.10),
e = the acceptable margin of error (precision).

Cochran's formula calculates sample sizes for large populations based on desired precision, confidence level, and estimated proportion. 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, with a conservative variance of 0.5 (p = 0.5). the calculated sample is given by:

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

The calculated sample size for the study was 272 respondents. During the survey, however, the actual sample that was collected and used for analysis was 388. This is acceptable because the larger the sample the better the inference from sample to the population from which it is drawn (Asiamah et al., 2017). Table 1 shows the sample representation per university and the total sample.

Table 1: *Sample Representation Per University*

	Copies of Questionnaires Issued	Copies of Questionnaires Returned	Copies of Questionnaires 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 the number of copies of the questionnaires that were issued, returned, and analyzed and; the percent sample representation. The ratio of number of copies of questionnaires analyzed per university as a percentage of all the questionnaires that were analyzed in the study equals the percentage sample representation per university.

Piloting and Instrumentation

The Students' E-Learning Questionnaire was used to gather data. A pilot-test was done involving 38 first-year e-learning students in one public university in Kenya using Google Forms and two e-mail reminders were sent out to all participating students. The pilot study revealed a 21% response rate (where eight out of 38 questionnaires were returned). This confirmed that the response rate of electronic surveys internationally is quite low (Yan & Fan, 2010, as cited by Saleh & Bista, 2017, Survey Response Rates, n.d.). However, the response rate varied widely depending on the target population, the type of items (closed or open ended), and length of questionnaire. Owing to the low return rate of the questionnaires the traditional paper-and-pen method for collecting data was used in the subsequent actual study.

The data collected were used for analysis and hypothesis testing. It was used to measure university students' PE and BI. The questionnaire was adapted from Venkatesh et al. (2003), and amended to suit the study where, the words "organization" and "manager" were substituted with "university" and "lecturer" respectively. The questionnaire had two sections; A (5 items) and B (8 items) in which the items in section A sought information relating to the university where the student was registered, gender, age, Internet experience, and academic programme. Section B consisted of a closed-ended, seven-point Likert type statements with scores ranging from 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 questionnaire covered constructs representing PE (four items) and BI (four items). The Cronbach's alpha coefficient was used to estimate the reliability of the questionnaire and returned a reliability coefficient of 0.78. The questionnaire was considered reliable and therefore suitable for use in the study because it surpasses the acceptable reliability coefficient threshold of 0.7(Santos & Reynaldo, 1999).

Data Analysis

The data were analyzed 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) on the SmartPLS software (Version 3.2 for Windows). This technique was preferred because it is suitable for small samples (below 500). Further analysis of the effect of the moderators on e-learning adoption was done using PLS-Multigroup analysis (MGA). Figure 2 shows the theoretical inner (or structural) model of the study which specifies the relationships between the independent and dependent latent variables.

Latent variables have their genesis from the works of Plato in *The Republic* and cannot be observed directly (Plato, n.d.). Thus, in Fgure 2, PE is an exogeneous variable (arrows pointing outwards) while BI is an endogenous variable (arrows pointing towards it).

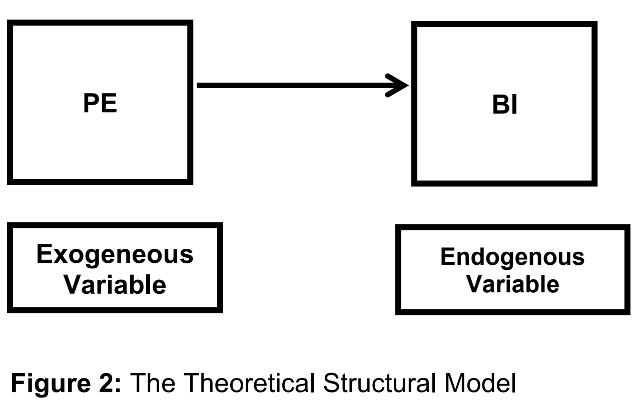

Figure 2: The Theoretical Structural Model

On the other hand, the outer model specifies the relationships between the latent variables and their observed indicators. Figure 3 shows the theoretical outer (or measurement) model which essentially represents a combination of the inner (or structural model) together with all the indicators for each latent variable. In addition the figure illustrates the exogeneous variable, PE and the exogeneous variable BI, each represented by four indicators as shown.

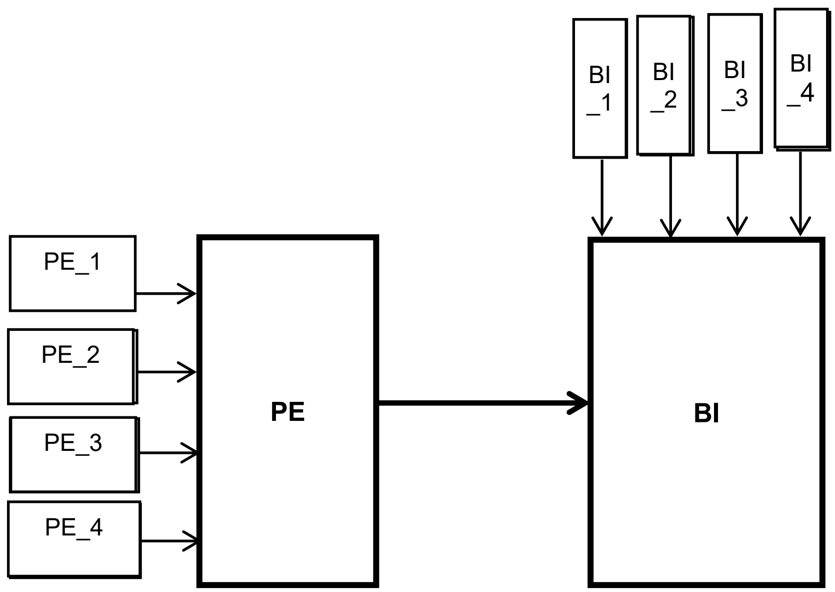

Figure 3: The Theoretical Measurement Model

Accordingly, Table 2 below shows the latent variables and their indicators and the labels that were used for analysis.

Table 2: *Latent Variables and Indicators*

Latent Variable	Label	Indicators
Performance Expectancy	PE	
	PE_1	Usefulness of e-learning
	PE_2	Quick accomplishment of tasks
	PE_3	Increased academic productivity
	PE_4	Increased chances of getting a high grade
Behavioural Intention	BI	
	BI_1	Improved academic productivity
	BI_2	Ease of use
	BI_3	Approval by role models
	BI_4	Availability of assistance

This study merged two somewhat similar procedures developed by Hair et al. (2012), and Kline (2011) into a 5-step procedure for using PLS-SEM to analyze the data as follows:

i) Specification and identification of the structural and measurement model
ii) Collecting and examining the data
iii) Evaluation of the measurement model
iv) Evaluation of the structural model
v) Estimating and assessing the moderators

Table 3 shows the hypotheses of the study, the independent and dependent variables and the statistical tests used:

Table 3: *Statistical Tests*

Hypothesis	Independent Variable	Dependent Variable	Statistical Test
H_{O1}: There is no statistically significant relationship between performance expectancy and the behavioural intention to adopt e-learning.	PE	BI	• *t*-test • R^2
H_{O2}: There is no statistically significant moderating effect of gender, age, and internet experience on the relationship between the PE and BI	GND, AGE, IXP	BI	*p*-value

Multi-group analysis (MGA) in Warp PLS software was used to determine the moderating effects of gender, age and Internet experience on the direct relationships between PE and BI. A requirement for MGA is to use categorical variables as opposed to continuous variables in determining the moderating effects (Moulder, 2018). While GND ("male" and "female") was already a categorical variable, AGE and IXP were not. Therefore, to achieve the criterion for categorical variables, AGE was categorized into "young" and "old" and; IXP was categorized into "experienced" and "inexperienced". Latif (2022) argued that MGA helps users to test if predefined groups have significant differences in their group-specific parameters (such as outer loadings and path coefficients). The method was used by Khawaja, et al. (2022) to determine the role of service quality, reputation, student satisfaction and trust on the relationship between university social responsibility and performance in Pakistan and China.

Assessing the Measurement (Outer) Model of the Structural Equation

The outer model specifies the relationships between the latent variables and their observed indicators. The results of assessing the outer model of the structural equation involved the determination of:

i) convergent validity (CV) and measured using Cronbach's alpha (CA), Average Variance Extracted (AVE) and Variance Inflation Factor (VIF).
ii) discriminant validity (DV) of the constructs, assessed using two criteria, namely; the Cross Loadings Test and the Heterotrait-Monotrait (HTMT) ratio matrix. These tests were used to determine whether the data used in the study are reliable and valid to prove the hypotheses.

Table 4 shows the CA, AVE and VIF values of the study constructs; PE and BI.

Table 4: *Convergent Validity Tests*

Construct	Items	CA	AVE	VIF
PE	4	0.75	0.57	1.51
BI	3	0.70	0.63	1.23

As shown in Table 4, CA was 0.75 for the PE and 0.70 for BI. Abma et al. (2016) argued that a value of CV greater than 0.5 is considered adequate to prove convergent validity of a construct. Additionally, CV was further tested by assessing the AVE and all the values exceed the threshold value of 0.40 (Hair et al., 2017) for the study constructs. However, Hair et al. (2017) suggest a VIF cut-off value below five (<5.0) as a general model assessment guideline. This study adopted the VIF values suggested by Hair et al. (2017) because it is more sensitive (imposes a stricter condition) and therefore discriminates better. Given that all the VIF values were below 5.0, the indicators for PE and BI could be relied upon to prove the hypotheses.

Discriminant Validity

The assessment of Discriminant Validity (DV) is a mandatory requirement in any study involving latent variables to avoid multicollinearity (Hamid et al., 2017). DV was assessed using two criteria; Cross Loadings Test and Heterotrait-Monotrait (HTMT) Ratio Matrix. The results on the cross-loading test are presented in Table 5 while those of HTMT are presented in Table 6.

Table 5: *Cross Loading Test*

Indicators	PE	BI
PE_1	**(0.77)**	0.10
PE_2	**(0.77)**	0.05
PE_3	**(0.75)**	-0.15
PE_4	**(0.72)**	-0.00
BI_1	0.11	**(0.87)**
BI_2	-0.13	**(0.81)**
BI_4	0.01	**(0.69)**

Note: Cross-loadings above 0.60 are in bold and in parenthesis; The indicator BI_3 has been dropped and does not appear in the model.

The results in Table 5 indicate that all the values of the cross loadings (shown in bold) exceeded the suggested threshold of 0.50 (Hair et al., 2017). Thus, there was a satisfactory contribution of the indicators to the assigned constructs. In addition, the individual constructs' indicator's outer loading was higher than all its cross-loadings with other constructs, indicating that DV was achieved (Hensler et al., 2015). However, the data in Table 5 shows that the indicator BI_3 has been dropped from the resulting model and therefore has no role in determining the measurement model. This means that the ensuing measurement model for the study has three indicators for the latent variables BI while all those of PE has all the four indicators retained in the measurement model. Practically, this implies that approval by role models is not considered an important indicator for BI to adopt e-learning. Improved academic productivity, ease of use, and availability are therefore the only indicators for BI to adopt e-learning.

Table 6: *Heterotrait-Monotrait (HTMT) Ratio Test*

Constructs	PE	BI
PE		
BI	0.43	

(n = 388)

The HTMT value for the relationship PE → BI in Table 6 is 0.43, showing that all the indicators passed the DV test regardless of the HTMT threshold value chosen. This confirms that the data used in the study is reliable and valid to prove the hypotheses. Figure 4 shows the resulting empirical outer (measurement) model of this relationship.

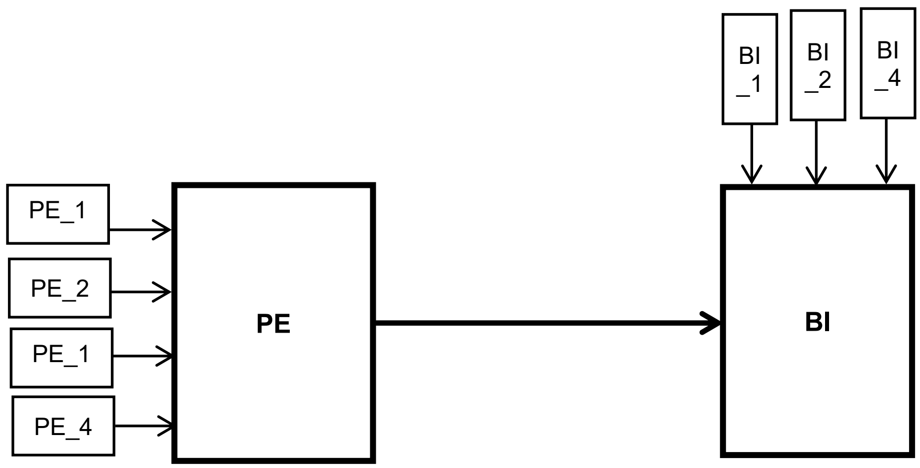

Figure 4: The Empirical Measurement Model

RESULTS

Demographic Characteristics of the Respondents

The data in Table 7 below represents the frequency and the associated percentage of each of the demographic characteristics of the respondents.

Table 7*: Demographic Characteristics of the Respondents*

		Frequency	Percentage
Academic Programme	Arts	176	45.4
	Science	120	30.9
	Business	92	23.7
	Total	388	100.0
Gender	Male	236	60.8

		Frequency	Percentage
	Female	152	39.2
	Total	388	100.0
Age	18 - 30 years (Young)	296	76.3
	31 – 60 years (Old)	92	23.7
	Total	388	100.0
Internet Experience	0 - 3 years (Inexperienced)	168	43.3
	4 - 6 years (Experienced)	220	56.7
	Total	388	100.0

(n = 388)

According to the data presented in Table 7, the respondents were drawn from three academic programmes, namely; Arts, Science and Business. The majority of the students were male, representing slightly over 60% while the minority were female, representing slightly below 40% of all respondents. Similarly, over three-quarters of the students were aged between 18-30 while those aged 31-60 were slightly less than a quarter of all respondents. In this study, those undergraduate students aged 18 - 30 are referred to as 'young' while those aged 31-60 are referred to as 'old' for purposes of analysis. There was near - parity in terms of Internet experience while slightly less than half had less than three years of Internet experience. In this study, those with four and above years of Internet experience were considered 'experienced' while those with below four years of Internet experience were considered 'inexperienced'.

Is PE a Predictor of BI?

The first hypothesis of the study, H_{01}, states that: "there is no statistically significant relationship between PE and BI", (PE → BI). Descriptive statistics for the indicators of PE and BI are presented in Table 8.

Table 8:*Descriptive Statistics*

Latent Variable	Indicator Label	Indicators	Mean	S.D.
Performance Expectancy	PE			
	PE_1	Usefulness of e-learning	6.45	1.11
	PE_2	Quick accomplishment of tasks	5.89	1.61
	PE_3	Increased academic productivity	5.80	1.52
	PE_4	Increased chances of getting a high grade	5.65	1.61
Behavioural Intention	BI			
	BI_1	Improved academic productivity	6.47	0.91

Latent Variable	Indicator Label	Indicators	Mean	S.D.
	BI_2	Ease of use	6.34	1.24
	BI_3	Approval by role models	5.38	2.15
	BI_4	Availability of assistance	6.38	1.32

(n = 388)

The tests of significance were performed above the 90% level of confidence ($p < .10$). Table 9 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 9: *Path Coefficients and Structural Model Assessment*

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

* Denotes significance at $p \leq .10$; SE denotes standard error of mean

The results in Table 9 indicate that PE is a significant predictor of BI and the hypothesis was rejected ($\beta = .15$, $t = 3.16$, $p = .002$*) Further, from the results in Table 9, the contribution of PE on the variance of BI is 15%.

Does Gender, Internet Experience and Age Moderate the Relationship between PE and BI?

Table 10 shows the results of testing the moderating effect of gender, age and internet experience on the relationship between PE and BI using MGA. It shows the individual 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 Gender, Age and Internet Experience on PE→ BI*

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
GND	Male	Female	Male	Female	Male + Female	Male + Female
	- 0.11	0.47	.01*	.001*	4.77	.00*
AGE	Young	Old	Young	Old	Young + Old	Young + Old
	0.28	0.08	.001*	.18	1.20	.12
IXP	Inexp	Exp	Inexp	Exp	Inexp + Exp	Inexp + Exp
	0.44	0.06	.00*	.21	1.26	.11

* Denotes significance at $p \leq .10$

The data in Table 10 indicates that gender is the only significant moderator of the relationship between PE and BI (p = .00*). The significance of the moderation effect is surprisingly the same for both male and female students (p = .01* for male and p = .00* for female). On the other hand, AGE and IXP are not significant moderators of the relationship between PE and BI; with p = .12 for AGE and p = .11 for IXP. These results are summarized in Figure 5 which presents the empirical PE → BI e-learning adoption model for undergraduate students in Kenya's public universities.

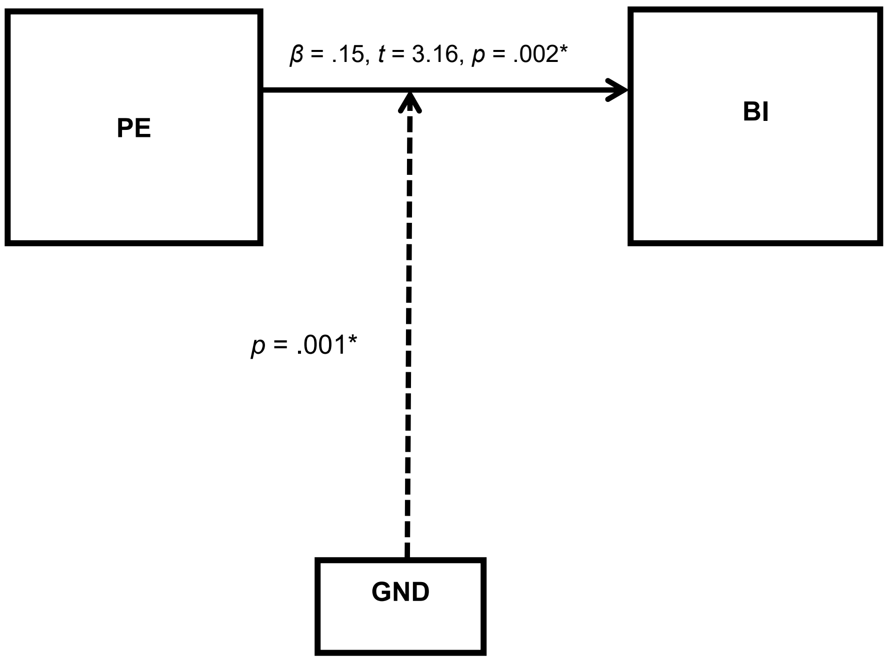

Figure 5:The Empirical PE → BI E-learning Adoption Model

DISCUSSION

The findings of this study agree with previous research which show that performance expectancy influences intention (Bellaaj et al., 2015; Chao, 2019; Mahande & Malago, 2019). In a somewhat different context Abbad (2021) and Bellaaj et al. (2015) found that PE is an antecedent of intention to continue using an e-learning system, however, as far as moderation of the relationship between PE and BI by gender is concerned, the findings contradict Adams et al. (2018). Adams et al. (2018) established that female students are perceived to be more proficient in Microsoft Office software and use mobile gadgets more frequently to communicate, and possess complementary skills as well as a propensity towards e-learning. This study found no gender differences related to the intention to use e-learning.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The findings of this study confirms that PE is a direct and significant predictor of e-learning adoption in Kenya's public universities. It further confirmed that the relationship between PE and BI is significantly moderated by GND only – with both male and female students contributing equally to the moderation; where the strength of moderation is the same for both male and female students. This relationship is, however, not moderated by AGE or IXP.

Recommendations

This study recommends the inclusion of PE as one of the predictors of BI in the model for e-learning adoption. Secondly, we recommend testing the effect of other predictors of BI on e-earning adoption as stipulated in studies on e-learning adoption models. Studying these predictors of e-learning adoption is important because learner needs are typically generalized and therefore end up obscuring the actual antecedents of e-learning adoption in higher education.

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