A MODEL FOR PREDICTING UNDERGRADUATE STUDENTS' ADOPTION OF E-LEARNING IN SELECTED PUBLIC UNIVERSITIES IN KENYA

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DECLARATION AND RECOMMENDATION

Declaration

This thesis is my original work has not been presented in this or any other university for the award of a degree.

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For Sarah, May, Mila and Michelle.

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ABSTRACT

The teaching and learning of science employ several approaches, each of which attempts to improve the quality of students' learning. One approach that is gaining prominence in higher educational institutions (HEIs) is e-learning. However, e-learning adoption among students in Kenya's HEIs is not succeeding the way it is expected because of both institutional and individual shortcomings. In this study, the University Students' E-learning Adoption Model (USeLAM) was developed with the aim of providing a basis for decision making in the adoption of e-learning among undergraduate students in selected public universities in Kenya. The study adopted a cross-sectional survey design based on the Unified Theory of Acceptance and Use of Technology (UTAUT). The sample consisted of 388 undergraduate university students who answered 24 questions on a 7-point Likert Scale in the Students' E-learning Adoption Questionnaire (SeLAQ). The SeLAQ was validated by six educational research experts at Egerton University and yielded Cronbach - Alpha reliability coefficient of 0.78. Six hypotheses were tested above the 90% level of confidence ($p < .100$) by applying the Partial Least Squares, Structural Equation Modelling (PLS-SEM) techniques. The results indicate that there were positive and statistically significant relationships between Performance Expectancy (PE) and Behavioral Intention to adopt e-learning (BI) ($\beta = .15$, $t = 3.16$, $p = .002$) and; between Effort Expectancy (EE) and BI ($\beta = .18$, $t = 4.32$, $p < .001$). However, Social Influence (SI) was not a statistically significant predictor of BI ($\beta = .00$, $t = 0.07$, $p = .945$). On the other hand, BI was found to be a positive and statistically significant predictor of Actual Use Behaviour of e-learning (UB) ($\beta = .08$, $t = 1.83$, $p = .067$) while Facilitating Conditions (FC) was a negative but statistically significantly predictor of UB ($\beta = -.11$, $t = 1.79$, $p = .073$). Further analysis of the effect of moderators on the relationship between predictors and outcomes of students' adoption of e-learning was done using the PLS-Multi Group Analysis (MGA). The results indicate that students' age (AGE), gender (GND) and internet experience (IXP) significantly moderate students' e-learning adoption in varying degrees. In the final analysis, the USeLAM accounted for 24% ($R^2 = .24$) of the variance in BI and 15 % ($R^2 = .15$) of the variance in UB. In conclusion, therefore, the study underscores the significant influence of PE and EE on students' BI as well as that of BI and FC on students' UB. The implications of this study extend to educational policy makers in general, and public university management, in particular, in improving e-learning adoption in HEIs. Further, it lays the groundwork for future research in predicting e-learning adoption in Kenya's HEIs and buttressing the multidisciplinary nature of the application of e-learning in HEI's.

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LIST OF ABBREVIATIONS AND ACRONYMS

AI	Artificial Intelligence
ASTD	American Association for Training and Development
BI	Behavioural Intention to Adopt E-learning
CB-SEM	Covariance-Based Structural Equation Modelling
C-TPB-TAM	Combined Theory of Planned Behaviour/Technology Acceptance Model
CUE	Commission for University Education
DOI	Diffusion of Innovations
ECAR	EDUCAUSE Centre for Applied Research
EE	Effort Expectancy
EGU	Egerton University
EUREC	Egerton University Research Ethics Committee
FC	Facilitating Conditions
HEI	Higher Educational Institution
ICT	Information, Communication and Technology
IoT	Internet of Things
IRR	Inter-rater Reliability
IS	Information Systems
IT	Information Technology
JKUAT	Jomo Kenyatta University of Agriculture and Technology
KCSE	Kenya Certificate of Secondary Education
KENET	Kenya Education Network
KU	Kenyatta University
KUCCPSB	Kenya Universities' and Colleges Central Placement Service Board
LCMS	Learning Content Management System
LMS	Learning Management System
MIT	Massachusetts Institute of Technology
MM	Motivational Model
MMUST	Masinde Muliro University of Science and Technology
MOE	Ministry of Education
MOOC	Massive Open Online Course
MPCU	Model of Personal Computer Utilization
MU	Moi University
NACOSTI	National Commission for Science, Technology and Innovation

NDU-K	National Defence University of Kenya
ODEL	Open, Distance and E-learning
OECD	Organization for Economic Co-operation and Development
OUK	Open University of Kenya
PBL	Problem-Based Learning
PE	Performance Expectancy
PLS	Partial Least Squares
PWPER	Presidential Working Party on Education Reforms
ROK	Republic of Kenya
SAS	Statistical Analysis System
SCT	Social Cognitive Theory
SeLAQ	Students' E-learning Adoption Questionnaire
SI	Social Influence
SODEL	School of Open, Distance and E-learning (JKUAT)
SODL	School of Distance Learning (Egerton University)
SPSS	Statistical Package for Social Scientists
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TSC	Teachers' Service Commission
TTI	Technical Training Institute
TVET	Technical Vocational Education and Training
UB	Actual Use Behaviour of E-learning
UFB	Universities' Funding Board
UK	United Kingdom
UoN	University of Nairobi
USeLAM	University Students E-learning Adoption Model
PLS-SEM	Partial Least Squares Structural Equation Modelling
USA	United States of America
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization
WWW	World Wide Web

CHAPTER ONE
INTRODUCTION

1.1 Background

University education in Kenya has a history spanning over 55 years, beginning with the founding of the University of Nairobi (UoN) in 1970. Initially, UoN provided its first programs through distance learning as an academic partner of the University of London (Bogonko, 1992). This trend has continued at UoN which, through its extramural centres has spread throughout the country. Using expertise from a central location, learners from all backgrounds are able to access UoN courses from centres near them across the country. This expertise is shared across the centres through distance learning materials and visiting lecturers. More recently, e-learning - a subset of distance education - uses technology for course delivery and is widely accepted and practiced in Kenya's HEI's. Currently, the technology in use for e-learning is predominantly internet-based where the internet is used as both the medium through which the content is conveyed and delivered to the learners. Further, application of e-learning, by its nature is not discipline-specific. This is because e-learning can be used to teach any subject in the curriculum provided the e-learning experiences are planned in such a way as to meet the desired objectives or learning outcomes. Therefore, from this background, this study takes a wholistic and cross-cutting approach in terms of the target groups for e-learning.

The teaching of science employs several approaches, including traditional classroom teaching, distance education and e-learning. While traditional approaches have existed for a comparatively longer time, the e-learning approach is relatively new in Kenya. E-learning, being an extension of distance education, has grown out of and relies almost exclusively on developments in technology. Regardless of the approach in the teaching of science, the American Association for the Advancement of Science (AAAS, 2023) argue that science teaching should be consistent with the nature of scientific inquiry, reflect scientific values, aim to counteract learning anxieties, extend beyond the school and allow students' time for exploring, making observations, testing ideas and drawing evidence for improving their understanding of the world around them. From this argument, it is clear that in teaching science, or indeed any discipline, three things are important, namely: the material being taught; the learners' background, and; the conditions under which instruction takes place.

The material being taught, particularly in higher education is organized into disciplines of study. The disciplines of study have emerged from a concentration in narrower yet smaller fields of scientific inquiry. For example, science as a discipline is considered to consist of

Physics, Chemistry and Biology. With the advent of technological innovation, where a lot of teaching content can easily and readily be generated by Artificial Intelligence (AI), obtaining materials for teaching is no longer an issue of concern for the academic community. Similarly, public universities in Kenya have tended to put less and less emphasis on student characteristics but instead have emphasized infrastructural development at the expense of everything else.

Researchers in education agree, almost unanimously that student-centred approaches produce the best results in teaching and learning. When making a choice about whether or not to choose e-learning as a mode of study, students hold expectations about e- learning including those about their performance - referred to as Performance Expectancy (PE) and effort - referred to as effort expectancy (EE). These expectations affect students' confidence as they engage in e-learning and determines to a great extent, the success or failure in their academic endeavours. Similarly, students tend to value what others think of them especially on the choice of mode of study. Peers, parents, guardians and friends all have a critical role to play on the choices students make regarding their choice of mode of study. These factors, referred to as Social Influence (SI) in this study are an important consideration to explore alongside the Facilitating Conditions (FC) under which e-learning takes place. Collectively, PE, EE, SI and FC are referred to as predictors of e-learning adoption in this study.

A university student's persistence as an online learner is characterized by strong intentions (BI) and subsequently, increased use (UB) of the online mode of study. Theoretically, a student's expectations affect their e-learning adoption behaviours. However, only a few studies have been conducted in Kenya (Maina & Nzuki, 2015; Nyagorme, 2014; Omwenga et al., 2004) to prove this theoretical position. This is because of the fact that e-learning has not matured to the extent of attracting increased research activities. This implies that students and lecturers alike are using e-learning for the first time and are still grappling with basic issues on technology use including; proficiency with computer hardware and software, social influence, availability of power and internet connectivity among others. According to Tarhini et al. (2014), the effectiveness of e-learning is largely influenced by learners' willingness to embrace and utilize the technology. Consequently, examining how students accept and adopt e-learning becomes an essential area of study. Within the field of Information Systems (IS), investigations into technology acceptance represent one of the most extensively explored domains (Venkatesh et al., 2003). This prominence is attributed to the development of multiple theoretical models designed to account for users' intentions and actual usage of technology. However, the application of these models to the education sector, particularly higher education, remains uncommon. This underscores the necessity of tailoring certain models to align with the academic environment. Moreover, it is likely that learners will select their study approach based on factors such as gender, age, program of study, or level of internet proficiency. Likewise, the widespread availability of digital tools in modern society highlights the growing relevance of e-learning within academic institutions (Abbad, 2021).

In planning for instruction, effective teachers draw on a rapidly changing body of knowledge about the nature of learning. Typically, educators take into account the specific characteristics of the material to be learned, the profile of their students, and the conditions under which teaching and learning will occur (American Association for the Advancement of Science, 1990). According to a study conducted by Lewis (2009) in Australia; the e-learning experiences of mature-aged learners are always different from the experiences of younger learners and these are predicated on previous educational experiences, skill and self-efficacy with Information Technology (IT), and the various commitments they have, both in the home and workplace. Some of these aspects will alter generationally, most particularly issues related to IT skills (including internet experience) and confidence.

Research indicates that the majority of distance learners are commonly between 25 and 50 years of age (Moore & Kearsley, 1996). In Kenya, many students join university after attaining the age of 19 (Odhiambo & Onyango, 2009). Accordingly, distance education learners and university students constitute adult learners. As a result, a focus on adult learning principles is necessary to better interpret the drivers behind e-learning adoption. Cercone (2008) examined andragogy, experiential learning, self-directed learning, and transformational learning; and explored how these theories could be applied to virtual learning. The study revealed that:

i) the learning characteristics of adults are significantly different from those of children, thus confirming Knowle's (1980) assertions on andragogy that adult learners need to know why they are learning, use practical hands-on problem-solving approach to learning, want to apply the learned skills immediately, are autonomous and self-directed, have a lifetime experience, and want to be shown respect. With this in mind, it is imperative to infuse andragogy in the training of university lecturers who are only grounded in pedagogical methodologies.

ii) most adults were taught in a traditional and passive classroom. This implies that they would attempt to apply the same principles of teaching where learners only become "recipients" of knowledge.

iii) online learning environments are new to instructors, who have to learn new methods for teaching in this kind of setting. New technologies are continually being developed; closely followed by methods of harnessing the technologies to improve teaching and learning.

iv) learners and instructors both need to adapt and change as they learn how to use this new medium.

v) adult learners are different from traditional college students because many adult learners have responsibilities such as families and jobs. They also face different situations in terms of transportation, childcare, domestic chores and the need to earn an income that can interfere with the learning process.

Thus, in conclusion, Cercone (2008) argues that a single theory is not sufficient in explaining how adults learn but that each theory provides a framework or a model which contributes something to the understanding of adult learning. This conclusion supports a similar one made earlier by Merriam and Caffarella (1999).

Moreover, advances in information and communication systems, particularly the internet, have transformed educational practices (Lwoga, 2014). The growing integration of e-learning within Higher Educational Institutions (HEIs) is linked to globalization and the modernization of academic programs. Consequently, universities worldwide have adopted e-learning in various formats, ranging from fully online courses to traditional classroom-based delivery (Islam et al., 2015).

Between 2009 and 2014, the e-learning industry worldwide attracted investments amounting to 6 billion US dollars. Additionally, Andre (2015) projected that the global market would generate revenues of more than US $15 billion by the end of 2016 This is supported by the fact that, in China, for instance, between 2004 and 2014, the e-learning market increased nearly fivefold with the number of e-learners reaching 100 million (Andre, 2015). A more recent study estimated the global e-learning industry to be worth US $174 billion in 2022, with revenues expected to expand by approximately 15 percent annually between 2022 and 2029, ultimately reaching US $414 billion over that period (Market Maximum Research, 2022). This contradicts an earlier prediction that education would experience the most radical technology-driven change in 2015 behind only to news organisations and publishing (Pew Internet and American Life Project, 2005). Such change continues to be out of reach because of persistent global and local disparities in digital access. The reason why this is the case is explained by Clarke (2002) who argues that for technology to improve learning, it must “fit” into students’ lives and not the other way around. Despite the increased revenues and an increase in the number of online learners worldwide, it is evident that the use of technology in education has not kept pace and lags substantially behind the other sectors such as banking, entertainment and communications.

Most scholars agree that e-learning in Africa is still at its infancy (Makokha & Mutisya, 2016; Unwin, 2008). This is despite a 50-fold expansion of sub-Saharan Africa's higher education sector between 1970 and 2015 (Nhanda, 2015). With an already stretched resource base in all sectors of the economy, African countries are struggling to meet the demands of increased student enrolment at its universities. While e-learning is regarded by many a university senate as a solution to the problem of access to quality higher education in Africa the success rates for establishing e-learning in African universities has been dismal. For instance, in Tanzania, Mtebe and Raisamo (2014a) argue that despite significant investments by institutions in acquiring and managing various educational technologies, insufficient attention has been given to developing content for learners. Additionally, as the cost of commercial textbooks continues to rise, there is a tendency to rely on outdated books, old course content, and poorly designed teaching and learning materials.

Attwell (2006) argues that among the community of e-learning developers and practitioners there has been a growing preoccupation with software and platforms and only limited attention to pedagogy and learning. In Kenya, Makokha and Mutisya (2016) conducted a study to assess the status of technology-supported learning in seven public institutions. They found that public universities lacked senate approved e-learning policies to guide structured development. Similarly, only 32% of the lecturers and 35% of the learners used technology while 10% of the university courses were offered online; and 87% of learning materials were simply lecture notes that were not interactive.

Since independence, teaching and learning in Kenya has witnessed tremendous transformation at all levels. From the apprenticeship-type learning at independence to present day e-learning there exists a complex continuum that has seen curricula changes (Nganga & Kambutu, 2010; ROK, 2017) as well as the methods of teaching. While all the levels of education (primary, secondary, and tertiary) stand to benefit from e-learning as a delivery method the learners at university level appear to be the "perfect" target group for e-learning. This is because these learners come from various geographical locations, have a quest for higher and specialized qualifications, and the upward trend in preference for studying through online platforms (owing to availability of bandwidth, computer network infrastructure as well as digital proficiency).

In a 2013 e-readiness survey of 20 public and 10 private universities in Kenya, representing 80% (or 423,664) of the entire enrolment of university students in Kenya at the time, Karshoda and Waema (2014) established that only 11% of the students were taking some of their courses in a blended e-learning mode. Similarly, despite the fact that only 58.8% of available bandwidth in Kenya was utilized in 2014, the number of internet users increased by 23.0% to reach 26.2 million users as compared to the previous year (Republic of Kenya, 2015). This is explained by the fact that there was a preference for online newspapers and mobile money transfers owing to a reduction of data bundle prices and the availability of affordable internet-enabled telephones (Republic of Kenya, 2015). Despite the low uptake of e-learning in Kenyan universities, Karshoda and Waema (2014) concluded that the university community in Kenya was ready for the uptake of learning, teaching, research and management. Therefore, there is some potential of e-learning becoming the preferred delivery mode for education and training in Kenya in the near future.

According to (CUE, 2022), Kenya's higher education landscape comprises 77 universities, organized into six major categories However, with the addition of the OUK, the number of universities increased to 78 while the categories remain the same because OUK and the National Defence University of Kenya (NDU-K) are both in the category of specialized degree-awarding universities (see the full list of universities in Appendix 2). This positions Kenya's university sector among the largest in Africa (CUE, 2019). Table 1 presents the different categories of universities in the country:

Table 1

Categories of Universities in Kenya

Category of University	Number of Universities
Public chartered universities	35
Private chartered universities	25
Institutions with letter of interim authority	8
Constituent colleges of private universities	3
Constituent colleges of public universities	5
Specialized degree awarding universities	2
Total	78

Table 1 shows that there are 78 universities in Kenya divided into six categories. It shows that the majority of universities are public chartered and private chartered universities numbering 35 and 25 respectively. Eight universities are operating with letters of interim authority while three are constituent colleges of private universities and five are constituent colleges of public universities. There are two specialized degree awarding universities – the NDU-K, established in 2021 and the OUK, established in 2023. Specialized degree-awarding universities in Kenya, although established under the Universities Act of 2012, differ from their non-specialized counterparts in that the former are established through parliamentary approval while the latter require approval from CUE.

Sharma and Mishra (2010) observe that adoption and diffusion of technology are closely related. Adoption is the decision to implement a technology (Carr, 1999), whereas diffusion is its spread and integration into regular use (Rogers, 2003). Since adoption commonly precedes diffusion, both ideas are essential to the present research.

Across the globe, numerous models have been introduced to explain how individuals adopt and use technology in fields like banking, industry, and management. These models seek to clarify determinants of users' inclinations towards embracing new technologies. Among the most recognized are the Technology Acceptance Model (TAM) and Rogers' Diffusion of Innovations (DOI). More recently, the Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh et al. (2003), has gained prominence in multiple fields. 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.

The e-learning landscape in Kenya has been shaped and dictated by internal and external influences. Internally, the most significant political influence that has affected e-learning in Kenya was characterized by the election and coming into power of the new *"Kenya Kwanza"* government in 2022, the subsequent appointment of the Presidential Working Party on Education Reform (PWPER) immediately thereafter and the establishment of the OUK in August 2023 (Naliaka, 2023). The university has established a structured framework to support distance and online learning, reflecting its commitment to broadening access to higher education. As part of this initiative, eight flagship programmes were introduced, including degrees in Business, Economics, Data Science, Cyber Security, Agri-Technology and Food System and Digital Forensics, as well as Technology. In addition, postgraduate diplomas in Leadership and Accountability and in Learning Design and Technology were launched to strengthen professional and academic capacity. In future, more programmes will be added to the inaugural ones and the concept of the open university publicized to reach a larger audience.

Externally, the forces influencing e-learning include internationalization and modernization of education. The external forces seek to break the barriers imposed by geographical boundaries as well as those brought about by the constraints of classroom walls. In recognition of these forces, E-learning in public universities in Kenya is being implemented through active collaboration with both international and local players in the education sector. For example, universities in the West have since demystified the boundaries between academic disciplines and subjects such that disciplines and subjects have been merged for purposes of solving real-life problems and life-long learning. This kind of merging has resulted to what is referred to as "Design Thinking" in some universities. The Aalto Global Impact team in Finland pioneered the idea of design thinking and to effect its tenets opened the first "Design Factory" in the world in 2008 (Aalto Business Hub, n.d). The design thinking concept has spread to over 30 universities in Europe and is still growing. The similarity between universities that have embraced the design thinking approach is that they almost all refer to themselves as "Universities of Applied Sciences". Notable examples of Universities of Applied Science include; Universiteit Koln in Germany, HAMK University of Applied Sciences in Finland and Amsterdam University of Applied Sciences in the Netherlands. These universities use the Problem-Based Learning (PBL) methodology in teaching and learning. Getuno et al. (2022) examined the challenges surrounding PBL in Africa's HEIs. They identified the key obstacles hindering its uptake as; lack of basic teaching and learning infrastructure, structural institutional constraints related to affording frequent curricula review across disciplines, large class sizes, information overload from various sources with the attendant lack of tools to keep up tracking the progress of learners; time constraints in implementing PBL, human capital constraints that limit the number of trainings in pedagogy to enhance PBL skills among the academic staff, lack of technology and poor implementation of PBL itself that further impedes its practice and adoption. These factors equally constrain the uptake of e-learning in Africa.

In Kenya, the closest to the Design Factories in Europe is probably the C4D lab at the University of Nairobi (About the C4D Lab, n.d.). In a typical design factory, ideas are turned into reality by producing real-life products that are used to improve marketing, industrial processes and the quality and efficiency of life in general. The focus is the "problem" being solved. In this case various perspectives are employed to solve problems. For example, to produce an electric car, ideas are needed from engineering, ergonomics, marketing and sociology. Thus, product development is also at the heart of the design factory. In a practical design factory, students are presented with a problem to solve by the industry. The students, with the guidance of their faculty, develop solutions as part of their learning and at the end earn credits that contribute to their overall grades for graduation. This double-pronged approach is useful in ensuring societal benefits from university courses. By leveraging insights from the

"Design Factory" and C4D lab models, e-learning demonstrates promising potential, particularly through the design of practical environments aimed at resolving adoption challenges in HEIs.

1.2 Statement of the Problem

In Kenya, several universities have invested in digital learning infrastructure and launched online programmes. Despite these efforts, online instruction has not achieved the expected outcomes, particularly regarding learners' engagement, sustained participation, and adoption behaviours. Existing global models of technology-enhanced education were largely designed for the IS sector in industrialized contexts, limiting their applicability to higher education in emerging economies. Within Kenyan universities, the absence of a guiding framework, coupled with emphasis on infrastructure rather than strategy, has hindered progress. To address this gap, the USeLAM model is being introduced to predict undergraduate learners' uptake of technology-based learning. This new model presents an excellent way of explaining relationships between predictors as well as outcomes in e-learning adoption while acting as a useful instrument for guiding decisions. It is flexible, capable of accommodating new predictors that yield additional prediction parameters on a case-to-case basis. USeLAM is expected to enhance growth in e-learning by improving decision processes in Kenya's public universities.

1.3 Purpose of the Study

The purpose of the study was to develop a model for predicting the adoption of e-learning among undergraduate students in Kenya's public universities.

1.4 Objectives of the Study

The objectives of the study were to determine:

i. the relationship between performance expectancy (PE) and the behavioural intention (BI) to use the e-learning mode of study;
ii. the relationship between effort expectancy (EE) and BI to use the e-learning mode of study;
iii. the relationship between social influence (SI) and the behavioural intention (BI) to use the e-learning mode of study;
iv. the relationship between facilitating conditions (FC) and the actual use behaviour (UB) of e-learning;

v. the relationship between behavioural intention (BI) to use e-learning as a mode of study and the actual use behaviour (UB) of e-learning.
vi. the moderating effect of gender, age and internet experience on the relationship between the predictors and outcomes of e-learning adoption

1.5 Research Hypotheses

The following null hypotheses were tested in this study:

HO_1: There is no statistically significant relationship between performance expectancy and the behavioural intention to use e-learning mode of study.

HO_2: There is no statistically significant relationship between effort expectancy and the behavioural intention to use e-learning mode of study.

HO_3: There is no statistically significant relationship between social influence and the behavioural intention to use e-learning mode of study.

HO_4: There is no statistically significant relationship between facilitating conditions and the use behaviour of e-learning.

HO_5: There is no statistically significant relationship between the behavioural intention to use e-learning mode of study and use behaviour of e-learning.

HO_6: There is no statistically significant moderating effect of gender, age, and internet experience on the relationship between the predictors and outcomes of e-learning adoption.

1.6 Significance of the Study

This study developed the USeLAM, model for predicting undergraduate university students' adoption of e-learning in Kenya. The findings of the study are useful in designing and managing robust e-learning environments in Kenya's public universities. In addition, the findings would help university management and instructors understand how e-learning programmes can be integrated within the university course offerings as well as establishing the most appropriate target groups for e-learning. The rationale of the study is thus summed up as:

> Student enrollment has expanded, while learners' requirements, expectations, and demands have grown increasingly diverse. Learners are now considerably more assertive, particularly when perceiving themselves as fee-paying clients. With reduced time allocated for study, learners have also become increasingly technologically adept, though

> they may not consistently know how best to apply technology for learning purposes (Ellis & Goodyear, 2009, p.3).

Furthermore, findings from this research are beneficial to principal stakeholders in the digital learning domain, including prospective and current online learners, online tutors, subject-matter experts, university leaders, and education policymakers in Kenya. This is because USeLAM specifically offers a valuable mechanism for evaluating the determinants that encourage student adoption of digital learning. This is especially critical for university leaders seeking to identify the drivers of digital learning acceptance and integration, thereby enabling them to craft targeted interventions for undergraduate learners in Kenya. The relevance of this research is further emphasized in the post-COVID-19 context, when social distancing and stay-at-home directives were widely enforced (WHO, 2021). This period constituted the most appropriate time for remote instruction.

1.7 Scope of the Study

The study was conducted in three chartered public universities in Kenya, each with a student population exceeding 15,000 (R.O.K., 2023b). This is because chartered public universities with student populations below 15,000 had not started engaging in innovative learning practices such as e-learning. The study targeted undergraduate students pursuing their courses using various modes of e-learning delivery or combinations thereof. These included students enrolled in pure online studies or blended e-learning where a certain proportion of the study is online while the other is face-to-face. The study was also cross-cutting as it targeted all the undergraduate students in faculties, schools and departments offering e-learning programmes in the participating universities. Thus, the results obtained represent the model of e-learning adoption across the various academic programmes and e-learning delivery modes.

1.8 Assumptions of the Study

In Kenya's public universities, the provision of e-learning differs from one institution to another while at the same time, the lecturers in these institutions receive different kinds of preparation to teach online. Owing to these differences, this study was carried out based on three assumptions; first, that the difference in the type of e-learning (fully on-line, blended, or use of e-learning as supplementary learning material) offerings by public universities in Kenya, did not affect the results of this investigation. This is explained owing to the fact that delivery of technology-supported learning for public universities in Kenya varies from one university to the other and takes on many different forms. Secondly, that the lecturers teaching online programmes at public universities in Kenya had some basic level of proficiency in delivering online programmes at the undergraduate level. The proficiency required to teach online include *inter alia*, developing online content, working with a Learning Management System (LMS), and online tutoring skills. While lecturers exhibit the proficiency to teach online differently, a basic understanding and application of online teaching skills is mandatory; otherwise, the learning outcomes and the adoption of e-learning will differ depending, regrettably, on the online teaching skills of the lecturer. The third assumption was that, public universities with student populations above 15,000 had matured enough to start offering e-learning in a meaningful manner. This is because they are deemed to have been in existence for a longer period compared to the more recently established ones. The public universities that fit into this criterion apparently were those that were established before the year 2000(ROK, 2023b).

1.9 Limitations of the Study

In Kenya's HEIs there are obviously more face-to-face students in public universities compared to e-learning students. This was considered a limitation in terms of obtaining a proportionally representative number of subjects across all the universities given that the public universities themselves have widely varying numbers of students. To minimize the effects of this limitation, the selection of universities was done such that public universities with more students enrolled in e-learning programmes were preferred.

The measurement of e-learning adoption, especially in terms of actual usage is quite a complicated process. For instance, measuring e-learning adoption would be too simplistic if depended on quantifying the hits or logins by students in the university's e-learning platform. To effectively measure adoption of e-learning, one would need to find out what students do while online – be it accessing content pages, messaging (in chats and discussion forums) or completing assessments. Therefore, this study used students' self-reported measures on frequency and duration of access to account for the actual usage of the e-learning platform which in turn exposes the results of the survey to social desirability biases of the respondents (Larson, 2019).

1.10 Definition of Terms

The terms in this study are defined as follows:

Adoption – Signifies the act of accepting or taking up a behaviour, idea, or practice (Vocabulary.com, 2023a). Specifically, in the context of technology, it describes the point at which a tool or system is chosen for implementation by a person or organization (Carr, 1999). In this research, the concept encompasses both the intent to use and the actual engagement with e-learning platforms. Put simply, it reflects undergraduate students' readiness and acceptance to continue utilizing e-learning technologies.

Behavioural Intention – Describes a plan or decision to engage in a particular action (Vocabulary.com, 2023b). Within the scope of this study, it denotes students' willingness to continue utilizing e-learning as their preferred mode of study, both throughout the semester and beyond. Indicators of behavioural intention in this context include enhanced academic efficiency, user-friendliness of the e-learning platform, encouragement from influential figures, and access to support when using e-learning tools. In this research, behavioural intention emerged as one of the key outcomes associated with the adoption of e-learning.

Blended Learning – Involves the deliberate and cohesive combination of in-person and digital methods and tools to enhance learning experiences (Vaughan et al., 2013). This interpretation served as the working definition throughout the current study.

Effort Expectancy - Describes how simple and straightforward users perceive the e-learning system to be (Venkatesh et al., 2003). In this study, effort expectancy was measured through factors such as how easily learners understood the system, acquired relevant skills, navigated its features, and learned how to use it effectively. It was identified as one of the key variables influencing the adoption of e-learning in this research.

E-learning - Refers to the use of Information and Communication Technologies (ICTs) to support distance learning, promote open access to education, increase flexibility in learning processes, and allow educational activities to take place across multiple settings (CUE, 2014). In the context of this study, it describes a learning approach that integrates both online and in-person instructional methods, where students participate in courses continuously for a duration of at least one full semester.

Facilitating Conditions - relates to the extent to which an individual perceives that the necessary technical infrastructure is in place to support the use of e-learning (Venkatesh et al., 2003). In this study, it encompasses students having access to the essential tools, resources, and skills required for effective participation in e-learning. It also includes the compatibility of e-learning with other learning methods students are familiar with, as well as the presence of dedicated individuals or support teams to assist with any challenges encountered during its use. Facilitating conditions were identified as one of the key factors influencing the adoption of e-learning in this research.

Model – represents a simplified representation of a concept or phenomenon under investigation. In the context of e-learning, it is occasionally used interchangeably with the term "theory." In this study, it specifically refers to a visual illustration—such as a diagram—that depicts the connections between the factors influencing e-learning adoption and its resulting outcomes.

Outcomes – These are the behavioural intention to adopt e-learning (BI) and the actual use behaviour of e-learning (UB) respectively. The same definition was used operationally in this thesis.

Performance Expectancy - It is the degree to which a student believes that using an e-learning mode of study will help him or her to attain gains in academic performance. In this study it refers to the fact that using the e-learning mode of study is useful and will enable a student to accomplish tasks more quickly and; increase academic productivity; increase chances of students scoring higher grades in the courses they are pursuing. Performance Expectancy was one of the predictors of e-learning adoption.

Predictors of E-learning Adoption – These are factors that predict e-learning adoption. In this study, they are represented by PE, EE, SI and FC. The same definition was used operationally in this thesis.

Social Influence - It is the degree to which an individual perceives that others believe he or she should use the e-learning mode of study. In this study it means that those people who are important and influence the behaviour of students think that they (students) should pursue their studies using the e-learning mode; that the course instructors are useful to the students and that the university adequately supports the e-learning mode of study. Social Influence was one of the predictors of e-learning adoption.

University – Is a higher institution of learning. It is also referred to as a Higher Educational Institution (HEI) in this study. According to ROK (2023a) the definition of HEI excludes TVET institutions.

Use Behaviour - Refers to a self-reported measure on the frequency of using the e-learning mode of study in the previous three months. The indicators for use behaviour were; daily login to the e-learning platform, reading, downloading and printing e-learning materials. Use Behaviour was one of the outcomes of e-learning adoption in this study.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This chapter presents a comprehensive analysis of the scholarly discourse surrounding digital learning, with a specific focus on its adoption within the context of Kenyan public universities. The review commences by exploring global trajectories and transformative developments in the e-learning domain. It then narrows to scrutinize the condition of public university education in Kenya, critically examining the legislative, organizational, and demand-side factors that shape its operational landscape. A detailed inquiry into the varied definitions of digital learning is provided to establish conceptual clarity.

Subsequently, the literature survey delves into global internet penetration metrics, positioning Kenya's digital infrastructure within the broader African and global context. The strategies for implementing digital learning in Kenyan Higher Education Institutions (HEIs), as guided by national ICT policy frameworks, are thoroughly evaluated. This is followed by an assessment of the e-readiness of these universities, identifying gaps between policy ambition and institutional reality.

Theoretical underpinnings are established through a critical examination of technology adoption models, with particular emphasis on the Unified Theory of Acceptance and Use of Technology (UTAUT). The constructs and moderating variables relevant to this research are justified, leading to the presentation of a refined UTAUT framework that illustrates the hypothesized relationships between variables. A survey of related empirical studies, both local and international, is presented to contextualize this research within existing knowledge. The chapter culminates in an exposition of the conceptual framework that guides this investigation.

2.2 Global Trajectories in Digital Learning

On a global scale, the proliferation of digital learning has been a multifaceted, dynamic, and often contested phenomenon. Its application spans a diverse spectrum of domains, including pedagogical innovation on traditional campuses, the expansion of distance education, institutional transformation, knowledge sharing, and novel avenues for income generation (Organization for Economic Cooperation and Development [OECD], 2005). A pivotal development in this evolution has been the advent of Massive Open Online Courses (MOOCs) pioneered by elite institutions like Stanford and MIT, disseminated through platforms such as *Coursera* and *FutureLearn*. These initiatives emerged in direct response to a growing demand for more flexible and accessible learning modalities from both enrolled students and external learners.

These platforms embody an interactive and inclusive educational philosophy. As FutureLearn (2021) articulates, learners can “learn anything,” “learn together,” or “learn with experts.” This vision resonates with the original, forward-looking impetus behind the creation of the World Wide Web, as both were conceived as revolutionary tools for democratizing knowledge dissemination. In essence, digital learning inherits the Web's core principles of portability, cross-platform compatibility, and inherent adaptability to continuously evolving formats. The ongoing global transformation of teaching and learning is being further accelerated by the integration of emergent technologies, most notably the Internet of Things (IoT), big data analytics, and artificial intelligence (AI). Within the AI domain, sub-fields like machine learning, deep learning, and natural language processing hold profound potential for reshaping digital educational ecosystems.

The Internet of Things (IoT) can be defined as an interconnected ecosystem where physical objects, people, or animals are equipped with unique identifiers and possess the capability to transmit data over a network without necessitating direct human-to-human or human-to-computer interaction (Gillis, n.d.). In an educational context, this might manifest as an instructor automatically receiving a notification when a student submits an assignment to the university's learning management system, exemplifying the broader trend of real-time interconnectivity between devices and individuals (Anderson & Rainie, 2014).

Concurrently, the utilization of big data has become a cornerstone of modern online education. Digital learning environments inherently generate vast quantities of data related to learner behaviours, including prior knowledge states, progression pace, and academic performance metrics. The analytical interrogation of this data can be leveraged to significantly enhance instructional effectiveness and personalize the learning journey. Big data is distinguished by its unprecedented volume, velocity, variety, and complexity, encompassing formats ranging from emails and numeric records to unstructured text documents and multimedia files (Statistical Analysis System [SAS], n.d.). A significant challenge, however, is that without systematic organization and robust analytical frameworks, this deluge of information can rapidly overwhelm institutional capacities. Consequently, advancements in big data analytics must outpace the rate of data accumulation to truly augment the efficacy of digital learning.

Artificial Intelligence is similarly poised to redefine educational paradigms by transforming core areas such as content development, learner assessment, and curricular personalization. AIpowered systems facilitate the tailoring of learning materials to align with individual learners' abilities, preferences, and unique characteristics (Docebo, 2018). The technological foundations of AI rest upon machine learning, deep learning, and natural language processing methodologies (Pillai & Tedesco, 2024). The central principle involves systems autonomously recognizing patterns and executing tasks—such as facial recognition or complex information retrieval—based on repeated exposure to and learning from data. A key advantage of these AI-driven processes is their operation in the background, requiring users only to understand how to effectively leverage the outputs they generate.

Identifying the most critical area of scholarly inquiry within e-learning remains challenging due to the field's competing priorities and diverse facets. For instance, learning analytics has garnered increasing attention as a vital domain of study. Illustratively, Macfadyen and Dawson (2012) conducted an analysis of Learning Management System (LMS) usage patterns at a major U.S. research university, generating actionable data to inform an institutional review and strategic planning process. Their findings suggested that educational quality is less contingent upon institutional budgets, research grant volume, or contact hours, and more strongly correlated with how effectively universities deploy their resources to optimize student learning outcomes (Gibbs, 2010). Corroborating evidence from a Malaysian study indicated that while undergraduates most frequently utilized tools for accessing course content and communication, they made comparatively limited use of institutional support services or links to external learning resources (Sam, 2015).

The COVID-19 pandemic, first identified in Wuhan, China in late 2019, served as a profound and unforeseen accelerant for the global adoption of e-learning. The outbreak caused unprecedented disruption to education systems worldwide, prompting governments, including Kenya's, to implement containment measures such as travel restrictions, mandatory mask-wearing, hand hygiene protocols, and physical distancing requirements (World Health Organization [WHO], 2020). Within the education sector, widespread closures of schools and universities effectively rendered the 2020 academic calendar a "lost year."

In response, educational institutions universally pivoted to online instruction as a continuity strategy. In higher education, the scale and speed of this digital adoption were without precedent. At Egerton University (EGU), for example, the user base on the e-learning platform expanded dramatically from approximately 1,500 in early 2020 to more than 12,000 by December of the same year. However, this surge was largely reactive, propelled by urgency and a fear of academic exclusion rather than being grounded in deliberate strategic planning. Consequently, significant student dissatisfaction emerged, with some cohorts even seeking legal recourse to challenge the imposition of mandatory online examinations (Kigotho, 2020). While the rapid escalation in participation demonstrated the potential for scaling educational access, it also starkly highlighted the more formidable challenge of ensuring sustainable, high-quality success (Maritim & Getuno, 2018). Although the initial fervour for online learning in Kenya's public universities has subsided from its peak during the pandemic (2020–2022), digital platforms have enduringly established themselves as an essential complement to conventional face-to-face education.

2.3 Determinants of Public University Education in Kenya

The landscape of university education in Kenya is predominantly shaped by a tripartite set of influencing factors. The first encompasses the government-mandated legal and organizational structures that govern university operations. The second is the integration and reliance on online learning methodologies. The third is the dynamic demand for higher education, which is itself influenced by both the perceived quality of instruction and the evolving requirements of the labour market.

2.3.1 Legislation and Organizational Frameworks Governing University Education

The foundational legislation governing university education in Kenya is the Universities Act, Number 42 of 2012 (ROK, 2012). This act established the Commission for University Education (CUE) as the successor to the Commission for Higher Education (CHE). Its provisions encompass the comprehensive development of university education, including the establishment and accreditation of universities, the creation of the Universities Funding Board (UFB), and the Kenya Universities' and Colleges Central Placement Service (KUCCPS). As the principal regulatory agency, CUE commenced its mandate in 2013 by issuing charters to universities that predated the Act. This explains why all public universities in Kenya formally received their charters after 2013 (CUE, 2022). A notable historical anomaly is that several constituent colleges of public universities had received their charters in 2011, two years prior to their "parent" universities. These include Murang'a University College (under JKUAT), Machakos University College (under KU), and others. Prior to the 2012 Act, each public university was established through its own specific Act of Parliament, all of which were repealed upon the commencement of the unified Universities Act (ROK, 2012). CUE has further promulgated specific standards for guiding open, distance, and e-learning (ODeL) to be utilized by all universities in Kenya (CUE, 2014).

Historically, among public universities, only Moi University (MU) and the Open University of Kenya (OUK) originated as fully-fledged universities. The majority evolved from constituent colleges of more established institutions or from non-degree granting training institutes. Only four universities achieved standalone status before 1990: the University of Nairobi (UoN, 1970), Moi University (MU, 1984), Kenyatta University (KU, 1985), and Egerton University (EGU, 1987). Jomo Kenyatta University of Agriculture and Technology (JKUAT) and Maseno University attained full status in 1994 and 2001, respectively, with many others chartered in the mass accreditation of 2013. The pioneering universities in terms of establishment also tend to lead in student enrolment. According to ROK (2014a) and Nganga (2014), KU leads with over 70,000 students, followed by UoN with over 64,000, and MU with approximately 31,500. Consequently, the remaining public universities are relatively "young" and often grapple with foundational administrative, managerial, and sustainability challenges, potentially limiting their capacity for innovative educational undertakings like e-learning in the immediate term. Nonetheless, it is imperative for all universities to strive towards enhancing instructional effectiveness through the adoption of modern technological platforms.

The administrative organization of the Ministry of Education (MOE) is subject to change. As per Executive Order Number 1 of 2023 (ROK, 2023a), the MOE was re-organized into three State Departments: Basic Education; Technical, Vocational Education and Training (TVET); and Higher Education and Research. The State Department for Higher Education and Research (SDHER) is vested with the functions of university education policy and standards, management of public universities, and education research. The institutions under its purview include CUE, KUCCPS, NACOSTI, HELB, and the Universities Funding Board, alongside 35 public universities and four university colleges. It is critical to note that the structure of the MOE often undergoes revisions aligned with the nation's five-year political election cycle and the priorities of new administrations. While such restructuring aims to improve efficiency, it can also disrupt policy continuity, as initiatives of previous governments may be shelved in favor of new approaches, potentially compromising sustained, cumulative development in the education sector.

2.3.2 The Inception and Evolution of e-learning in Kenya's Universities

In response to the dual pressures of modernization and escalating demand for tertiary education, several Kenyan universities have embarked on delivering courses electronically. According to Tarus et al. (2015), the University of Nairobi (UoN) was the pioneer, implementing e-learning in 2004. It was followed by Kenyatta University (KU) in 2005, Jomo

Kenyatta University of Agriculture and Technology (JKUAT) in 2006, Moi University (MU) in 2007, and Egerton University (EGU) in 2014.

The establishment of the first university in Kenya in 1970 preceded the invention of the World Wide Web in 1989 (Fox & Rainie, 2014). Consequently, the advent of the Web and, by extension, e-learning, can be reasonably viewed as a disruptive force to the traditional operational models of universities. These technologies have permeated societal structures with such speed and depth that they are now considered the "new normal." This implies that universities, despite their historical legacy, are in a constant state of adaptation to keep pace with digital advancements.

Concurrently, teaching and learning in Kenyan universities are undergoing unprecedented scrutiny (Jowi et al., n.d.). This is driven by escalating student numbers—stemming from a population-wide quest for higher education—juxtaposed against a limited and often overstretched teaching staff. Jowi et al. (n.d.) further argue that the recent national shift towards a knowledge-oriented development policy, with its heightened emphasis on the Science-Technology-Innovation model and internationalization, has subjected Kenyan universities to critical analysis. This scrutiny is essential for illuminating the existing potentials, gaps, and capacity deficits within Kenya's e-learning landscape.

The implementation of e-learning in public universities is not monolithic. Holmes (2020) delineates several types of e-learning, including:

i) **Fixed e-learning**, where all learners receive the same type of information as determined by the instructors. Since the learning materials rely on the instructors, fixed e-Learning is rigid and does not adapt to the students' preferences. Such a type is best suited to environments where learners have similar schedules and skills. It is also known as synchronous e-learning.

ii) **Adaptive e-learning** where all learning materials are designed to fit the learning preferences of the learners. This type of e-learning pays attention to aspects such as skills, abilities, and individual performance. Using such factors to tailor one's learning needs means that one can switch things up whenever they feel like they are lagging behind, or change based on their course completion goals. Adaptive eLearning works well where learners prefer to study at their own pace. One, however, needs to be highly disciplined to stick to their pace in adaptive eLearning.

iii) **Asynchronous e-learning** where students study independently from different locations. Here, learners can study on their own time, depending on their schedule.

If done in an engaging way, this would include user-generated content. For example, instead of multiple-choice exams, learners could submit a video of themselves proving their newly-learned skills.

iv) **Interactive e-learning** where both teachers and students can communicate freely, allowing both parties to make changes to the learning materials as they see fit. An open line of communication also allows for better interaction, resulting in a better learning process should any queries arise. Interactive eLearning works well in a limited and close-knit group environment that allows for flexibility.

v) **Individual e-learning** where students learn on their own without any peer communication. Individual e-learning helps students learn based on personal attributes such as goal achievements rather than relying on their teachers' and peers' standards. However, it restricts all forms of communication, resulting in isolation. Here, one is required to learn solely on their own and complete their goals by themselves, making it only suitable in highly specialized situations where learners are highly motivated and skilled.

vi) **Collaborative e-learning** which focuses on teamwork, allowing students to work together. Learning materials and goals rely on combined effort from all students for completion of the course. If one prefers this type of learning, they have to factor in their strengths and weaknesses, as well as that of their peers.

In practice, Kenyan public universities have adopted diverse e-learning models. Some use it primarily as a digital repository for class notes and assessment records, supplementing but not replacing face-to-face instruction. Others have implemented active Learning Management Systems (LMS) where tutors facilitate learning through online chats, forums, and interactive content. Where both physical and online elements are strategically combined, the mode is termed "blended learning" (Vaughan et al., 2013).

2.3.3 The Demand Dynamics for University Education in Kenya

Public universities in Kenya have witnessed a dramatic surge in student enrolment since 2013. For instance, the 2014 intake saw a 35% increase compared to the previous year (Nganga, 2014). This trend persisted until 2016 when KUCCPS expanded its mandate to include placing students in private universities, diverting approximately 11% of qualified candidates due to capacity constraints in public institutions. However, this trend reversed in 2017 when a significantly smaller cohort met the minimum university entry requirements. Research suggests the previously high numbers were partly attributable to rampant examination malpractice.

Nyamwange (2018) reported a 70% increase in cheating cases during the 2015 Kenya Certificate of Secondary Education (KCSE) examinations, a situation rectified in 2016 through stringent invigilation measures, thereby revealing a previously "artificial" inflation of demand.

The genuine increase in demand, however, stems from a more diverse and evolving body of prospective students. Beyond recent secondary school graduates, this includes mature, employed learners seeking professional development and those balancing academic pursuits with employment. This new demographic requires unprecedented flexibility, compelling public universities to move beyond admission models constrained by physical infrastructure like classrooms and hostels. There is an urgent need to embed flexibility into all aspects of teaching and learning. E-learning is posited as the pivotal solution for providing this necessary adaptability. As argued by Dziuban et al. (as cited in Vaughan et al., 2013, pp. 2-3), the context, technology, and student profiles in contemporary higher education are fundamentally different, and teaching practices must evolve to accommodate these differences.

2.4 Conceptualizing E-learning: A Tapestry of Definitions

The absence of a universally accepted definition for e-learning complicates the sharing of research findings and best practices across the academic community (Sener, 2015). Arkorful and Abaidoo (2015) similarly contend that the lack of a shared lexicon to distinguish among the myriad variations of e-learning poses a significant challenge. Consequently, the term's meaning is highly contextual, ranging from the simple act of students watching a video documentary in a classroom to the complex delivery of an entire degree programme online. To bring clarity to this conceptual ambiguity, several researchers have proposed definitions.

Dewath (2004) offers a broad definition, describing e-learning as the employment of technology to aid and enhance learning. Other notable definitions include:

i) Instruction delivered electronically, either partially or entirely, via a web browser, the internet, an intranet, or multimedia platforms like CD-ROM or DVD (Hall, 1997).
ii) The structured and purposeful use of electronic systems or computers to support the learning process (Allen, 2003).
iii) A broad set of applications and processes, including web-based learning, computer-based learning, virtual classrooms, and digital collaboration, delivered via internet, intranet, audio/videotape, satellite broadcast, interactive TV, and CD-ROM (ASTD, 2001).

iv) Training delivered on a computer, designed to support individual learning or organizational performance goals (Clark & Mayer, 2003).
v) Web-based training that integrates instructional practices and internet capabilities to guide learners toward achieving specified competencies (Conrad, 2000).
vi) The application of information and communication technologies (ICTs) to enhance distance education, implement open learning policies, and increase flexibility in learning activities (CUE, 2014).

For the specific purposes of this study, e-learning is conceptualized as a programme of study delivered over a continuous period of not less than six months, utilizing various combinations of online and face-to-face modalities. It encompasses orientation, content delivery, and assessment through a synergistic blend of online platforms (e.g., Google Meet, Zoom), Learning Management Systems (e.g., Moodle, Canvas), social media tools (e.g., WhatsApp), mobile phone text messaging, and traditional face-to-face interactions. The operational definition adopted herein is: an innovative web-based system that incorporates digital tools alongside supplementary instructional materials, with the overarching objective of offering students a customized, student-cantered, open, engaging, and interactive environment that facilitates and strengthens the process of acquiring knowledge (Rodrigues et al., 2019).

2.5 Global Internet Penetration and its Implications for E-Learning

Internet penetration refers to the ratio of all internet users to a country's total population. According to the estimates from Internet World Stats (2015; 2022) the African continent has had the lowest internet penetration rate of all the world's continents at 29% in 2015 and 46.8% in 2022. The other parts of the world had the following internet penetration values; North America – (88% in 2015; 93.4% in 2022), Europe – (74% in 2015; 89.6% in 2022), Oceania/Australia – (73% in 2015; 71.5% in 2022), Latin America/Caribbean – (56% in 2015; 81.8% in 2022), Middle East – (52% in 2015; 78.9% in 2022), and Asia – (40% in 2015; 67.4% in 2022). This translates to a worldwide average internet penetration of about 46% in 2015 and 69.0% in 2022. However, in terms of the number of internet users, Africa has moved from fourth place (in 2015) to third place (in 2022) with 602 million users. In 2015, Africa was behind Asia, Europe and Latin America but in 2022 it was behind Asia (2,917 million users) and Europe (747 million users).

From the foregoing, it is evident that Africa has now surpassed Latin America regarding the volume of internet users. It is, therefore, important to emphasize that internet user counts (as distinct from internet penetration) represent absolute figures rather than proportional measures. Thus, as a marketing destination, Africa remains a potential target for firms that sell computers and related services, including e-learning. Similarly, the number of end-user ICT devices such as computers, printers, scanners and other peripherals is dependent on the number of active users of the internet.

Similarly, a 2007 *World Bank Institute* survey summed up the condition of ICT infrastructure in African universities as:

> "Too little, too expensive, and poorly managed … the average African university has bandwidth capacity equivalent to a broadband residential connection available in Europe, [and] pays 50 times more for their bandwidth than their educational counterparts in the rest of the world."
>
> Farrel (2007)

Fortunately, the situation is changing for the better noting that internet penetration is not equal among all African countries and varies widely. For example, Kenya is leading Sub-Saharan Africa in terms of internet penetration at 85.2% (Internet World Stats, 2022b). which is way above the world average of 64.2%. This puts Kenya ahead of the African economic giants like South Africa (57.5%), Egypt (51.9%) and Nigeria (73.0%).

The countries that had internet penetration values above the world average, are; Libya (94.8%), Algeria (83.8%), Morocco (60.6%), Kenya (85.2%), Nigeria (73.0%), Mauritius (72.2%), Morocco (68.5%), Tunisia (68.4%) and Re-Union (67.4%). On the other hand, 16 countries had internet penetration values below 20%. These are Gambia (19.0%), Ethiopia (17.7%), Democratic Republic of Congo (17.4%), Congo (16.2%), Liberia (14.9%), Malawi (13.8%), Niger (13.4%), Chad (13.0%), Burundi (12.8%), Somalia (12.8%), Togo (11.9%), Central Africa Republic (11.2%), Madagascar (10.1%), Southern Sudan (7.9%), Eritrea (6.8%), and Western Sahara (4.6%). Therefore, Kenya is the well-placed country to introduce e-learning in HEIs Africa because of the high internet penetration and adult literacy rates (WB, n.d.). This is because internet penetration and adult literacy are indicators that are consistent with learner profiles for e-learning.

2.6 Strategic Frameworks for E-Learning in Kenyan Higher Education

The Kenya National ICT policy (ROK, 2006) cites the absence of a policy framework on e-learning as hampering its development and utilization. In this regard, it proposes:

i) Provision of affordable infrastructure to facilitate dissemination of knowledge and skill through e-learning platforms;
ii) Promoting the development of content to address the educational needs of primary, secondary and tertiary institutions;
iii) Creating awareness of the opportunities offered by ICT as an educational tool to the education sector;
iv) Facilitating the sharing of e-learning resources between institutions;
v) Promoting centres of excellence to host, develop, maintain and provide leadership of better learning resources and implementation strategy;
vi) Exploiting e-learning opportunities to offer Kenyan education programmes for export; and;
vii) Integrating e-learning resources with other existing resources.

There is no evidence to show the extent of implementation of this policy. In this respect, there has been minimal growth of online education as far as the proposals contained in the policy are concerned. As a consequence, and given the changes in technology and methods of delivery, new policies were developed by the MOE.

Similarly, the Kenya National ICT Master Plan (ROK, 2014b) proposed the provision of an integrated infrastructure backbone to enable cost effective delivery of ICT products and services to Kenyans; and an integrated information infrastructure geared towards enhancing the standard of e-Government provisions and enable the country to transition to a knowledge-based society. The Master Plan identifies flagship projects that will be implemented to realize these objectives in the HEI sector, namely; provision of affordable and quality broadband infrastructure to underserved areas, and; establishment of five centres of Excellence in ICT education and training by 2018. In these centres, one of the key guiding principles is technology neutrality where the use of common, interoperable standards and protocols must be encouraged (ROK, 2014b: p.39). This will enhance data sharing among HEI's, reduce operational inefficiencies and wastage of resources and therefore limit the number of personnel required to sustain the highly technical infrastructure (p. 65). The Kenya Education Network Trust (KENET) has been in the fore front in providing ICT infrastructure to HEI's in Kenya. It has achieved this through, among others, the provision of broadband internet and an open-source web conferencing platform for HEI's and individual academic staff across their more than 140 member institutions (KENET, 2022).

Other flagship projects were the school laptop project to provide teaching and learning tools for pupils entering standard one in primary schools in Kenya from the beginning of 2014 and automation of academic and administrative processes at all levels of education in order to have all education information online (ROK, 2014b: p.79). The school laptop project was expected to transform education and help to create a knowledge society and included: review of school curricula, conversion of courseware into digital form, ICT training for teachers, and broadband internet connectivity to the schools. On the other hand, the automation project included the development of an education e-portal that provides services and summary statistics to the public.

While the laptop project failed to take off from the onset and appears to have been abandoned, the automation project succeed with the development of new education e-portals and enhancement of the existing ones, such as the National Education Management Information System (NEMIS) for storing and updating students' data, the Kenya National Examinations Council (KNEC) Portal for examination registration and results; the KUCCPS portal for selection of university and college programmes (including TVET). Taking the cue from government, individual universities, especially the private universities have developed their own e-portals for students' admission, registration of study units and accessing examination results. Most of these information e-portals, in addition to regular web access, have a mobile alternative where users enter a code and are able to receive instant feedback for their questions. The reasons for the failure of the school laptop project remain unknown. However, a plausible reason lies with the high cost of purchasing the high number of laptops needed for all grade one pupils as well as the logistical complexities of configuring, distributing and storing the laptops. Similarly, the training of teachers to use the laptops to teach was a major challenge.

The review of the 2006 ICT Strategy for Kenya to align it to Kenya's new constitutional dispensation and Vision 2030 culminated in the *National ICT Policy* (ROK, 2019; ROK, 2020). A policy objective outlined in the *National ICT Policy Guidelines* (ROK, 2020) that is related to education is:

> … to position the country to take advantage of emerging trends such as the shared and gig economy by enhancing our educational institutions and the skills of our people and by fostering an innovation and start-up

> ecosystem that is able to lead in the adoption of emerging trends on a global scale (ROK, 2020; p. 3065).

The National ICT policy focuses on four key areas, namely;

i) **Mobile first** - this is a focus on internet access via mobile phones. Currently, 99.9% of Kenyans have internet access mostly via mobile phones. It is nowadays common practice for students entering college in Kenya to own a mobile phone. It therefore makes sense to focus on things that can be done especially with an internet-connected phone such as e-learning. This is not only convenient but also allows students to engage in learning anywhere, any time.

ii) **Market** - by the year 2030, Kenya's population is estimated at 66 million, with over 200 million devices and sensors connected to the internet. This implies that all aspects of our lives including education, money, governance and health among others will fully and seamlessly be integrated into the digital economy. In addition, about 1 million youth enter the work force every year. Therefore e-learning in Kenya's HEI's will continue to grow as ICT becomes an enabler of education and training.

iii) **Skills and Innovation** – this policy takes cognizance of the fact that technology is changing fast and the need to not only keep up but be prepared to embrace the change. For university graduates to find gainful work there is need to align education systems with global market requirements. The Kenyan HIE curriculum therefore needs to take into account the changing trends in technology to generate highly skilled workforce that is in demand globally. This will produce innovators in the current Fourth Industrial Revolution that is re-shaping the world. To do this, our HIEs need to innovate and create globally competitive educational institutions by embracing new methods of teaching and learning.

iv) **Public service delivery** - this policy envisages availability of all public services in Kenya online. This does not exclude education, ensuring that services are delivered quickly and fully at the time they are needed. Online transactions by their nature promote efficiency, security and openness. For instance, in e-learning, students can submit assignments efficiently, within a verifiable and secure network long after the action.

CUE has developed standards and guidelines supporting digital learning in universities. However, the extent to which this policy has been implemented remains undocumented. Even so, Kenyan universities have since created policies to guide technology integration in teaching and learning. Although these standards and guidelines are important, they are still not specific enough to be practically useful. This is because, integrating ICTs in university education requires a paradigm shift and new thinking that focuses on learners' needs. This means the development of effective learning environments that are enhanced through thoughtfully crafted resources (Reigeluth & Duffy, 2007). Khan's eight-step principles (Khan, 2003) for e-learning strategy is a plausible starting point in exploring the strategic requirements for e-learning in HEIs. The eight principles are: institutional, pedagogical, technological, interface design, evaluation, management, resource support and ethical.

The institutional framework addresses three key domains: administrative functions such as needs assessment, readiness evaluation, organizational change, admissions, graduation, and alumni engagement. The second domain relates to academic matters, including instructional quality, faculty and staff assistance, workload management, class size, remuneration, and intellectual property considerations. Finally, the framework encompasses learner services, which include pre-enrolment activities, orientation, academic advising, support for students with disabilities, and library access.

The pedagogical dimension in digital learning emphasizes the processes involved in instruction and knowledge acquisition. It covers aspects such as content analysis, understanding the audience, defining learning goals, selecting appropriate media, determining design approaches, organizing materials, and employing effective instructional methods and strategies. The technological dimension addresses the infrastructure that supports e-learning environments. This includes planning for technology, establishing standards, managing metadata, creating learning objects, and ensuring the availability of appropriate hardware and software.

Interface design in e-learning encompasses the overall appearance and user experience of the program, including page layout, site structure, content presentation, navigation, usability testing, and accessibility. Evaluation in e-learning entails examining both learner outcomes as well as the efficiency of the instructional design and overall learning setting. E-learning management focuses on maintaining the learning platform and distributing information effectively. The resource support dimension encompasses the provision of instructional and technological assistance, career guidance, as well as additional digital and physical materials that enhance meaningful learning experiences. Ethical considerations in e-learning address issues like policies and guidelines, privacy, plagiarism, and copyright compliance.

Collectively, these eight dimensions provide a comprehensive framework for institutional e-learning strategies in HEIs.

2.7 Assessing University E-Readiness

E-readiness refers to the level of preparedness of an organization or an individual to utilize electronic means to carry out their duties or functions. This study examines the preparedness of public universities and their students to effectively participate in digital learning. Tubaishat and Lansari (2011) identified key components of readiness for online education as technology, internet usage, institutional culture, and foundational knowledge of electronic learning. Olatokun and Opesade (2008) argue that when assessing institutional readiness, parameters such as infrastructural availability, access to infrastructure, manpower availability, and the policy and regulatory framework should be considered.

The Kenya Education Network (KENET) conducted comprehensive studies on ICT application for enhancing learning quality, instruction, and research in Kenya in 2006, 2008, 2013, and 2015. These studies encompassed public as well as private chartered universities and were modelled on the annual EDUCAUSE surveys initiated in the USA in 2004 (Educause Research, n.d.). The investigations focus on understanding technology's contribution within higher education while also expanding the evidence base that supports institutional decision-making and planning.

The EDUCAUSE Centre for Applied Research (ECAR) in 2012 collaborated with 195 institutions to collect responses from over 100,000 undergraduate students from around the world (Dahlstrom, 2012). The information gathered was about students' perceptions of technology, how various technologies contribute to their overall academic experience and how technology contributes to their academic achievement. The findings reflect four general themes;

i) students prefer blended learning modalities,
ii) students continue to bring their own devices to college that are both prolific and diverse,
iii) students have strong and positive perceptions about how technology is being used and how it benefits them in their academic work, and;
iv) students are selective about the communication modes they use to connect with instructors, institutions and other students.

On the other hand, KENET, in 2013, collected data from about 15,000 students (92 % of whom were undergraduate students) located in 42 campuses of 20 public and 10 private universities in Kenya (Karshoda & Waema, 2014). The purpose of the study was not to rank the universities but to provide them with information that would assist them to use ICT to realize their mission and goals. In the study, 17 e-readiness (a measure for a university or institution to improve learning, instruction and inquiry) indicators were analyzed. The indicators (and sub-indicators) were categorized into five as follows: Network access (with four indicators – information infrastructure, internet availability, Internet affordability, network speed and quality), Networked campus (two indicators – network environment, e-campus), Networked learning (with four indicators – enhancing education with ICTs, developing the ICT workforce, ICT research and innovation, ICTs in libraries), Networked society (with four indicators – people and organizations online, locally relevant content, ICTs in everyday life, ICTs in the workplace), and Institutional ICT strategy (with three indicators – ICT strategy, ICT financing, ICT human capacity).

Each indicator in the 2013 KENET study was assigned a score from 0 to 4 where 0 was the minimum score (or stage) while a score of 4 indicated the maximum stage of achieving the indicator in question. The results showed that, on average, the universities only achieved stage 3 and above in only two of the 17 indicators. These were ICT at the workplace and networked campus environment. In addition, 2013 saw a limited accession to higher stages for most of the indicators as compared to the 2008 values, which all remained below stage 3. Other notable findings are that universities are spending less than 0.5% of their budgets on internet bandwidth (against the 1% recommended), and that 60% of the students in universities consider their campus network as "unstable" – suggesting low ICT technical capacity, that is, universities do not have the necessary staff with requisite skills and qualifications to manage the large and complex campus networks. This led to the conclusion that accession to higher levels for the indicators is a slow process that requires universities to work in earnest in order to implement their strategic plans.

The indicator in the KENET study that bears the closest association with this research is "Enhancing education with ICT," which falls under the broader category of "Networked Learning." This indicator consists of four sub-indicators: integration of ICT into the curriculum, availability and deployment of e-learning platforms, application of ICT in student projects, and integration in instruction through technology by faculty. For this, universities were positioned at stage 2.8 in applying ICT within teaching and learning processes. This finding reflects significant progress with respect to ICT utilization in universities. It was also noted that data on the percentage of courses supplemented by e-learning materials was not available for 63% of the 30 universities in the study. The results further point to the fact that universities have not adopted effective strategies for accession to higher levels of e-readiness in networked learning.

In an article that examined the utility of distance learning approach for training teachers in Kenya, Maritim (2009), critically interrogates the readiness of distance education providers, and; the learning and policy environments. They argue that most distance learning providers in Kenya are dual-mode institutions and offer their education - regrettably - as dictated by the vagaries of market forces. The implication of this is that the nature of distance learning in dual-mode universities will always be overshadowed by the revenue generation motive.

Secondly, as far as the policy framework on teacher-training is concerned, Maritim (2009), further argues that there is a policy contradiction regarding the policy provisions of the Kenya Vision 2030, the Ministry of Education and the Teachers' Service Commission, TSC (the teachers' employer in Kenya). He argues for the establishment of a single-mode institution dedicated to distance education. Such an institution is expected to reduce the unit cost of learning owing to the economies of scale. Examples of such institutions are, the Open University of Tanzania (http://www.out.ac.tz/), Zimbabwe open university (http://www.zou.ac.zw/), Open State university of New York (http://open.suny.edu/), Canada's Athabasca university (http://www.athabascau.ca/), the Open University, United Kingdom (http://www.open.ac.uk/), the African Virtual University (http://www.avu.org/), Saudi Arabia's National centre for e-learning and distance learning (http://elc.edu.sa/?q=en), India's Indira Gandhi National Open University(http://www.ignou.ac.in/), Japan Open University (http://www.ouj.ac.jp/eng/) and the Open University of Kenya (https://ouk.ac.ke/)

The Open University, United Kingdom's website (http://www.upou.org/) aptly describes open universities as:

> Universities that have a less formal structure than traditional universities. They are also known for open-door entry policies, where no particular academic qualifications are needed for entry into degree granting or other academic enrichment programs...attract and are ideal for students who are older or who wish to achieve advanced degrees while continuing their careers...are ideal for continuing education that is either desired or required to advance within a profession or speciality. Programs offered by open universities include distance or online learning, correspondence courses, a combination of on-site lectures and distance learning, as well as degree programs which grant credit for life experience including work experience. Open universities are found throughout

> the world, and programs offered range from technical training to advanced degrees in Commerce, Finance and even Law. While open universities are usually private institutions, they offer instruction at prices that tend to be far lower than those of even some public institutions which offer similar courses. Degrees granted by open universities are often well respected in the workplace because they show the graduate's commitment to obtaining further knowledge and training while remaining committed to his or her career (Up to Open Universities, n.d.).

The findings of Maritim's (2009) study confirm the findings by Spooner et al. (1999) that the more experience students have with distance education conditions, the more comfortable they become with that mode of interaction. From the foregoing it is therefore expected that students' behavioural intention (BI), actual use behaviour (UB) and hence adoption of e-learning will improve the longer students use digital learning methods. Thus, a determination of e-readiness in HIEs cannot be over-emphasized. This is because of its importance in understanding the optimum conditions necessary for e-learning adoption to take place.

2.8 A Survey of Related Studies on Technology Acceptance and E-learning Adoption

This section presents related studies in e-learning adoption from both a local and international perspective. It highlights the nature of investigation as well as the results of the studies presented. Additionally, it provides a critique in light of the best practices in user acceptance studies.

In formulating the UTAUT, Venkatesh et al. (2003) investigated eight prominent concepts and frameworks, gathering data from 215 respondents across four organizations over a six-month period, using a longitudinal research design with three measurement points. In two of the organizations, the use of technology was voluntary, while in the other two, the use of technology was mandatory. In one of the former organizations focusing on product development in the entertainment industry the sample consisted of 54 respondents while in the second one focusing on sales in the telecommunication services industry, the sample consisted of 65 respondents. In addition, one of the latter organizations had a sample of 58 respondents chosen from the Business Account Management functional area in the Banking industry. Finally, in the second of the latter organizations, there were 38 respondents selected from the Accounting Department of a Public Administration sector. Based on their data analysis, Venkatesh et al. (2003) theorized that four key constructs significantly influenced user acceptance and usage behaviour of technology. These constructs served as direct determinants of how individuals adopt and engage with technological systems. The determinants were: PE, EE, SI, and FC. From these constructs they developed the UTAUT consisting of the four determinants of technology adoption. This study had 388 respondents from three similar universities where the use of technology was mandatory.

Al-Harbi employed a model grounded in the TPB, hypothesizing that gender and internet experience would serve as moderators of students' attitudes, subjective norms, and behavioural control in relation to their intention to adopt digital learning. Utilizing a mixed-methods design comprising two exploratory qualitative phases and one primary quantitative phase, the study revealed that the model accounted for 20% of students' intention to adopt digital learning as a supplementary tool and 41% of their intention to engage in digital learning for distance education. The findings further demonstrated that gender moderated only the association between behavioural control and the intention to adopt digital learning for distance education. Conversely, internet experience moderated both the relationship between behavioural control and the intention to adopt digital learning for distance education, as well as the connection between students' attitudes and their intention to adopt digital learning as a supplementary tool. While prior research has identified age as a moderating factor in the intention to adopt digital learning (Levy, 1998; Plude & Hoyer, 1985; Venkatesh et al., 2003), Al-Harbi's (2010) study did not address this variable. By contrast, the present study incorporates the individual user dimension of digital learning and explicitly includes age as a moderating variable within this context.

In a descriptive and correlational investigation on factors influencing e-learning in Kenya, Ngamau (2013) examined the underlying challenges to effective implementation within a public university. The analysis was framed around individual, organizational, and system-level factors. The results, collected from 146 faculty, showed that the faculty's computer literacy was significantly correlated to the period of Learning Management System (LMS) usage, frequency of LMS use and adoption. On the other hand, computer anxiety and age were negatively correlated with LMS adoption. Similarly, only about half of the faculty had access to internet, were adequately trained and had insufficient incentives to adopt e-learning. Ngamau's study does not present a complete picture of the factors affecting e-learning in Kenya because of failing to investigate the student-related factors. This study addresses this deficit by focusing on students. This is because students, as the ultimate recipients of e-learning instruction, are best placed to provide this information.

Ansong et al. (2016) presented a paper focusing on a multi-dimensional perspective encompassing students, tutors, and e-learning administrators in Ghana. Utilizing a survey research design, their findings indicated that several factors - such as technological infrastructure, perceived usability, organizational alignment, anticipated benefits, academic partnerships, strategic advantage, instructional content, and the digital learning curriculum - collectively contributed to adopting e-learning. The authors emphasized the multi-dimensional nature of their study as a key strength, particularly highlighting that the program of study (including content and curriculum) is a crucial determinant of e-learning adoption. This aspect is significant as it extends beyond the traditional factors typically associated with e-learning adoption. However, a multi-dimensional study appears superfluous and unable to distinguish specifically and in-depth the factors that stand out as true determinants of e-learning. This is because, each dimension consists of almost an inexhaustible list of factors, thereby making it easy to compromise analytical rigour.

Nyagorme (2014), conducted a study to compare e-learning adoption in one public university in Kenya and another in Ghana. Using a descriptive survey research design, they sampled 472 students, 160 lecturers and 68 members in the top management of both universities to participate in the study. Specifically, they set to establish the major challenges facing e-learning adoption in the two universities. The challenges were theorized and placed in four categories, namely; managerial, perceived e-learning attributes, institutional and end-user. Further, he conceptualized the challenges within Roger's (1962) DI Theory and Fishbein and Ajzen's (1980) Theory of Reasoned Action. On the other hand, he used the Framework for ICT Technical Support (FITS) and the e-learning Maturity Model (EMM) to underpin his study. The findings indicated that the extent of electronic learning uptake within both universities was limited. This has contributed to the motivation for developing of a model aimed at enhancing adoption of digital learning practices among undergraduate students in Kenya's public universities.

In Kenya, Hadullo et al. (2017), conducted a study on e-learning quality. The study obtained an LMS-assisted e-learning quality model and proposed its evaluation using Structural Equation Modelling techniques. The model was obtained by employing six dimensions of e-learning quality as a basis for reviewing existing e-learning quality frameworks and models. The six dimensions of e-learning were: course development, assessment, learner support, institutional factors, user characteristics and overall performance of an educational system. The reasons for using these dimensions were that they had been found to be responsible for the unsuccessful implementation and growth of e-learning in Africa.

On the other hand, the e-learning frameworks and models were; Khan's (2004) People, Process and Product (P3) Course Evaluation Model, Zhang and Cheng's (2012) Planning, Development, Process and Product (PDPP) evaluation model, Masoumi and Lindstrom's (2012) e-learning Quality Framework, Omwenga and Rodrigues' (2006) Technology-Mediated Learning Evaluation (TMLE) framework; and Marshall's (2007) E-learning Maturity Model (EMM). The weakness of their study lies in the fact that it proposes a framework for e-learning quality without testing it and providing the results of the test. Instead, it alludes to a test that would be carried out in future. The study can thus be viewed as a work-in-progress and does not in itself provide conclusive results. This begs the question on whether it is acceptable to present a framework based only on literature review without backing it up with empirical data. In contrast to Hadullo's study, the present study used both literature review and empirical data to develop the USeLAM.

Jaber (2016) examined the determinants of electronic learning adoption across academic institutions in Jordan. The investigation drew responses from 198 participants—comprising students, faculty, IT personnel, and administrative staff. The analysis showed that the intention to adopt e-learning systems was shaped more strongly by perceived ease of use than by perceived usefulness. Nonetheless, both constructs were found to positively influence adoption intentions. Furthermore, the research underscored the significance of cultural dimensions, demonstrating that they served as predictors of individuals' attitudes toward these perceptions. Descriptive results further indicated that cultural factors, particularly risk perception, play an essential role in shaping attitudes toward digital learning in the Jordanian context.

In the African context, Omwenga et al. (2004) developed a model for introducing and implementing e-learning for delivery of educational content. Their model modified Rodgers' DOI theory in which they contextualized various parametric values that are dependent on cost, level of infrastructural support and staff motivation and commitment. Apparently, there appears to be limited studies that have tested Omwenga's model, resulting in its low usage and application. The reason for this is likely related to the model's limitation of addressing both university staff and students' implementation of e-learning at the same time. From a critical angle, the model addresses university-wide adoption and makes no distinction between staff or students' adoption factors.

2.9 Predictors of E-learning Adoption

From the eight theories and models that make up the UTAUT, Venkatesh et al. (2003) theorized that BI would be impacted by three constructs while one construct would directly influence UB. These constructs, regarded as predictors of e-learning adoption, were adapted for this study. The three predictors that directly influence BI in this study are PE, EE, and SI while FC directly influences UB. Each predictor is a composite construct arising from some of the eight models or theories that, together, make up the UTAUT. Following is a definition of each predictor and the underlying model (s) or theory (theories) from which it has been derived.

2.9.1 Performance Expectancy (PE)

When students join university, they have expectations about the grades they would obtain or the competencies they will 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. 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. argue that PE is the strongest predictor of BI, an assertion that was tested in this study. According to Venkatesh et al. (2003), PE is made up of: 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.

2.9.2 Effort Expectancy (EE)

In this study, EE refers to the "degree of ease" (Venkatesh et al., 2003, p.450) associated with the use of the e-learning mode of study. In some studies, the expression, "free from effort" (Mehta et al., 2019) has been used in place of "degree of ease". This construct has been chosen because its definition and measurement scale is similar to those representing EE in the underlying theories and models.

In formulating the UTAUT, Venkatesh et al. (2003) found that the EE construct is significant in both voluntary and mandatory usage contexts. However, its significance tends to diminish after the initial training or orientation to e-learning, becoming non-significant during extended periods of usage. Over time, these concerns often give way to instrumentality considerations (Davis et al., 1989; Szajna, 1996; Venkatesh, 1999). Additionally, Venkatesh and Morris (2000) suggest that EE may be more relevant for women than for men. Consequently, EE was proposed as a predictor of BI in this study.

2.9.3 Social Influence (SI)

Mehta et al. (2019), define SI as the 'perception of group influence on an individual's decision'. In an educational context, learners perceive technology as being useful if referent others, such as parents, employers, friends, and peers endorse it. Mtebe and Raisamo (2014b) and Kolog (2015) found varying effects of SI on BI among university students in East Africa and Ghana respectively. In the former, while all predictors were significant, SI was the least significant predictor of BI to adopt mobile learning when compared with PE, EE and FC. In the latter, only PE and SI were significant predictors while EE and FC were not significant predictors of Ghanian university students' adoption of e-counselling.

It is plausible to expect learners to be more likely to have intentions of using e-learning if it is endorsed by referent others within their social environment (Mehta et al., 2019). While the constructs have different labels, each of them behaves similarly when model comparisons are performed. Venkatesh et al. (2003), found a complex relationship between SI and BI that is moderated by gender, age, voluntariness, and experience.

However, it is worth noting that in this study, voluntariness, as a moderator, was not studied because it was mandatory where a student had already made the decision of studying online. On the other hand, experience is regarded as "internet experience". In mandatory settings, the role of SI tends to diminish with the passage of time (Venkatesh & Davis, 2000).

Social influence has an impact on individual behavior through three mechanisms: compliance, internalization, and identification (Venkatesh & Davis, 2000; Warshaw, 1980). The last mechanism, identification, occurs when an individual identifies with those endorsing the use of technology. This is because it creates a sense of belonging with the group especially if referent others have the ability to offer rewards or punish behavior for compliance/non-compliance behaviour.

However, the decision of an individual to comply with the BI to use a new technology adoption in mandatory settings is influenced by the opinions of others, particularly in the early stages of use when an individual's opinions are relatively ill-informed (Agarwal & Prasad 1997; Hartwick & Barki 1994; Taylor & Todd, 1995). Therefore, it is theoretically reasonable to expect that at later stages of experience, the influence of SI on BI diminishes, paving way to a more instrumental basis for an individual's decision making. This study therefore, includes SI as a predictor for e-learning adoption.

2.9.4 Facilitating Conditions (FC)

In HEIs, FC refer to the availability of computers, reliable internet connection, people to assist learners with difficulties and other related hardware and software resources. This definition, according to Venkatesh et al. (2003) captures concepts embodied by: perceived behavioral control (in TPB, C-TAM-TPB), facilitating conditions (in MPCU), and compatibility (in DOI).

Venkatesh et al. (2003) argue that when both Performance Expectancy (PE) and Effort Expectancy (EE) constructs are present, Facilitating Conditions (FC) become non-significant in predicting Behavioral Intention (BI). Additionally, empirical results indicate that FC has a direct influence on usage that extends beyond what is explained by BI alone. In fact, the effect of FC is expected to increase with user experience, as technology users discover multiple avenues for assistance and support, thereby reducing barriers to sustained usage (Bergeron et al., 1990). Consequently, in the proposed model of this study, both FC and BI are considered antecedents of Use Behavior (UB).

2.10 Outcomes of E-learning Adoption

The outcomes of digital learning adoption in this investigation are represented by BI and UB. These outcomes were derived from a general assumption in human behaviour that once there is an intention to perform an action, there is a high probability of actually carrying it out. For example, within this investigation, it is assumed that students' behavioural intention to participate in digital learning results in a preference for, and subsequent use of, the digital learning mode rather than the conventional in-person mode. However, the theoretical basis for the claim that intention precedes behaviour is grounded in the idea that humans act rationally rather than emotionally—an aspect of behavioural control (Ajzen, 1991). Tzeng et al. (2022) carried out an investigation to predict technology adoption among college students. Their findings indicated that self-evaluation strengthened the influence of intentions on behaviour and enhanced the accuracy of predictions. This implies that the association between intention and behaviour cannot be directly predicted but is moderated by additional factors that shape this association.

2.11 Moderating the Relationship Between Predictors and Outcomes of E-learning Adoption

In this study, 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. While certain relationships are direct, others, such as that between BI and UB are theorized to be direct, without any moderating effect. In this study, the following moderators were theorized as having an effect on the relationship between the predictors of e-learning adoption and the outcome variables: age, gender, and internet experience. While a student's academic programme was thought to have a moderating effect on e-learning adoption, there was no sufficient support of this premise in the literature. The next sub-sections provide a description of each of the moderators.

2.11.1 Age as a Moderator of E-learning Adoption

A person's age is likely to dictate their 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, Fleming et al. (2017) studied employees' overall acceptance, satisfaction, and future use of e-learning. Their findings suggest that, contrary to common stereotypes, age does not significantly influence either future use intentions or satisfaction with e-learning. In contrast, they identified three key variables as effective predictors of future organizational e-learning usage intentions; low complexity, authenticity, and technical support. On the contrary, Venkatesh et al. (2003), in formulating the UTAUT, found that age was an important consideration in e-learning studies.

From the foregoing arguments, age tends to affect e-learning adoption differently with respect to context. For example, Plude and Hoyer (1985) showed that advanced age decreases an individual's efficacy with technology. Further, Morris and Venkatesh (2000), argue that differences in learners' ages have an influence on technology use.

2.11.2 Gender as a Moderator of E-learning Adoption

Many research studies in technology adoption include gender as a consideration in disaggregating research results (Shaouf & Altaqqi, 2018). In a study involving 302 Computer Science undergraduate students at a public university in Iraq, Al-Azawei (2019) included gender as a moderator of the relationship between e-learning self-efficacy (among other constructs) and BI towards acceptance of Learning Management Systems (LMSs). The results showed that gender differences had only a slight moderating effect on the relationship between e-learning self-efficacy and LMS acceptance where self-efficacy had a stronger impact on the intention to use LMSs among men than among women.

Other studies suggest that women are generally more responsive to social influence, as they tend to be more attuned to others' perceptions and opinions; consequently, social influence (SI) plays a more significant role in shaping their intention to adopt new technologies. (Miller 1976; Venkatesh et al., 2000). Moreover, research on gender differences indicates Men are generally perceived to be more task-oriented, emphasizing the completion of specific objectives and the attainment of measurable outcomes. This orientation often reflects a preference for efficiency, problem-solving, and performance-driven behaviour, particularly in contexts that require analytical thinking or goal-directed action (Minton & Schneider 1980). This can be attributed to the existence of gender-based differences that have been widely documented in the context of technology adoption. Prior research (Morris & Venkatesh 2000; Venkatesh & Morris 2000) indicates that men and women often exhibit distinct behavioural patterns, motivational drivers, and decision-making approaches when evaluating or adopting new technologies, thereby influencing the extent and manner of their engagement with technological innovations. This study therefore, explored gender as a moderating variable in e-learning adoption.

2.11.3 Internet Experience as a Moderator of E-learning Adoption

As e-learning offering in higher education is predominantly internet-based, experience with the internet provides the learner with some knowledge on how to use e-learning with less effort and time (Al-Harbi, 2010). Learners' success in e-learning depends on technical skills in computer operation and internet navigation as well as the ability to cope with the substantive subject matter (Kerka, 1999). Furthermore, Morss (1999), found empirical evidence that students who had more experience of with technology used a learning management system more than students with less experience of IT.

Moreover, Venkatesh (2003), showed that the relationships among the constructs appearing in the C-TPB-TAM were moderated only by user experience. Thus, in designing e-learning systems the user's level of experience should be taken into account because less experienced users will tend to rely on different factors compared to experienced ones. This means that experience (or lack thereof) with the internet and IT 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.

Figure 1

Relationships Between the Variables

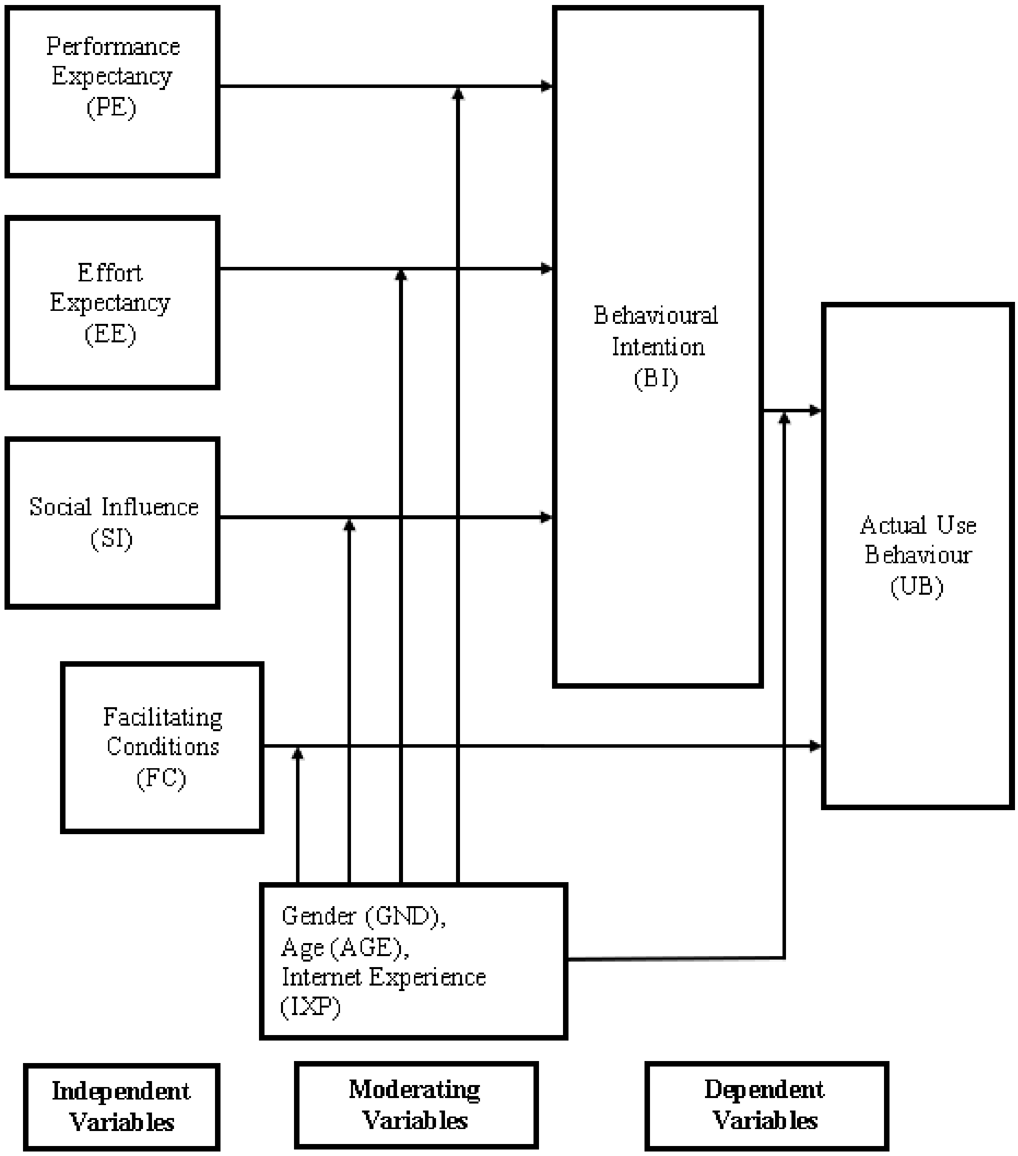


Figure 1 shows the relationships between the independent, moderating and dependent variables. There are four direct determinants of e-learning adoption and three moderators. The direct determinants are PE, EE, SI and FC while the moderators are GND, AGE, and IXP. The dependent variables are BI and UB. It is worth noting here that in this study, e-learning adoption is a composite of both BI and UB and that each of the four direct relationship is moderated by three moderators. Further, BI is a dependent variable for the predictors PE, EE and SI but also a predictor of UB. Thus, the action BI is that of a mediator in this study.

2.12 Theoretical Framework

The investigation of how users adopt technology across various sectors—including banking, industry, management, and education—has been extensively guided by established technology acceptance theories and models. These conceptual tools have been advanced to decipher and predict user behaviour towards new technologies. Among the most prominent are the Technology Acceptance Model (TAM), the Diffusion of Innovations (DOI) theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT, being the most recent of these, has gained considerable prominence. Although its application within educational contexts is not yet as widespread as in other fields, it is selected as the foundational theory for this study due to its robust explanatory power and validated reliability in technology adoption research globally.

The UTAUT centres on two pivotal concepts: the "acceptance" and "use" of technology. While "use" is understood in its conventional sense, "acceptance" carries a more specific meaning. Dillon (2001) defines technology acceptance as the "demonstrable willingness" to employ information technology for task performance. In this study, "willingness" is synonymous with "acceptance" and corresponds to an individual's intention to use IT. Collectively, "acceptance" and "use" constitute the broader concept of adoption. The degree of adoption is contingent upon the extent of use and can be measured by the variance between behavioural intention and actual use behaviour. Consequently, the adoption of e-learning in this context refers to the demonstrable willingness of undergraduate students to persistently engage with the e-learning mode of study. The application of such technology acceptance models is a valuable mechanism for understanding and steering technology initiatives within education (Atif & Richards, 2012).

The UTAUT's versatility is evidenced by its application in diverse global contexts. For instance, it has been employed to study e-government adoption by citizens in Kuwait (AlAwadhi & Morris, 2008), e-learning adoption by university students in Saudi Arabia (Al-Harbi, 2010), mobile learning adoption in East Africa (Mtebe & Raisamo, 2014b), e-counselling adoption in Ghana (Kolog, 2015), and internet banking acceptance in Sudan (Khater, 2016). The consistent utility of UTAUT across these varied studies affirms its comprehensiveness, validity, and reliability, thereby encouraging its application in the present research.

It is critical to note that the UTAUT was formulated through a systematic review, mapping, and integration of eight foundational theories and models:

i) The Theory of Reasoned Action (TRA)
ii) The Technology Acceptance Model (TAM)
iii) The Motivational Model (MM)
iv) The Theory of Planned Behaviour (TPB)
v) A combined Theory of Planned Behaviour/Technology Acceptance Model (C-TPB-TAM)
vi) The Model of PC Utilization (MPCU)
vii) The Diffusion of Innovation (DOI) theory
viii) The Social Cognitive Theory (SCT)

These constituent theories are primarily designed to explain technology adoption at the individual, rather than the institutional, level (Al-Mamary et al., 2016). In scholarly literature, the terms "theory" and "model" are often used interchangeably, as their fundamental similarity allows for comparison and integration. However, a nuanced distinction exists:

> A theory is a conceptualized framework. It is a generalized phenomenon which is accepted by many people in the society. A model, on the other hand, is a physical, symbolical, or verbal representation of a concept which has been found in order to make the understanding of something clearer. The main difference between model and theory is that theories can be considered as answers to various problems identified especially in the scientific world while models can be considered as a representation created in order to explain a theory (Pediaa, 2015).

This study opts for a model-based approach, utilizing diagrams alongside associated statistical metrics to represent the relationships between predictors and outcomes of e-learning adoption. These diagrams serve to simplify the comprehension of complex variable interactions, enhancing understanding when interpreted in conjunction with the accompanying statistical analyses and explanations.

The influence and application of UTAUT have been the subject of systematic reviews. Williams et al. (2000), in an analysis of 450 citations, found that only 43 studies actually utilized the theory or its constructs. A later review of 174 articles by Williams et al. (2015) gathered data on demographics, methodologies, limitations, and construct relationships. Their findings indicated that research within the UTAUT context predominantly examined both general-purpose and specialized business systems, employing cross-sectional surveys and

Structural Equation Modeling (SEM) as the primary methodologies, with SPSS as the key analytical tool. A weight analysis revealed Performance Expectancy (PE) and Behavioural Intention (BI) to be the strongest predictors. A frequently cited limitation across studies was the use of single-subject designs or biased samples.

Li and Kishore (2006) sought to evaluate the acceptance of online community Weblog systems among 265 business school undergraduates. Using multiple group invariance analysis, they assessed the stability of UTAUT scales across subgroups defined by gender, computing knowledge, and Weblog experience. The results indicated that the scales for the four core UTAUT constructs were not invariant across all subgroups. Consequently, the authors advise researchers to exercise caution in interpreting UTAUT-based results, as a lack of robust and stable scales across different settings can significantly impact the interpretation of findings, highlighting a potential weakness in the model's application.

Maldonado et al. (2011) empirically validated a modified UTAUT model in a South American context by incorporating an "e-learning motivation" construct. Their investigation across 47 schools revealed that Social Influence (SI) positively affected Behavioural Intention (BI), whereas Facilitating Conditions (FC) did not impact portal usage. Furthermore, Use Behaviour (UB) positively influenced motivation for technology adoption, and the variable "region" functioned as a significant moderator. Before presenting the specific modified theory used in this study, a detailed description of each of the eight contributing theories and models, including their applications, constructs, and critiques, is provided.

2.12.1 Theory of Reasoned Action (TRA)

Developed by Fishbein and Ajzen (1975), the Theory of Reasoned Action (TRA) posits that an individual's intention to perform a behaviour is the most immediate and important predictor of whether that behaviour will be executed. The theory further suggests that stronger intentions lead to greater effort expenditure, thereby increasing the likelihood of the behaviour being performed. The TRA aims to explain how pre-existing attitudes and behavioural intentions shape actions. According to Venkatesh et al. (2003), TRA comprises two core constructs: attitude toward the behaviour and subjective norm (the perceived social pressure to perform or not perform the behaviour, referred to as Social Influence (SI) in this study). Applications of TRA in technology acceptance (Davis et al., 1989) and medicine (LaCaille, 2013) have confirmed its utility in explaining actual behaviour as stemming from behavioural intention. Venkatesh et al. (2003) demonstrated that both experience and voluntariness of use moderate an individual's technology acceptance and utilization. A primary critique of TRA is that attitudinal theories are not always reliable predictors of human behaviour, a limitation that prompted the development of the Theory of Planned Behaviour (TPB) and the Reasoned Action Approach (RAA).

2.12.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis (1989), was specifically designed to explain user acceptance and utilization of technology. It proposes that when a new technology is introduced, users base their usage intentions on two primary beliefs: Perceived Usefulness (PU), the degree to which a person believes that using a system would enhance their job performance, and Perceived Ease of Use (PEOU), the degree to which a person believes that using a system would be free from effort (Davis, 1989). TAM provides a framework for unpacking the process of integrating new pedagogies in educational or professional settings (Zheng et al., 2017). The model has been refined over time, resulting in TAM 2 (Venkatesh & Davis, 2000) and TAM 3 (Venkatesh & Bala, 2008), which incorporate external variables such as individual differences, system characteristics, social influence, and facilitating conditions as determinants of PU and PEOU. In TAM 3, the influence of PEOU on PU, computer anxiety on PEOU, and PEOU on BI are moderated by experience (Lai, 2017). Venkatesh (2003) also showed that experience, voluntariness, and gender moderate technology acceptance.

Despite being the most frequently used theory in Information Systems (IS) research among the eight underpinning UTAUT, TAM has faced significant criticism, leading to its multiple revisions. Criticisms include its questionable heuristic value, limited explanatory and predictive power, triviality, and lack of practical utility (Chuttur, 2009). Other critiques highlight its assumption that individuals can freely act on their intentions without constraints (Bagozzi et al., 1992) and the unrealistic expectation that a single model can fully explain behaviour across all technologies, contexts, and users (Bagozzi, 2007).

2.12.3 The Motivational Model (MM)

The Motivational Model (MM), first developed by Keller in 1979, was designed to explore strategies for enhancing learning motivation. Grounded in Vroom's (1964) expectancy-value theory, it posits that motivation is driven by the expectation of success and the perceived value of the outcomes. The MM comprises four components for creating and sustaining motivation: attention (stimulation and curiosity), relevance (satisfaction of personal needs), confidence (feeling competent), and satisfaction (positive self-perception). A substantial body of psychological research validates general motivation theory as a key explanation for human behaviour. Venkatesh (2003) identifies the core constructs of MM in a technology context as extrinsic and intrinsic motivation. Vallerand (1997) further distinguished between different types of internalized motivational forces. While Bagozzi et al. (1992) applied motivational theory to technology adoption, Venkatesh (2003) found that none of the UTAUT moderators (experience, voluntariness, gender, age) significantly influenced relationships within the MM. This may explain its relatively limited use in technology adoption studies. Nonetheless, the MM's robust conceptual framework has informed the development of constructs within this study's conceptual framework.

2.12.4 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) is a theoretical framework for systematically investigating factors that influence behavioural choices (Ajzen, 2012; Hassan et al., 2018), thereby creating a link between beliefs and behaviour. The TPB extends the TRA by incorporating an additional construct: Perceived Behavioural Control (PBC), which reflects the perceived ease or difficulty of performing the behaviour (Ajzen, 1985). This addition allows the TPB to predict actual behaviour more accurately by acknowledging that intended behaviour is subject to limitations of volitional control (Hassan et al., 2018). Intention alone does not always lead to action, a phenomenon known as the "intention-behaviour gap" (Sniehotta et al., 2014). Ajzen (1991) argues that intentions can be accurately predicted from attitudes, subjective norms, and PBC, and that these intentions, combined with PBC, account for significant variance in actual behaviour. The TPB and its variants have been successfully applied to understanding individual acceptance of various technologies, such as in Shalender and Sharma's (2020) study on electric vehicle adoption in India.

The TPB has received criticism, particularly in behaviour change research. Falko et al. (2014), in a health behaviour review, provide several critiques:

i) It fails to explain sufficient variance in behaviour, and its mediation assumptions are sometimes contradicted by evidence (e.g., beliefs often predict behaviour beyond intentions).
ii) 'Extended TPB' models may undermine the novel concepts they aim to test, providing undue support to a framework stretched beyond its original form.
iii) The theory implicitly claims to explain all volitional human behaviour without defining its range of application, making its hypotheses difficult to falsify.

iv) The balance between parsimony and validity is questioned; can a theory claiming to explain all volitional behaviour be sufficient with only four core concepts?

2.12.5 Combined Theory of Planned Behaviour and Technology Acceptance Model (C-TPB-TAM)

Taylor and Todd (1995) merged constructs from the TPB and TAM to form the C-TPB-TAM. This hybrid model posits that behaviour is influenced by behavioural intention, which is in turn shaped by attitude, subjective norm, perceived behavioural control, and perceived usefulness. It also proposes that perceived behavioural control can have a direct effect on behaviour. Within this model, PU and PEOU are determinants of attitude, and PEOU directly affects PU (Panagopoulos, 2010). Venkatesh et al. (2003) note that the C-TPB-TAM integrates the three predictors of TPB with the perceived usefulness construct from TAM. An application by Tavallaee et al. (2017) to investigate mobile learning acceptance in Tehran universities suggested that while TAM constructs predict intentions, TPB constructs are better suited for predicting actual use. The C-TPB-TAM has not been widely used in the literature and, as a result, has not yet attracted substantial critical appraisal.

2.12.6 Model of Personal Computer Utilization (MPCU)

The Model of Personal Computer Utilization (MPCU) was developed by Thompson et al. (1991) based on a study of 212 knowledge workers. Their findings indicated that social norms and three components of expected consequences—job-fit, complexity, and long-term results—strongly influenced PC use. The MPCU is derived from Triandis' (1977) theory of human behaviour, which offers a perspective that competes with the TRA and TPB (Khater, 2016). It posits that behaviour is determined by a combination of desires (attitudes), perceived obligations (social norms), habits, and anticipated outcomes (Altman & Chemers, 1980). Thompson et al. (1991) argued that user support is a key facilitating condition influencing system utilization. They adapted Triandis' model for Information Systems contexts to predict individual acceptance (Atif & Richards, 2012), making it suitable for a range of information technologies. Venkatesh (2003) showed that, similar to the C-TPB-TAM, only experience moderates user intentions in the MPCU. Its use in e-learning adoption studies is minimal, except when combined with other models, and it has therefore not been subjected to the same level of critical examination as theories like TAM or DOI.

2.12.7 Diffusion of Innovations (DOI) Theory

The Diffusion of Innovations (DOI) theory was first proposed by Rogers in the 1960s and has been revised and updated over time (Rogers, 1995; Rogers, 2003). It was later adapted for individual technology acceptance studies by Moore and Benbasat (1991; 1996). The theory's flexibility is demonstrated by its application to diverse contexts, such as the diffusion of Twitter in Turkey (Isman & Dagdeviren, 2018), the promotion of universal design in college instruction (Scott & McGuire, 2017), and the adoption of ICT at the University of Botswana (Dintoe, 2019). Rogers (2003) defines diffusion as "the process by which an innovation is shared through specific channels over time among members of a social system" (p.5). The theory consists of four main elements: the innovation, communication channels, time, and a social system. The innovation-decision process unfolds through five sequential stages: knowledge, persuasion, decision, implementation, and confirmation (Sahin, 2006). Rogers also identified five attributes of an innovation that influence its rate of adoption: relative advantage, compatibility, complexity, trialability, and observability. The core constructs of DOI theory adapted for UTAUT include relative advantage, ease of use, image, visibility, compatibility, results demonstrability, and voluntariness of use (Venkatesh et al., 2003). In formulating UTAUT, Venkatesh et al. (2003) found that experience and voluntariness of use moderate an individual's technology acceptance.

In the African context, Omwenga et al. (2004) developed a model modifying Rogers' DOI theory to promote accessible and context-sensitive e-learning in higher education. Their model contextualizes adoption parameters based on cost, infrastructural support, and staff motivation. However, this model has seen limited testing and application, likely because it addresses university-wide adoption without distinguishing between the different factors affecting staff and students.

Criticisms of DOI theory include the difficulty of quantifying diffusion due to the complexity of social systems (Damanpour, 1996) and identifying the precise causes of diffusion. In education, this is problematic as implementers need to understand learners' specific circumstances, which the DOI might overlook (Greenhalgh, 2001). Rogers (2003) himself identified a "pro-innovation bias," where the theory implies all innovations are beneficial and should be adopted. Another weakness is the assumption of a one-way communication flow without feedback mechanisms, which is an oversimplification (Robertson et al., 1996).

2.12.8 Social Cognitive Theory (SCT)

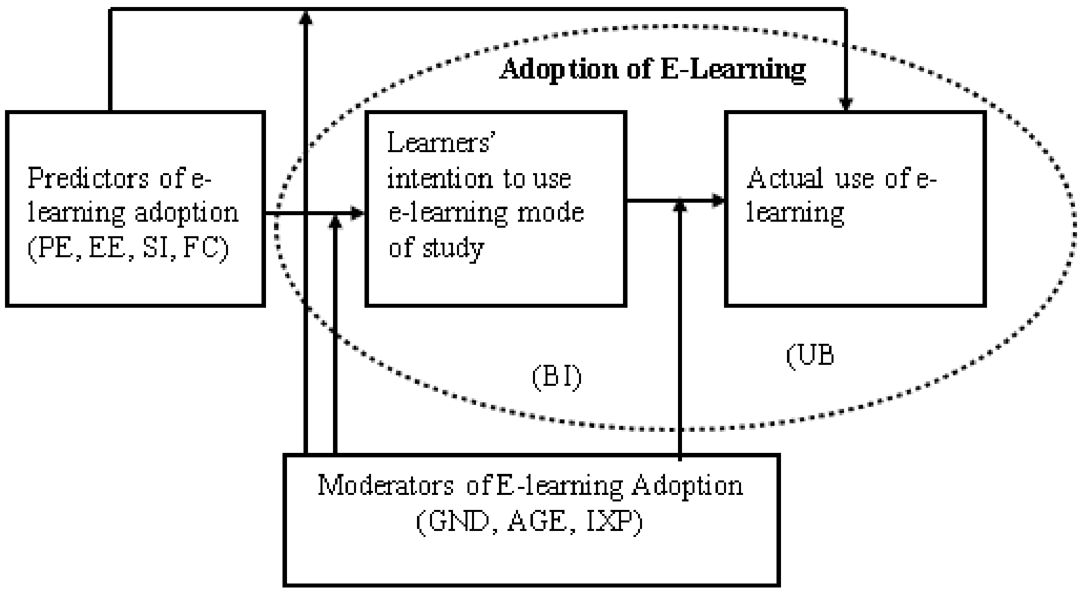
The Social Cognitive Theory (SCT), developed by Bandura (1986) as an extension of Social Learning Theory, is premised on the idea that people learn through observation within social contexts (Atif & Richards, 2012). A key principle of SCT is "reciprocal determinism," where personal factors, environmental influences, and behaviour all interact and influence each other bidirectionally (Zhou & Brown, 2015). Compeau and Higgins (1995) applied and extended SCT to the context of computer utilization. Although initially used for computer use, its nature allows for generalization to information technology acceptance at large (Al-Mamary et al., 2016). The core constructs of SCT in this context are performance outcome expectations, personal outcome expectations, self-efficacy, affect, and anxiety. Venkatesh (2003) showed that, similar to the MM, none of the UTAUT moderators (experience, voluntariness, gender, age) play a role in moderating the relationships within the SCT.

A primary criticism of SCT is that it is not a fully unified theory (Zhou & Brown, 2017), meaning its various components are not seamlessly interconnected. For example, the link between observational learning and self-efficacy is not entirely clear. The theory's breadth means not all its parts are fully integrated into a single, coherent explanation of learning, and many findings associated with it are preliminary. Furthermore, the theory is limited because not all social learning is directly observable, making it difficult to quantify SCT's impact on development. Finally, it tends to ignore developmental maturation, applying the same principles of observational learning to both children and adults without differentiation.

2.13 Conceptual Framework

The conceptual framework for this study is adapted from the work of Venkatesh et al. (2003) and Vroom (1964), with terminology re-contextualized to fit the specific focus of this research. The framework centres on individual technology adoption, utilizing behavioural intention and actual use as dependent variables, a common approach in the field (Bagozzi & Warshaw, 1989; Compeau & Higgins, 1995; Venkatesh & Davis, 2000). Vroom's expectancy model provides a cognitive explanation of human behaviour, portraying individuals as active, thinking agents who continuously predict outcomes in their environment. Individuals are seen as constantly evaluating the consequences of their behaviour and subjectively assessing the likelihood that various actions will lead to desired outcomes (Chen et al., 2012). The specific conceptual framework guiding this study is presented in Figure 2.

Figure 2
Conceptual Framework



Adapted from Venkatesh et al. (2003, p.427) and Vroom (1964)

The conceptual model illustrates the progression of an individual learner's adoption of e-learning over a period of time. This framework conceptualizes e-learning adoption as a process encompassing two sequential and interrelated components: the formation of behavioural intention to use the digital learning mode and the subsequent manifestation of actual use behaviour. Within this paradigm, four key predictors are theorized to directly influence these outcomes: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC).

The model posits a distinct mechanistic pathway for these predictors. Specifically, the constructs of PE, EE, and SI are hypothesized to exert an indirect effect on the learner's actual use of e-learning. This influence is mediated through their impact on Behavioural Intention (BI). In other words, a student's perception of the system's usefulness, ease of use, and the social pressure to use it, collectively shape their intention to engage with e-learning, which in turn propels actual use. In contrast, the construct of Facilitating Conditions (FC) is postulated to exert a direct influence on Use Behaviour (UB), bypassing the mediation of intention. This accounts for situations where even a strong intention to use technology may be thwarted by inadequate resources or support, or conversely, where excellent support structures can facilitate use even when intention is not the primary driver.

Consequently, Behavioural Intention—a futuristic and plan-oriented construct—functions as the critical mediating variable between the initial perceptions of the technology (PE, EE, SI) and the ultimate outcome of actual utilization. The pivotal role of intention as a proximal predictor of use behaviour is a cornerstone principle, well-established and empirically validated within Information Systems research (Ajzen, 1991). Finally, to account for the role of prior exposure and habit, the model incorporates the individual learner's retrospective self-reporting regarding the frequency of their previous e-learning use, acknowledging that past experience can shape current intentions and behaviours.

RESEARCH METHODOLOGY

3.1 Introduction

The methodology outlines the research design adopted for the study. It then defines and specifies the population parameters, including the general, target, and accessible populations. Following this, the rationale for the chosen sampling techniques and sample size is explained, alongside a detailed description of the data collection instrument. The chapter further addresses the procedures used to establish both the validity and reliability of the instrument, as well as the methods employed for data collection and analysis. The final section highlights the ethical principles that guided the conduct of the study.

3.2 Research Design

The 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 following are some of the advantages of the cross-sectional survey:

i) the data collection exercise is quick and accurate. This is true especially if the data collection instrument has already been pilot-tested. This condition was met by pilot-testing the research questionnaire used in this study.

ii) it allows the investigator to gather information from a large population and compare differences between groups. In this study, comparison on e-learning adoption was made across age, gender and internet experience of the students;

iii) it captures a specific moment in time. For instance, the current study provides a snapshot of the status of e-learning in Kenyan public universities as captured within a semester.

Further, Thomas lists the following disadvantages the cross-sectional survey research design as follows:

i) it cannot establish a cause-effect relationship among the variables under study. In this study the researcher sought to establish correlations between the constructs being studies as opposed to causes and effects. For instance, predictors of e-learning are not necessarily responsible for the attendant outcomes but are related to them in some way;

ii) it cannot be used to analyze behaviour over a period of time or to establish long-term trends. Since the focus of this study was on measuring relationships, this design made it possible to determine the relationships between predictors of e-learning and e-learning adoption. It was therefore possible to interrogate the variables under study in a way that other types of survey designs could not achieve;

iii) the data snapshot may be unrepresentative of behaviour of the group as a whole. This is the greatest shortcoming of the survey design because its utility depends on the timing of the survey. If, for instance, the data were collected at the beginning of the semester, then, whatever the outcome of the study, it might appear that the outcome had some relationship with the predictors even if it is clear that it didn't. That is the reason why the data was collected after the students had had some experience with e-learning.

3.3 Location of the Study

This study was conducted in Nairobi, Kiambu and Nakuru Counties in the Republic of Kenya. In Nairobi County it was conducted at Kenyatta University main campus located at Kahawa, in Kasarani Sub-County, approximately 17.5 Km North-East of Nairobi City Centre. In Kiambu County, it was conducted at Jomo Kenyatta University of Agriculture and Technology, Juja, approximately 36 Km North-East of Nairobi City Centre. In Nakuru County it took place at Egerton University, located at Egerton, off the Njoro-Mau Narok road, approximately 182 Km from Nairobi.

3.4 Population of the Study

Systematically defining a population of study is important in many ways for researchers. A well specified population improves the generalizability of findings of a study from sample to population while a poorly specified population compromises the credibility of the study. Asiamah et al. (2017a), argue that a proper definition or specification of the population is critical because it guides others in appraising the credibility of the sample, sampling technique(s) and outcomes of the research. They further argue that the difference between general, target and accessible population confuses many researchers and accounts for issues relating to poor population specification and sampling bias. Thus, to improve the credibility of this study, it was imperative to distinguish between the concepts used in defining a population in view of the fact that the understanding of these concepts forms the basis for effective population definition.

Chaudhury (2010) defines the general population as the entirety of a section of people from whom some information is being sought. Further, the target population is defined as the group of individuals or participants with the specific attributes of interest and relevance (Bartlett et al., 2001; Creswell, 2003). The target population is more refined and smaller in size when compared to the general population on the basis of containing no attribute that controverts a research assumption, context or goal (Asiamah et al., 2017a). Finally, the accessible population is reached after taking out all individuals of the target population who may not participate or cannot be accessed at the study period (Bartlett et al., 2001).

The general population of this study comprised of all new undergraduate students registered in all online study programmes in Kenya's public universities. Registration, in the context of e-learning is synonymous to admission to the university and has nothing to do with learning. A student who is registered is simply one who has been admitted and has not yet been placed into a programme of study. These are students whose mode of study is made up of various combinations of pure online study and the conventional classroom learning. The number of online undergraduate students in Kenya's public universities was estimated at 30,000 (Karshoda & Waema, 2014) as reported in *the 2013 Universities E-Readiness Survey.* The number is projected to have grown marginally because of the low uptake of online studies in Africa (Unwin, 2008), and Kenya in particular. The general student population can thus be described as one that uses hybrid distance learning such as: online with face-to-face, print-based materials with compact discs (CDs), online with print-based materials, print-based with video conferencing (Maritim & Mushi, 2011).

In the present case, the target population included new undergraduate university students enrolled in any e-learning degree programme (excluding diploma and postgraduate programmes), above 18 years of age, male or female and with or without experience in the use of internet. As far as online study is concerned, a student who is enrolled is one who has moved a step further from registration to actually being placed into a programme of study. Essentially, this is a student who is following courses that constitute a programme that is offered using the e-learning mode of study.

Finally, the accessible population of the study included those in the target population who were available, willing and capable of participating in the study. For the e-learning students, these were students who were available during orientation and could be reached physically or electronically (via e-mail or phone call) at the end of the semester. They comprised invariably of individuals who were employed (or self-employed) or unemployed, resident in or outside the university, living in remote geographical areas away from the university, married or unmarried, proceeding with their studies immediately after secondary school or returning to study after spending some time in other engagements.

3.5 Sampling Procedures and Sample Size

In selecting the sample, three public universities were selected using stratified random sampling. One public university was selected randomly from those that fall into each of the following three categories as specified by the researcher; first, very large (with more than 50,000 students) where KU and UoN fell into this category; secondly, large (with between 30,000 and 49,999 students) with MU, JKUAT and University of Eldoret falling into this category and thirdly, medium (with between 15,000 and 29,999 students), with EU and Maseno university falling into this category. The universities with below 15,000 students were not considered in this study because most of them were recently established (ROK, 2023b) 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). The formula is used to calculate sample sizes for large populations in which the following population attributes are known; the needed precision, the desired level of confidence and the estimated proportion of the attribute present in the population. The representative sample size was calculated by employing the formula:

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

In which:

n represents the sample size,

p represents the 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).

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, if we take 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. Table 2 shows the number of copies of the questionnaire issued, returned, and analyzed; and the sample representation per university.

Table 2

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 2 shows that 520 copies of the questionnaire were issued, while 410 were returned, and 388 were analyzed. More copies of the questionnaire than the threshold number of 272 were issued to cater for non-return as well as data cleaning resulting from incomplete copies of the questionnaire or those containing ambiguous responses. 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 this uncertainty. 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., 2017b).

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, KU had the highest sample representation, then JKUAT and lastly, EGU. Interestingly, the sample size representation per university is somewhat proportional to the number of students in each university (ROK, 2023b). Table 3 shows the number of undergraduate students in the sampled universities disaggregated by gender from 2019/2020 to 2022/2023 academic years.

Table 3

Undergraduate Students in the Sampled Universities

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

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

To further ascertain the representativeness of the sample, the researcher applied the Cohen’s d technique. Cohen d provides a measure referred to as “effect size”, which is a measure of correlation or a standardized measure of the magnitude of the observed effect. It can also be used as a tool to estimate the number of observations or sample size required in order to detect an effect in an experiment or survey (Brownlee, 2020). Van den Akker and Winkens (2014) argue for the inclusion of effect sizes in addition to significance testing in research. This is because statements of statistical significance alone can be very misleading since statistical significance depends on the effect size, the sample, the research design and the statistical test being employed.

Kish (1965) as cited in Singh and Masuku (2014, p.12). provide a table for estimating of sample size based on a value of Cohen d and the statistical power. Table 4 shows the recommended sample sizes for given pairs of values of Cohen d and the associated statistical power.

Table 4

Estimating Sample Size Using Statistical Power and Cohen's d

Cohen's d	Statistical Power							
	0.25	0.50	0.60	0.70	0.80	0.90	0.95	0.99
0.20 (small)	84	193	246	310	393	526	651	920
0.50 (medium)	14	32	40	50	64	85	105	148
0.80 (large)	06	13	16	20	26	34	42	58

Source: Singh and Masuku (2014, p.12)

In this study, the calculated sample size of 388 closely compares with a Cohen d of 0.20 and a statistical power of 0.80 and a sample size of 393. The effect size of a Cohen d value of 0.20 is considered "small" (Cohen, 1988). A small effect size does not mean that it is insignificant while a larger effect size is not necessarily better than a small or medium one. On the other hand, statistical power, which is the probability of observing a true effect, shows the confidence one might have in the conclusions drawn from the study. Thus, the sample size of 388 was considered sufficient for this study.

3.6 Instrumentation

One instrument was used for data collection, namely; the Students' E-Learning Adoption Questionnaire (SeLAQ). The instrument was pilot-tested with 38 first-year e-learning students in JKUAT from May to August 2018. The pilot study revealed a low response rate (eight out of 38 returned questionnaires or 21% response rate) for online questionnaires using *Google Forms* despite two e-mail reminders sent out to all participating students. This confirmed that the response rate of electronic surveys internationally is quite low (Saleh & Bista, 2017; Survey Response Rates, n.d.).). However, the response rate varies widely depending on the target population, the type of items (closed or open ended), and length of questionnaire. While this study intended to use an on-line survey for purposes of efficiency and timely collection, collation and analysis of data, it nevertheless, used the traditional paper-and-pen methods only for collecting data.

3.6.1 The Students' E-Learning Adoption Questionnaire (SeLAQ)

The data collected using SeLAQ was used for analysis and testing the hypotheses of the study. It was used to measure university students' BI and UB. It was adapted from its original form (Venkatesh et al.,2003) by substituting the words "organization" and "manager" with "university" and "lecturer" respectively. The questionnaire had two sections; A (15 items) and B (24 items) in which the items in section A sought information relating to the university where the student was registered, gender, age, internet experience, academic programme as well as other personal characteristics of the student with regard to e-learning. 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 PE (four items), EE (four items), SI (four items), FC (four items), BI (four items) and UB (four items).

3.6.2 Validity and Reliability of the Research Instrument

The validity of a data collection instrument is the degree of its "trustworthiness" in measuring a particular construct. By crafting sound questions and ensuring that they are appropriate for the targeted respondents, an instrument, together with the resulting data may be considered valid. The SeLAQ was validated by six educational research experts in the Faculty of Education, EGU. Although the number of experts required to validate a research instrument varies across studies, previous research studies indicate that a minimum of six experts in a field of study are sufficient to validate a questionnaire (Maria Paz et al., 2016; Oslon, 2010; Zurita-Ortega et al., 2018). The experts were selected on the basis of their ability to review, identify and propose improvements to problematic questions thus improving the overall quality of data collected using the questionnaire. Another criteria for the selection of the experts was that they held a Doctor of Philosophy degree in Education and were therefore familiar with questionnaire design and development. They specifically validated the appropriateness of the statements used in the research instrument.

On the other hand, a reliable research instrument is one which returns stable results when it is used to measure the same construct under similar conditions; the data obtained from it being non-varying affording the replication of a study. From a scientific perspective, a value, referred to as the reliability coefficient or index is often used to represent the reliability of a research instrument. The reliability coefficient is a fraction (or decimal number) ranging from zero to one, where zero represents the complete absence of reliability (or 0% reliability) and a one represents complete reliability (or 100% reliability). However, in certain instances, the reliability is not a calculated figure but a qualitative agreement among research experts (Donovan, 2019). The choice made in this study was that of computing the reliability coefficient. This is because it was possible to quantify the scores numerically. In estimating the reliability coefficient of the instrument, the following factors were considered;

i) the type of research instrument, in this case, a questionnaire,
ii) the number of filled and returned questionnaires,
iii) the number of items in the research instrument that were used to estimate the reliability, excluding the subjects' bio data such as telephone contact, e-mail or gender; and;
iv) the type of items in the research instrument, such as, open- or close-ended.

The SeLAQ had 24 close-ended items on a 7-point Likert scale. During the pilot study, the SeLAQ was administered electronically using *Google Forms* that were sent out to the students by e-mail. Thirty-eight responses were received and used to estimate the reliability of the instrument. The Cronbach's alpha coefficient 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

3.7 Data Collection Procedures

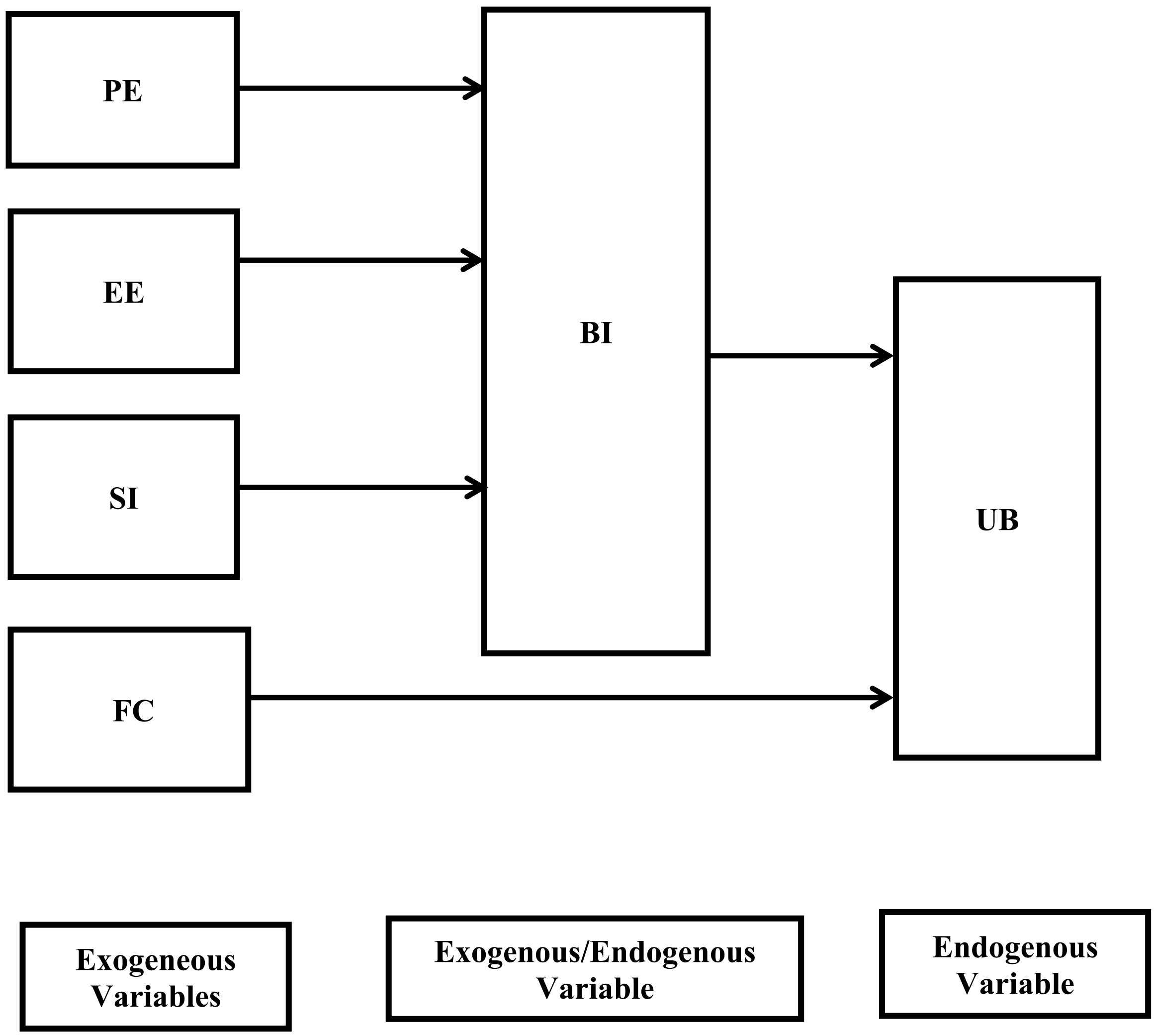
Before commencing the data collection, the researcher sought and obtained ethical approval from the EGU Research Ethics Committee (EUREC) and a research permit number NACOSTI/P/18/15243/21466 (Appendix 4) from the National Commission for Science, Technology and Innovation (NACOSTI). The research permit was obtained by applying for it through the Graduate School, EGU. Similarly, NACOSTI issued a research authorization letter (Appendix 5) together with the research permit. Thereafter, the researcher applied for, and obtained approval from the Vice-chancellors of the participating universities to collect data (KU – Appendix 7; JKUAT – Appendix 8; EGU – Appendix 9). Lastly, the researcher presented consent forms, in person, to the subjects of the study at their respective institutions. He explained the ethical considerations of the study and obtained consent from the subjects who signed the forms and returned them to the researcher. The consent forms were attached to the research instrument and were administered simultaneously at KU, EGU and JKUAT between December 2018 to May 2019.

3.8 Data Analysis

The main purpose of data analysis in this study was to test the hypotheses of the study and develop a corresponding model based on the results of these tests. 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 (between 100 - 200). 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 3 shows the theoretical inner (structural) model that was used to test the hypotheses in this study.

Figure 3

The Theoretical Structural Model



The inner model outlines the structural relationships that link the independent latent constructs to the dependent latent constructs within the proposed research framework. In a SEM, a latent variable is an underlying variable that cannot be observed directly. Latent variables have their genesis from the works of Plato in *The Republic* which states that "the many, as we say, are seen but not known, and the ideas are known but not seen" (Plato, 360 B.C.). Further, a variable within a structural model can be classified as either exogenous or endogenous. Exogenous variables serve as the sources of causal influence, characterized by having only outgoing paths and no incoming arrows directed toward them. Meanwhile, an endogenous variable is one that receives at least one causal path from another construct and, therefore, reflects the influence of one or more external variables. Within the structure of a structural equation model (SEM), a variable may function as either an independent or dependent construct in different segments of the model. However, any variable that has incoming paths—indicated by arrows directed toward it—is classified as endogenous. Thus, in figure 3, PE, EE, SI and FC are exclusively exogeneous variables; BI is both an exogeneous and endogenous variable while UB is exclusively an endogenous variable.

On the other hand, the outer model specifies the relationships between the latent variables and their observed indicators. Figure 4 shows the theoretical outer (measurement) model that was used in testing the hypotheses of this study. In reality, the figure represents a combination of the inner (structural model) together with all the reflective indicators for each latent variable.

Figure 4

The Theoretical Measurement Model

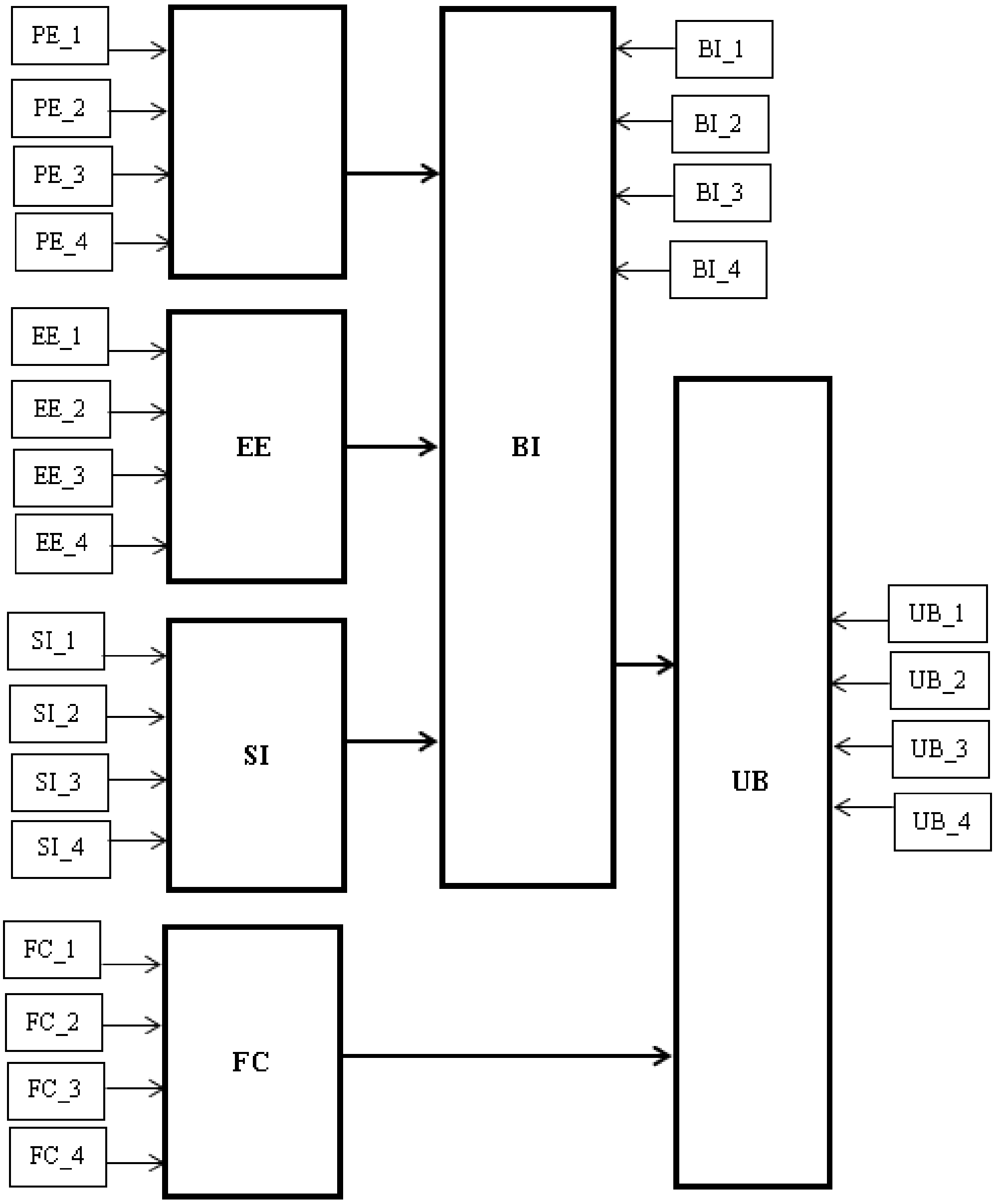


Figure 4 shows that the exogeneous variable, PE is represented by four indicators, PE_1, PE_2, PE_3 and PE_4; exogeneous variable, EE is represented by four indicators, EE_1, EE_2, EE_3 and EE_4; exogeneous variable, SI is represented by four indicators, SI_1, SI_2, SI_3 and SI_4; exogeneous variable, FC is represented by four indicators, FC_1, FC_2, FC_3 and FC_4. The variable BI, which is both exogeneous (on account of being influenced by PE, EE and SI) and endogenous (on account of influencing UB) 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 5 shows the latent variables and their corresponding indicators and labels that were used for analysis.

Table 5

Latent Variables and Indicators Used in the Study

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
Effort Expectancy	EE	
	EE_1	Easy to understand
	EE_2	Easy to acquire skills
	EE_3	Easy to use
	EE_4	Easy to learn
Social Influence	SI	
	SI_1	Influence of role models
	SI_2	Influencers of behaviour
	SI_3	Support from instructors
	SI_4	Support from the university
Facilitating Conditions	FC	
	FC_1	Possession of resources
	FC_2	Compatibility with other modes of learning
	FC_3	Knowledgeable in use the e-learning
	FC_4	Availability of assistance
Behavioural Intention	BI	
	BI_1	Improved academic productivity
	BI_2	Ease of use

Latent Variable	Label	Indicators
	BI_3	Approval by role models
	BI_4	Availability of assistance
Actual Use Behaviour	UB	
	UB_1	Login
	UB_2	Reading
	UB_3	Downloading
	UB_4	Printing

It is important to note that SEM consists of formative and reflective measurements (Wong, 2013). If the indicators cause the latent variable and are not interchangeable among themselves, they are formative. The indicators in this study are reflective because they are interchangeable, highly correlated and do not cause the latent variables.

PLS-SEM and Covariance-Based Structural Equation Modelling (CB-SEM) are the two approaches for estimating the relationships in a structural equation model (Hair et al., 2010; Hair et al., 2011). Each is appropriate for a different research context, and researchers need to understand the differences in order to apply the correct method (Hair et al., 2012). PLS-SEM fitted this study because the model being tested is theoretically supported.

In situations where theory is less developed or predictive accuracy is paramount, researchers should consider the use of PLS-SEM (Bacon, 1999; Hwang et al., 2010; Wong, 2010). This is particularly true if the primary objective of applying structural modelling is prediction and explanation of target constructs (Rigdon, 2012). According to Hair et al. (2011), Partial Least Squares Structural Equation Modelling (PLS-SEM) should be employed in the when the goal is to predict key target constructs or identify key "driver" constructs; when formatively measured constructs are included and when the data are not normally distributed. Since the primary focus of this study is prediction, PLS-SEM was found suitable for use. Further, Wong (2010, p.23) argues that PLS-SEM is recommended when “applications have little available theory, when correct model specification cannot be ensured, and when predictive accuracy is paramount.”

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. The procedure starts with the specification and identification of structural and measurement models. Model specification in SEM refers to translating theory into equations (Kenny, 2004). This was followed by model identification and the examination of data and model estimation. Thereafter, results of reflective model were assessed. When the data for the measures are considered reliable and valid (based on established criteria), the structural model was evaluated including the moderating effects. Finally, the findings of the study were interpreted and conclusions were made. The 5-stage procedure for applying PLS-SEM comprised of:

i) **Specification and identification of the structural and measurement model** - This stage entails constructing a schematic representation that depicts the constructs to be evaluated. Such a representation is commonly described as a path model. A path model functions as a schematic that links variables or theoretical constructs by drawing on established frameworks and logical reasoning, thereby providing a visual account of the hypotheses to undergo testing. These models typically consist of two key elements: (i) the structural model—also referred to as the inner model in PLS-SEM—which specifies the associations between latent variables, and (ii) the measurement model, which defines the links between latent constructs and their observed indicators. Finally, the model was identified. Model identification has nothing to do with the number of correlations between the measured variables but is the determination of whether the estimation of the parameters in a model is possible in the first place (Kenny, 2004).

ii) **Collecting and examining the data** - The application of PLS-SEM method requires that quantitative data are available. This study relied on primary quantitative data obtained from SeLAQ for SEM analysis. Among the data examination issues that were attended to include; missing data, suspicious response patterns (straight lining or inconsistent answers), outliers, and data distribution.

iii) **Evaluation of the measurement model** – Evaluation of a model involves estimation and assessment. The purpose of a measurement model estimation is to deliver data-driven evaluations of the associations between observed variables and their corresponding latent constructs. These empirical assessments allow researchers to evaluate the extent to which the hypothesized theoretical measurement framework aligns with the actual data, thereby providing evidence of the model's validity and the adequacy of its representation of theoretical concepts in real-world observations. There are two types of measurement model; reflective and formative. Further, formative indicators are assumed to be error free, which means that the internal consistency reliability concept is not appropriate (Diamantopoulos, 2006; Edwards & Bagozzi, 2000) for this study. Therefore, the model should be assessed using other measures, namely; a) Convergent validity, b) collinearity between indicators, and c) significance and relevance of outer weights.

iv) **Evaluation of the structural model** - Instead of assessing goodness-of-fit as is done with CB -SEM, PLS SEMs structural model is primarily assessed by a heuristic criterion that are determined by the model's predictive capabilities. The Model assessed in terms of how well it predicts the endogenous variables (or constructs) (Sarstedt et al., 2014). In practice, collinearity, path coefficients and R^2 are normally considered adequate to evaluate a structural model.

v) **Estimating and assessing the moderators** - In the final analysis, the effect of moderator variables on each direct relationship was established using the Multi-group Analysis (MGA) function of the Smart-PLS data analysis software. Moderation refers to a situation in which the relationship between two constructs varies depending on the values of a third variable, known as a moderator variable. This moderator variable can alter the strength or even the direction of the relationship between the two constructs in the model as analyzed in SPSS (Fields, 2013). To investigate this, moderation models were developed for all moderating variables, including Gender, Age, and Internet Experience. For ease of interpretation, the continuous variables; age and internet experience were transformed into categorical variables so that age was categorized into Young and Old (where young = 18 - 30 years while old = 31 - 60 years) while internet experience was categorized into Experienced and Inexperienced (where experienced = 0 - 3 years and while inexperienced = 4 - 6 years). This made it possible to use dummy variables in the analysis for all the moderating variables. All the moderating variables were subjected to PLS-MGA and the resulting outputs were tested for significance for each hypothesis of the study.

The model for predicting e-learning adoption was obtained by running the PLS-SEM software which has the capability of a graphic output. The model shows the predictors which are responsible for e-learning adoption among undergraduate students in Kenya's universities.

In summary, an aggregate of three direct and nine indirect determinants of students' BI to use e-learning were measured together with two direct and six indirect determinants of UB (refer to Figure 1). The three direct determinants of BI are PE, EE and SI while the 9 indirect determinants are those that show how each of the three direct determinants of BI is influenced by the three moderators. On the other hand, the two direct determinants of UB are FC and BI while the 9 indirect determinants are those that show how each of the three direct determinants of BI is influenced by the three moderators. Table 6 shows the hypotheses of the study, the independent and dependent variables and the statistical tests used to test the hypotheses:

Table 6

Statistical Tests Used to Test the Hypotheses

Hypothesis	Independent Variable	Dependent Variable	Statistical Test
HO_1: There is no statistically significant relationship between performance expectancy and the behavioural intention to adopt e-learning.	PE	BI	• t-test • R^2
HO_2: There is no statistically significant relationship between effort expectancy and the behavioural intention to adopt e-learning.	EE	BI	• t-test • R^2
HO_3: There is no statistically significant relationship between social influence and the behavioural intention to adopt e-learning.	SI	BI	• t-test • R^2

Hypothesis	Independent Variable	Dependent Variable	Statistical Test
HO4: There is no statistically significant relationship between facilitating conditions and the use behaviour of e-learning.	FC	UB	• *t*-test • R^2
HO5: There is no statistically significant relationship between the behavioural intention to adopt e-learning and use behaviour of e-learning.	BI	UB	• *t*-test • R^2
HO6: There is no statistically significant difference on the effect of gender, age, and internet experience on the direct relationship between the predictors and outcomes of e-learning adoption.	GND, AGE, IXP	BI, UB	• *p*-value

After the hypothesis were tested, the moderating effects of gender, age and internet experience were determined. 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 in the e-learning adoption structural model. A requirement for MGA is to use categorical variables as opposed to continuous variables (Moulder, 2018) in determining the moderating effects. 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". The next sections present the results of moderating effects of GND, AGE and IXP on the direct relationships between PE and BI, EE and BI, SI and BI, FC and UB and; BI and UB. Latif (2022) argues 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 Latif 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.

3.9 Ethical Considerations

Before commencing the study, the researcher sought and obtained ethical clearance and approval from the EGU's Research Ethics Committee (EUREC) (ethical approval letter number EUREC/APP/076/2018 in Appendix 6). The purpose of the ethical clearance was to ensure that the research is conducted responsibly from beginning to end, and especially with regard to human participants. Accordingly, the researcher ensured that every respondent consented to participate (Appendix 10) and was fully aware of the purpose of the study, its procedures, and the expected risks and benefits of participating. No incentives were given to the respondents for filling in the questionnaire while the data was stored as a password-protected file solely accessible to the researcher and the supervisors and; none of the responses were attributed to individual respondents. This ensured that all respondents participated based on their free will and that the data was kept safe from loss or misuse.

CHAPTER FOUR

RESULTS

4.1 Introduction

This chapter presents the results of the study. It begins with a description of the demographic characteristics of the respondents that were relevant to the study; namely: academic programme, gender, age and internet experience respectively. Thereafter, the results of testing each hypothesis without the effects of moderating variables are presented. This is followed by the model development process through a series of model assessments and iterations; First, the descriptive statistics of each of the four predictors of e-learning adoption (PE, EE, SI, and FC) and the two outcomes, namely; BI and UB are presented. Secondly, the results of the assessment of the outer model of the structural equation – consisting of the predictors and their indicators – is presented. Thirdly, the results of the effects of moderators on the direct causal relationships is presented. Finally, all the results are summarized and represented using two models; the first model shows e-learning adoption without the effect of moderators while the second model includes the effect of three moderators, namely: gender, age and internet experience.

4.2 Demographic Characteristics of the Respondents

The demographic characteristics of the respondents relevant to the study, namely; academic programme, gender, age, and internet experience are shown in Table 7. The table represents the frequency and the associated percentage of each of the characteristics.

Table 7

Demographic Characteristics of the Respondents

		Frequency	Percentage
Academic Programme	Arts	176	45.4
	Science	120	30.9
	Business	92	23.7
Gender	Male	236	60.8
	Female	152	39.2
Age	18 - 30 years (Young)	296	76.3
	31 – 60 years (Old)	92	23.7
Internet Experience	0 - 3 years (Inexperienced)	168	43.3

		Frequency	Percentage
	Over 4 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 three-fifths while the minority were female, representing slightly below two-fifths 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 of the respondents where over half of the respondents had four years or more of internet experience while slightly less than half had less than three years of internet experience. In this study, those with four or more years of internet experience were considered 'experienced' while those with less than four years of internet experience were considered 'inexperienced 'for purposes of analysis.

4.3 Assessing the Measurement (Outer) Model of the Structural Equation

As discussed in Chapter Three, Structural Equation Modeling (SEM) consists of two sub-models: the inner model (also referred to as the structural model) and the outer model (also called the measurement model) (Wong, 2013). The outer model defines the relationships between latent variables and their observed indicators. This section presents the results of the outer model assessment in the structural equation. The evaluation included determining convergent validity (CV) and discriminant validity (DV) of the constructs. CV is established when a set of indicators converge to represent a single underlying construct. Discriminant validity, on the other hand, demonstrates the distinctiveness of the indicators in relation to their respective constructs. DV was assessed using two criteria: the Cross Loadings Test and the Heterotrait-Monotrait (HTMT) ratio matrix. These tests helped verify whether the data used in the study are reliable and valid for supporting the proposed hypotheses.

4.3.1 Convergent Validity

Convergent validity is achieved when a set of indicators of a construct converge or represents a single underlying construct (Hair et al., 2017). In this study, CV was measured using Cronbach's alpha (CA), Average Variance Extracted (AVE) and Variance Inflation Factor (VIF). CA is a measure used to assess the reliability, or internal consistency, of a set of scale or test items (Goforth, 2015) while the AVE represents the average amount of variance that a construct explains in its indicator variables relative to the overall variance due to measurement error (Kock, 2019). The VIF measures the collinearity among the constructs of the model. In fact, it indicates if a predictor has a strong linear relationship with the other predictors (Field, 2013). Table 8 shows the CA, AVE and VIF values of all the constructs in this study.

Table 8

Convergent Validity Tests

Construct	Items	CA	AVE	VIF
PE	4	0.75	0.57	1.51
EE	4	0.77	0.60	2.05
SI	4	0.68	0.51	1.63
BI	3	0.70	0.63	1.23
UB	4	0.74	0.57	1.13
FC	3	0.61	0.56	1.86

As shown in Table 8, CA ranged from 0.61 to 0.77 for all the constructs. Abma et al. (2016) argue that CV is considered adequate if more than 75% of the hypotheses are correct or if the correlation with an instrument measuring the same construct is greater than (> 0.50). The CA for all constructs exceeded the minimum standard level of 0.50, hence internal consistency reliability was achieved. 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 all the constructs in the study. To test CV using VIF, some authors suggest a cut-off value of VIF below 10.00 as a general guideline in model assessment (Bowerman & O'Connell, 1990; Myers, 1990). Further, Bowerman and O'Connell (1990) suggest that if the average value of VIF is substantially greater than 1, then the regression may be biased. 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. Since all the VIF values in this study were below 5.0, as shown in Table 8, there was no multicollinearity among the predictors of the study.

Furthermore, according to Field (2013) a high value of collinearity poses three problems, namely: it increases the values of the standard errors for the beta coefficients, thus making them less trustworthy; it limits the size of R (the correlation between the predicted values of the outcome and the observed values), and; multicollinearity between predictors makes it difficult to assess the individual importance of a predictor. Further, Field argues that when two or more predictors are highly correlated, the overall variance in the outcome accounted for by the two predictors is only a little more than when only one predictor is used. In other words, increased collinearity renders the addition of more predictors to a model redundant. Interpreted differently, this means that the value of R^2 remains unchanged and therefore the variance in the outcome for which the model accounts is unaffected.

4.3.2 Discriminant Validity

The assessment of Discriminant Validity (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 two criteria; Cross Loadings Test and Heterotrait-Monotrait (HTMT) Ratio Matrix. The results on cross loading test are presented in Table 9.

Table 9

Cross Loading Test for Predictor and Outcome Constructs

Indicators	PE	EE	SI	BI	UB	FC
PE_1	**(0.77)**	0.06	-0.11	0.10	-0.05	-0.11
PE_2	**(0.77)**	0.04	0.06	0.05	-0.08	0.10
PE_3	**(0.75)**	-0.48	0.26	-0.15	-0.16	0.15
PE_4	**(0.72)**	0.39	-0.22	-0.00	0.29	-0.14
EE_1	-0.04	**(0.77)**	0.06	0.00	-0.02	0.26
EE_2	0.03	**(0.68)**	0.32	0.20	-0.13	-0.61
EE_3	0.22	**(0.79)**	-0.38	-0.12	0.14	0.23
EE_4	-0.19	**(0.83)**	0.04	-0.05	-0.00	0.05
SI_1	0.11	-0.20	**(0.74)**	-0.12	0.03	-0.16
SI_2	0.06	-0.33	**(0.69)**	-0.21	0.04	0.03

Indicators	PE	EE	SI	BI	UB	FC
SI_3	-0.10	0.21	**(0.76)**	0.15	-0.02	0.12
SI_4	-0.07	0.32	**(0.68)**	0.18	-0.05	0.00
BI_1	0.11	-0.16	0.06	**(0.87)**	-0.17	0.20
BI_2	-0.13	-0.19	0.13	**(0.81)**	-0.04	0.01
BI_4	0.01	0.41	-0.23	**(0.69)**	0.26	-0.26
UB_1	0.29	0.21	-0.24	-0.03	**(0.66)**	0.04
UB_2	0.17	-0.08	-0.03	0.17	**(0.78)**	-0.05
UB_3	-0.21	-0.08	0.03	-0.06	**(0.80)**	0.19
UB_4	-0.20	-0.01	0.21	-0.09	**(0.76)**	-0.19
FC_1	-0.23	-0.02	0.27	0.03	-0.18	**(0.77)**
FC_2	0.13	0.16	-0.13	0.16	0.12	**(0.77)**
FC_3	0.12	-0.16	-0.14	-0.20	-0.00	**(0.71)**

Note: Cross-loadings above 0.60 are in bold and in parenthesis

The results in Table 9 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-loading with other constructs, indicating that DV was achieved (Henseler et al., 2015). However, Table 9 shows that the indicators BI_3 and FC_4 have been dropped from the resulting model and therefore have no role in determining the measurement model. This means that the ensuing measurement model for the study has three indicators each for the latent variables BI and FC respectively while all other latent variables (PE, EE, and SI) have all their four indicators retained in the measurement model. In a practical sense therefore, this implies that approval by role models and availability of assistance in using the e-learning mode of study are not considered important indicators for BI and FC respectively. This study adopted a threshold of 0.85 for HTMT (Clark & Watson, 1995; Kline, 2011) as it is considered more sensitive and specific than 0.90 (Gold et al., 2001; Teo et al., 2008). Table 10 presents the HTMT values for the constructs used in the study.

Table 10

Heterotrait-Monotrait (HTMT) Ratio Test

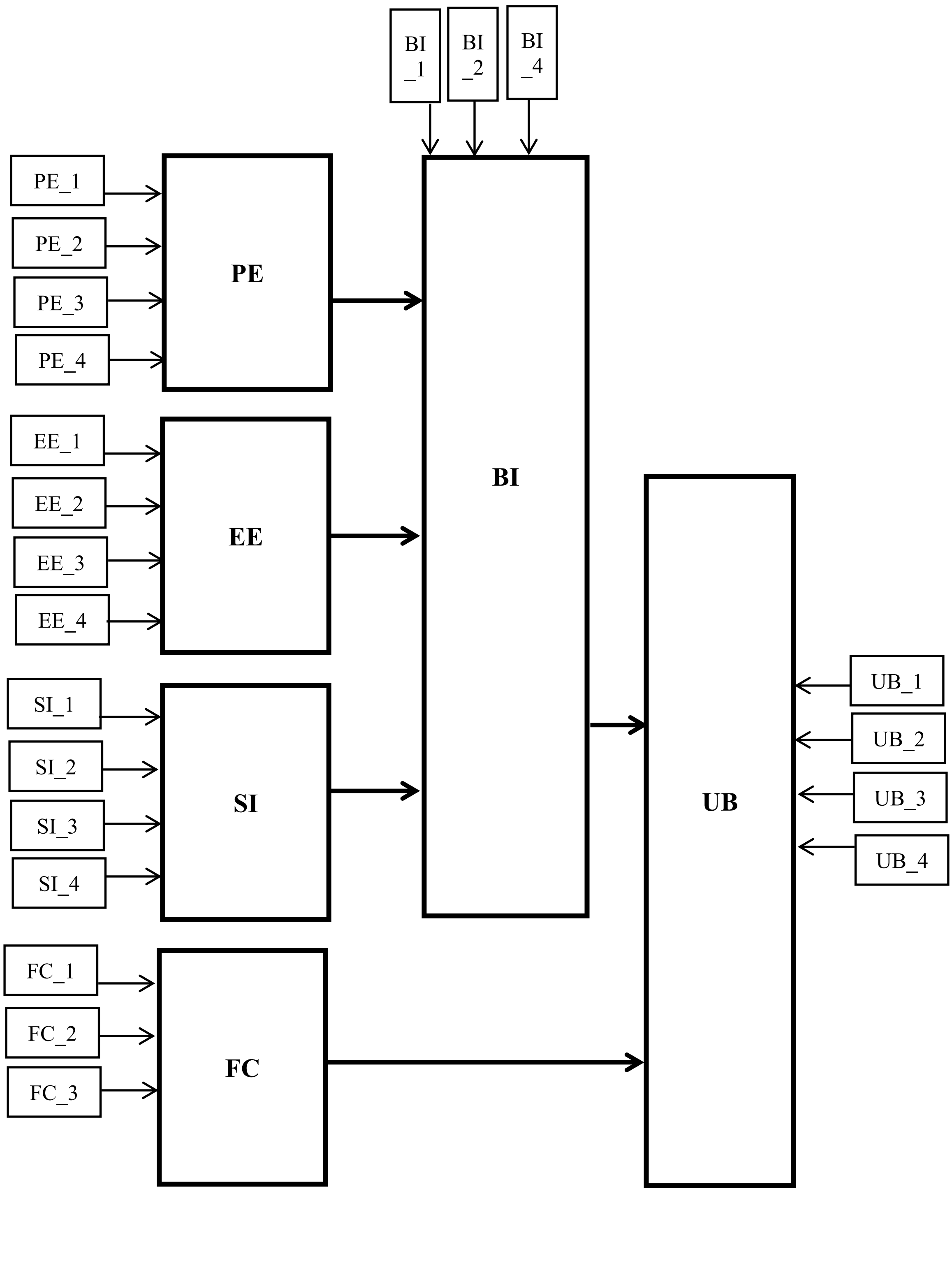
Constructs	PE	EE	SI	BI	UB	FC
PE						
EE	0.62					
SI	0.68	0.70				
BI	0.43	0.55	0.50			
UB	0.38	0.26	0.32	0.24		
FC	0.58	0.92	0.76	0.44	0.38	

(n = 388)

The values in Table 10 are all less than 0.85; showing that all the indicators passed the DV test. Thus, it can be concluded that the data used in the study are reliable and valid to prove the hypotheses. Figure 5 shows the resulting empirical outer (measurement) model of these relationships.

Figure 5

The Empirical Measurement Model



4.3.3 Predictive Power of the Constructs

The predictive power of a construct is its relative contribution towards a desired situation or outcome. In addition to testing the hypotheses of the study, it was necessary to find out the predictive power of the constructs of e-learning adoption. The outer model of the structural equation was assessed using the explanatory and predictive power of the constructs. The coefficient of determination (R^2) was adopted in estimating the predictive power of the constructs.

The results show that the model explained 24% of the variance in BI (R^2 = .24) and 15% of the variance in UB (R^2 = .15). Further, the results show that EE contributed more to R^2 (β = .18) in predicting BI, followed by PE (β = .15) and SI (β = -.00) in that order. Overall, the likelihood of a student having an intention to use e-learning is much stronger than that for actual use of e-learning. Additionally, the results show that BI contributed more to R^2 (β = .08) compared to FC (β = - .11). These results show that, there are indeed other factors which have an influence on students' BI and UB but were not considered in the model.

4.4 Results of Testing the Direct Relationships Between Predictors and Outcomes

This section presents the results of testing the first five hypotheses of the study. It begins with the descriptive statistics of the items representing each predictor and its associated outcome. Descriptive statistics comprising the mean (m) the standard deviation (SD) and percent scores of the items representing the predictors and outcomes were obtained for each hypothesis being tested. Thereafter, each of the five null hypotheses was tested.

4.4.1 Results of Testing the First Hypothesis of the Study

The first hypothesis of the study, HO_1, states that "there is no statistically significant relationship between PE and BI". This relationship is depicted as:

HO_1: There is no statistically significant relationship between PE and BI, (PE → BI).

Descriptive statistics for the indicators of PE are presented in Table 11.

Table 11

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 table shows the mean (m), standard deviation (SD) and the percentage scores of each indicator represented on a scale of 1 to 7. The first indicator, "the e-learning mode of study is useful for the degree programme I am pursuing" had a mean, m = 6.45 and SD = 1.11. The second indicator, "using the e-learning mode of study enables me to accomplish tasks more quickly" had m = 5.89 and SD = 1.61. The third indicator, "using the e-learning mode of study has increased my academic productivity" had a mean, m = 5.80 and SD =1.52. The fourth, and last indicator, "using the e-learning mode of study has increased my chances of getting a high grade", had a mean, m = 5.65 and SD = 1.61.

The results show that the means for each of the four indicators of PE in Table 11 are related in such a way that the item with the highest mean score is also the item with the highest number of respondents in the "strongly agree" category. For instance, the table shows that

72.2% of the respondents - corresponding with the highest mean of 6.45 - strongly agree to the statement; “the e-learning mode of study is useful for the degree programme I am pursuing”.

The table also shows that 52.6% (corresponding with the second highest mean of 5.89) of the respondents strongly agree that using the e-learning mode of study enables them to accomplish tasks more quickly while 46.4% (corresponding with the third highest mean of 5.80) of the respondents agree that using the e-learning mode of study increased their academic productivity. Finally, 42.3% of the respondents (corresponding with the lowest mean of 5.65) strongly agree that using the e-learning mode of study had increased their chances of getting a high grade.

The tests of significance were performed above the 90% level of confidence ($p < 0.10$). Table 12 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 12

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

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

The results in Table 12 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 and the significance of the relationship, PE→BI, is supported.

4.4.2 Testing the Second Hypothesis of the Study

The second hypothesis of the study, HO_2, states that “there is no statistically significant relationship between EE and BI”. This relationship is depicted as:

HO_2: There is no statistically significant relationship between EE and BI (EE → BI)

Descriptive statistics for the indicators of EE are presented in Table 13. It shows the mean (m), standard deviation (SD) and the percentage scores of each indicator on a scale of 1 - 7.

Table 13

Descriptive Statistics for EE

Items	Mean	S.D.	Percent Scores						
			1	2	3	4	5	6	7
1. My interaction with e-learning is clear	5.70	1.62	3.10	3.10	3.10	13.40	14.40	14.40	48.50
2. It has been easy for me to become skillful at using the e-learning mode of study.	5.92	1.47	2.10	3.10	4.10	4.10	13.40	24.70	48.50
3. The e-learning mode of study was easy to use.	5.59	1.66	5.20	2.10	3.10	11.30	15.50	22.70	40.20
4. Learning to use the e-learning mode of study is easy for me.	5.54	1.73	5.20	2.10	6.20	11.30	13.40	19.60	42.30

(n = 388)

The results in Table 13 show that the first indicator, which states that "my interaction with e-learning is clear and understandable" had a mean, $m = 5.70$ and $SD = 1.62$. The second indicator, which states that "it has been easy for me to become skilful at using the e-learning mode of study" had a mean, $m = 5.92$ and $SD = 1.47$. The third indicator, which states that "the e-learning mode of study was easy to use" had a mean, $m = 5.59$ and $SD = 1.66$ while the fourth, and last indicator, which states that "learning to use the e-learning mode of study is easy for me", had a mean, $m = 5.54$ and $SD = 1.73$.

These results further reveal that all the indicators of EE are in the "agree" category (where the range of means is between 5.54 and 5.92). Similar to the indicators of PE, a higher percentage of scores for the indicators of EE are in the "strongly agree" category. Thus, 48.5% of the respondents strongly agree that their interaction with e-learning is clear and understandable and that it has been easy for them to become skillful at using the e-learning mode of study. Similarly, 40.2% of the respondents strongly agree that it was easy to use the e-learning mode of study. Finally, the results in table 13 show that 42.3% of the respondents strongly agree that it was easy to learn to use the e-learning mode of study.

The tests of significance were performed above the 90% level of confidence ($p < 0.10$). Table 14 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 14

Path Coefficients and Structural Model Assessment for EE → BI

Path Relationship/Hypothesis	Effect Size	SE	t-value	p-value	Decision
EE→BI	0.18	0.04	4.32	< 0.001*	Supported

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

The results in Table 14 indicate that there was a significant positive relationship between EE and BI ($\beta = 0.18$, $t = 4.32$, $p < 0.001$) above the 99% level of confidence ($p<0.001$). Therefore, according to this study, EE is a significant predictor of BI and the hypothesis that 'there is no statistically significant relationship between EE and BI' was rejected and; the relationship EE → BI is supported.

4.4.3 Testing the Third Hypothesis of the Study

The third hypothesis of the study, HO_3, states that "there is no statistically significant relationship between SI and BI". This relationship is depicted as:

HO_3: There is no statistically significant relationship between SI and BI (SI → BI)

Descriptive statistics for the indicators of SI are presented in Table 15. It shows the mean (m), standard deviation (SD) and the percentage scores of each indicator on a scale of 1 - 7.

Table 15

Descriptive Statistics for SI

Items	Mean	S.D.	Percent Scores						
			1	2	3	4	5	6	7
1. My role models think that I should follow the e-learning mode of study.	4.84	2.26	17.50	4.10	6.20	7.20	17.50	9.30	38.10
2. Other people who influence my behaviour think that I should use the e-learning mode of study.	4.65	2.13	18.60	1.00	6.20	14.40	16.50	17.50	25.80
3. The instructors of this degree programme are helpful in the use of the e-learning mode of study.	5.58	1.75	7.20	2.10	2.10	8.20	17.50	20.60	42.30
4. The university supports me in the use of the e-learning mode of study.	5.70	1.87	6.20	4.10	6.20	4.10	10.30	14.40	54.60

(n = 388)

The results in Table 15 show that the first indicator, which states: "my role models think that I should follow the e-learning mode of study" had a mean, $m = 4.84$ and $SD = 2.26$. The second indicator, which states that "people who influence my behaviour think that I should use the e-learning mode of study" had a mean, $m = 4.65$ and $SD = 2.13$ The third indicator, which states that "the instructors of this degree programme are helpful in the use of the e-learning mode of study" had a mean, $m = 5.58$ and $SD = 1.75$. The fourth, and last indicator, which states that “the university supports me in the use of the e-learning mode of study”, had a mean, $m = 5.70$ and $SD = 1.87$.

According to Table 15, only 38.1% of the respondents strongly agreed that their role models thought they should follow the e-learning mode of study. A role model in this case refers to a person whose behaviour one would want to emulate because of their success in a career or venture. The results also indicated that only 25.8% of the respondents strongly agreed that the people who influence their behaviour (friends, peers) think that they should use the e-learning mode of study. Further, the results show that 42.3% of the respondents strongly agree that the instructors of their degree programme are helpful in the use of the e-learning mode of study. However, a proportionately higher percentage of the respondents (54.6%) strongly agreed that their universities support them in the use of e-learning mode of study.

The tests of significance were performed above the 90% level of confidence ($p < 0.10$). Table 16 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 16

Path Coefficients and Structural Model Assessment for SI→BI

Path Relationship/Hypothesis	Effect Size	SE	t-values	p-values	Decision
SI→BI	0.00	0.05	0.07	.945	Not Supported

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

The results in Table 16 indicate that there was a significant relationship between SI and BI ($\beta = - 0.00$, $t = 0.07$, $p = 0.945$). Therefore, according to this study, SI is not a predictor of BI. Thus, the hypothesis that ‘there is no statistically significant relationship between SI and BI’ was not rejected and therefore the relationship SI → BI, is not supported.

4.4.4 Testing the Fourth Hypothesis of the Study

The fourth hypothesis of the study, HO_4, states that “there is no statistically significant relationship between FC and UB”. This relationship is depicted as:

HO_4: There is no statistically significant relationship between FC and UB (FC → UB)

Descriptive statistics for the indicators of FC are presented in Table 17. It shows the mean (m), standard deviation (SD) and the percentage scores of each indicator on a scale of 1 - 7.

Table 17

Descriptive Statistics for FC

			Percent Scores						
Item	Mean	S.D.	1	2	3	4	5	6	7
1. I have the resources necessary to use the e-learning mode of study.	5.80	1.52	2.10	2.10	4.20	12.50	12.50	17.70	49.00
2. The e-learning mode of study is compatible with other modes of study I use.	5.59	1.63	3.10	3.10	5.20	13.40	13.40	19.60	42.30
3. I am knowledgeable in the use the e-learning mode of study.	5.89	1.49	4.10	0.00	3.10	7.20	15.50	21.60	48.50
4. A specific person (or group) is available for assistance with e-learning difficulties.	4.86	2.12	12.40	9.30	2.10	13.40	16.50	12.40	34.00

(n = 388)

The results in Table 17 show that the first indicator, which states: "I have the resources necessary to use the e-learning mode of study" had a mean, $m = 5.80$ and SD = 1.52. The second indicator, which states that "The e-learning mode of study is compatible with other modes of study I use" had a mean, $m = 5.59$ and SD = 1.63. The third indicator, which states that "I am knowledgeable in the use the e-learning mode of study" had a mean, $m = 5.89$ and SD = 1.49. The fourth, and last indicator, which states that "A specific person (or group) is available for assistance with e-learning difficulties", had a mean, $m = 4.86$ and SD = 2.12.

These results show that while all the indicators of FC fall in the “agree” category, only one; namely, “a specific person (or group) is available for assistance with e-learning difficulties”, falls in the “somewhat agree” category. Additionally, for all the indicators, the “strongly agree” category was the most represented score on the 7-point Likert measurement scale. Thus, a majority of the respondents (49.0%) strongly agreed that they have the resources necessary to use the e-learning mode of study while 42.3 % strongly agreed that the e-learning mode of study is compatible with other modes of study they use. The results also showed that 48.5% of the respondents strongly agreed that they are knowledgeable in the use of the e-learning mode of study. However, only 34.0% of the respondents strongly agreed that a specific person (or group) was available for assistance with e-learning difficulties.

The tests of significance were performed above the 90% level of confidence ($p \leq .10$). Table 18 shows the path relationship, 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 18

Path Coefficients and Structural Model Assessment for FC→ UB

Path Relationship/Hypothesis	Effect Size	SE	t-values	p-values	Decision
FC→UB	-0.11	0.06	1.80	.073*	Supported

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

The results in Table 18 show that there was a negative size effect and statistically significant relationship between FC and UB ($\beta = -0.11$, $t = 1.80$, $p = 0.073$) above the 90% level of confidence ($p<0.01$). Therefore, according to this study, FC is a statistically significant but negative predictor of BI. A negative size effect means that a unit increase in the predictor variable is associated with an 11% decrease in the dependent variable. Thus, the hypothesis that ‘there is no statistically significant relationship between FC and UB’ was rejected and the relationship FC → UB is supported.

4.4.5 Results of Testing the Fifth Hypothesis of the Study

The fifth hypothesis of the study, HO_5, states that “there is no statistically significant relationship between BI and UB”. This relationship is depicted as:

HO_5: There is no statistically significant relationship between BI and UB (BI → UB)

The descriptive statistics for the indicators of BI are presented in Table 19. It shows the mean (*m*), standard deviation (*SD*) and the percentage scores of each indicator on a scale of 1 - 7.

Table 19

Descriptive Statistics for BI

			Percent Scores						
Items	Mean	S.D.	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

			Percent Scores						
Items	Mean	S.D.	1	2	3	4	5	6	7
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 first indicator, "I intend to use the e-learning mode of study in the next three months if it will improve my academic productivity" had a mean, $m = 6.47$ and $SD = 0.91$. The second indicator, "I intend to use the e-learning mode of study in the next three months if it would be easy to use" had a mean, $m = 6.34$ and $SD = 1.24$. The third indicator, "I intend to use the e-learning mode of study in the next three months if my role models approve of it" had a mean, $m = 5.38$ and $SD = 2.15$. The fourth, and last indicator, "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", had a mean, $m = 6.38$ and $SD = 1.32$.

The results in Table 19 show that the mean scores of three indicators (one, two and four) in BI are in the "strongly agree" category (6.34 to 6.47) while one indicator (three) has a mean score in the category of "Agree" (mean = 5.38). Similarly, a proportionately higher percentage of responses are in the "strongly agree" category for all indicators. This is depicted by the fact that 70.1% of the respondents strongly agree that they intend to use the e-learning mode of study in the next three months if it will improve their academic productivity while another 66.0% strongly agree that they intend to use the e-learning mode of study in the next three months if it would be easy to use. On the other hand, 49.5% of the respondents strongly agree that they intend to use the e-learning mode of study in the next three months if their role models approve of it. Finally, 70.1% also strongly agree that they intend to use the e-learning mode of study in the next three months if someone is available to assist them with any difficulties with e-learning.

The tests of significance were performed above the 90% level of confidence ($p < 0.10$). Table 20 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 20

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

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

The results in Table 20 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 and the relationship BI →UB, is supported.

4.4.6 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 21 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 21

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)

The results in Table 21 show that the first indicator, "I have logged onto the e-learning platform a lot since my admission into this university" had a mean, $m = 6.01$ and $SD = 1.60$. The second indicator, "I have read the online learning materials a lot since my admission into this university" had a mean, $m = 5.64$ and $SD = 1.66$. The third indicator, "I have downloaded the online learning materials a lot since my admission into this university" had a mean, $m =$

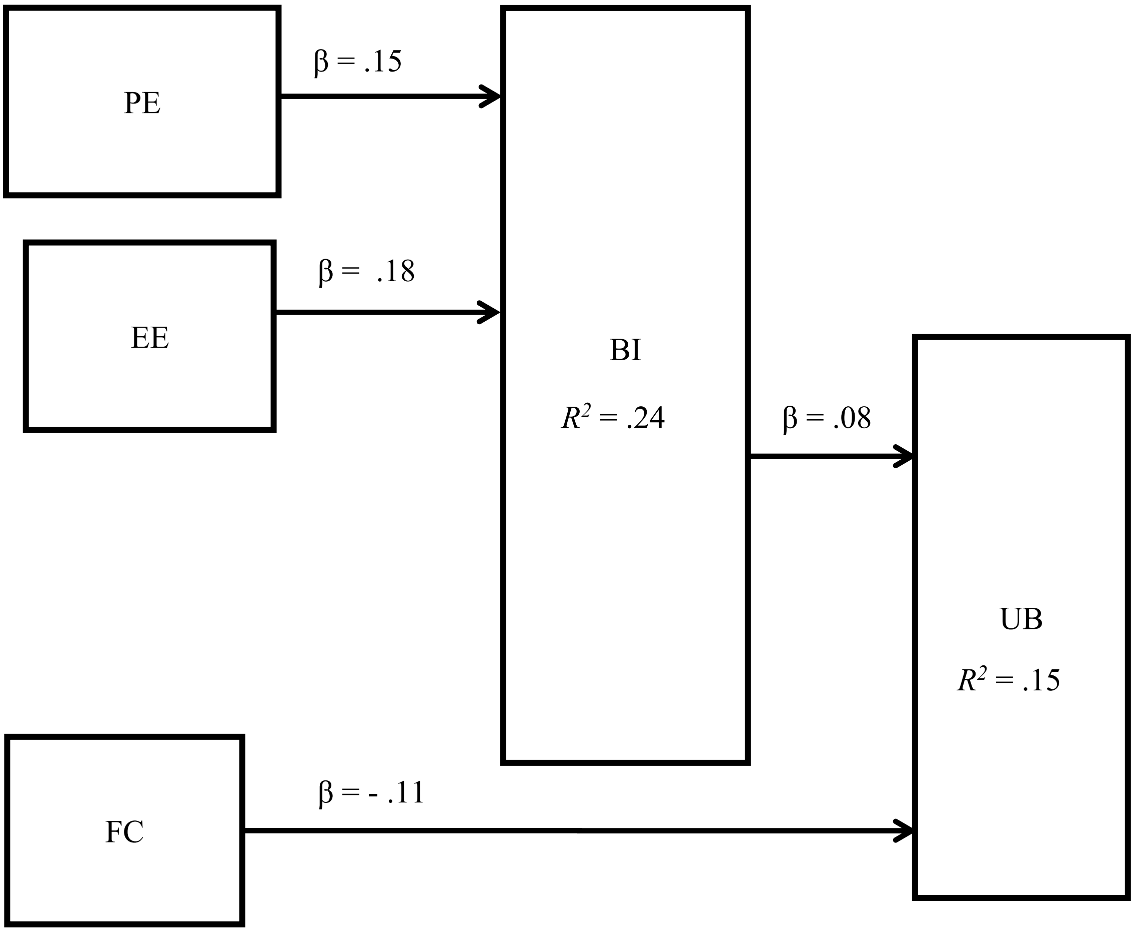
5.09 and SD = 2.02. The fourth, and last indicator, "I have printed the online learning materials a lot since my admission into this university", had a mean, $m = 4.20$ and SD = 2.20. According to these results there is a larger variability (as compared with other predictors and outcomes) of means across the UB items. It was observed that the mean for the first indicator is in the "strongly agree" category (m = 6.01), while the means for the second and third indicator are in the "agree" category (m = 5.64 and m = 5.09 respectively) and the mean for the fourth indicator is in the "somewhat agree" category (m = 4.20). Similar to the indicators for BI, most responses to each of the UB indicators were in the "strongly agree" category. Further, the results show that 60.8% of the respondents strongly agree to have logged onto the e-learning platform a lot since their admission into their university while 45.4% strongly agreed to have read the online learning materials a lot since their admission into their university. However, 38.1% of the respondents strongly agreed to have downloaded the online learning materials a lot since their admission into their university. Finally, only 21.6% strongly agreed to have printed the online learning materials a lot since their admission into their university. Thus, the largest contributor to UB is students log in to the e-learning platform while the other uses of e-learning such as reading, downloading and printing the e-learning materials have a progressively smaller contribution to UB. Thus, as far as UB is concerned, students exhibit increased actual use of e-learning by performing the following activities associated with e-learning usage: login into the platform, reading online materials, downloading e-learning materials and; printing the online materials.

4.5 The Preliminary E-learning Adoption Model (without moderation)

From the foregoing, Figure 6 presents the e-learning model without the moderating effect of age, gender, and internet experience.

Figure 6

The Empirical Structural Model (Without Moderation)



In this model, SI has been removed as a predictor of e-learning adoption while all other predictors (PE, EE and FC) remain. In the next phase of analysis, the effect of the moderators (age, gender and internet experience) will be assessed to determine which ones to include in the resulting overall model for e-learning adoption for HEI's in Kenya.

4.6 Results of Testing the Moderating Effects in the Study

The sixth hypothesis of the study states that "there is no statistically significant difference on the effect of gender (GND), age (AGE), and internet experience (IXP) on the direct relationship between the predictors and outcomes of e-learning adoption". Although ACP was proposed as a moderator in this study, its effect was not analyzed because of two reasons; first, the literature in support of ACP as a moderator of e-learning adoption was not adequate; secondly, the categorization of courses into Science, Arts or Business among public universities in Kenya is not universal both in Kenya and internationally making the generalization of the results of ACP as a moderator untenable. The next sections present the results of the moderating effects of gender, age and internet experience on the relationships between: PE and BI; EE and BI; SI and BI; FC and UB, and; BI and UB.

4.6.1 The Moderating Effect of Gender on PE → BI

Table 22 shows the results of the moderating effect of gender 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 22

Moderation Effects of Gender on the Relationship: 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	.005*	.001*	4.77	.001*

* Denotes significance at $p \leq .10$

The results in Table 22 show that gender is a significant moderator of the relationship between PE and BI (p = 0.001*). The moderation effect is however, not in favour of either male or female students because it is significant for both genders (p = 0.005* for male and p = 0.001* for female). Thus, the relationship between PE and BI is significantly and equally moderated by both male and female students.

4.6.2 The Moderating Effect of Age on PE → BI

Table 23 shows the results of the moderating effect of age on the direct 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 23

Moderation Effects of Age on The Relationship: PE→BI

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
AGE	Young	Old	Young	Old	Young + Old	Young + Old
	0.28	0.08	.001*	.179	1.20	.116

* Denotes significance at $p \leq .10$

The results in Table 23 show that age is not a significant moderator of the relationship between PE and BI (p = 0.116). The moderation effect is however, significant in favour of younger students compared to the older students (p = 0.001* for young and p = 0.179 for old). Thus, while the relationship between PE and BI is not significantly moderated by age, moderating effect is stronger for younger students than it is for older students.

4.6.3 The Moderating Effect of Internet Experience on PE → BI

Table 24 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 24

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

* Denotes significance at $p \leq .10$

The results in Table 24 show that internet experience 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 internet experience, the moderating effect is stronger for inexperienced internet users than it is for experienced internet users.

4.6.4 The Moderating Effect of Gender on EE → BI

Table 25 shows the results of the moderating effect of gender on the relationship between EE 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 25

Moderation Effects of Gender on The Relationship: EE→BI

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
GND	Male	Female	Male	Female	Male + Female	Male + Female
	0.14	0.33	.035	.001*	1.40	.081*

* Denotes significance at $p \leq .10$

The results in Table 25 show that gender is a significant moderator of the relationship between EE and BI (p = 0.081*). The moderation effects were significant for female students when compared to their male counterparts (p = 0.001* for female; p = 0.035 for male). Thus, the moderation effect of gender on the relationship between EE and BI was stronger for female students than it was for male students.

4.6.5 The Moderating Effect of Age on EE → BI

Table 26 shows the results of the moderating effect of age on the relationship between EE 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 26

Moderation Effects of Age on the Relationship: EE →BI

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
AGE	Young	Old	Young	Old	Young + Old	Young + Old
	0.21	0.33	.001*	.001*	3.33	.001*

* Denotes significance at $p \leq .10$

The results in Table 26 show that age is a significant moderator of the relationship between EE and BI (p = 0.001*). The moderating effect is significant for both young and old students (p = 0.001* for both “young” and “old”). Thus, the relationship between EE and BI is moderated significantly by age; the moderating effect being significantly strong for students of all ages.

4.6.6 The Moderating Effect of Internet Experience on EE → BI

Table 27 shows the results of internet experience on the relationship between EE 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 27

Moderation Effects of Internet Experience on the Relationship: EE → BI

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
IXP	Inexp	Exp	Inexp	Exp	Inexp + Exp	Inexp + Exp
	0.22	0.33	.005*	.001*	1.66	.048*

* Denotes significance at $p \leq .10$

The results in Table 27 show that internet experience is a significant moderator of the relationship between EE and BI (p = 0.048*). The moderation effects were significant for experienced or inexperienced internet users (p = 0.005* for inexperienced internet users; p = 0.001* for experienced internet users). Thus, the relationship between EE and BI was significantly moderated by both experienced and inexperienced internet users.

4.6.7 The Moderating Effect of Gender on SI → BI

Table 28 shows the results of the moderating effect of gender on the relationship between SI 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 28

Moderation Effects of Gender on the Relationship: SI → BI

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
GND	Male	Female	Male	Female	Male + Female	Male + Female
	0.384	0.054	.001*	.207	0.308	.379

* Denotes significance at $p \leq .10$

According to previous results of this study, the relationship between SI and BI is not statistically significant. However, some relationship still exists between the two variables. The overall results in Table 28 show that gender is not a significant moderator of the direct relationship between SI and BI (p = 0.379). However, it is interesting to note that the moderating effect is significant for male students (p = 0.001*) only while it is not for female students (p = 0.207). Therefore, while there exists a moderating effect for male students on the relationship SI → BI, the same is absent for the female students. The extent of this moderating effect is such that it has no influence on the overall moderating effect of gender on the relationship SI→ BI.

4.6.8 The Moderating Effect of Age on SI → BI

Table 29 shows the results of the moderating effect of age on the relationship between SI 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 29

Moderation Effects of Age on the Relationship: SI → BI

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
AGE	Young	Old	Young	Old	Young + Old	Young + Old
	0.08	0.54	0.114	.001*	5.26	.001*

* Denotes significance at $p \leq .10$

The results in Table 29 show that the relationship between SI and BI is significantly moderated by age (p = 0.001*). This effect is significant only for older students (p = 0.001* for "old"; p = 0.114 for "young"). Thus, the relationship between SI and BI is moderated by age; the moderating effect being stronger for older students than it is for younger students.

4.6.9 The Moderating Effect of Internet Experience on SI → BI

Table 30 shows the results of the moderating effect of internet experience on the relationship between SI 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 30

Moderation Effects of Internet Experience on the Relationship: SI→ BI

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
IXP	Inexp	Exp	Inexp	Exp	Inexp + Exp	Inexp + Exp
	-0.13	0.37	.040*	.001*	2.76	.003*

* Denotes significance at $p \leq .10$

Table 30 shows that the relationship between SI and BI is significantly moderated by internet experience (p = 0.003*). This effect is significant for both inexperienced and experienced internet users (p = 0.040* for "inexperienced"; p = 0.001* for "experienced"). Thus, internet experience is a significant moderator of the relationship between SI and BI; the moderating effect being significant for both inexperienced and experienced internet users.

4.6.10 The Moderating Effect of Gender on FC → UB

Table 31 shows the results of the moderating effect of gender on the relationship between FC and UB 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 31

Moderation Effects of Gender on the Relationship: FC→UB

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
GND	Male	Female	Male	Female	Male + Female	Male + Female
	0.25	0.15	.001*	.042*	0.74	.230

* Denotes significance at $p \leq .10$

The results in table 31 show that gender is not a significant predictor of the relationship between FC and UB (p = 0.230). Interestingly, the moderating effect is significant for both male students (p = 0.001*) and female students (p = 0.042*). Thus, the relationship between

FC and UB is not moderated by gender; there being no difference on the strength of this relationship in favour of either male or female students.

4.6.11 The Moderating Effect of Age on FC → UB

Table 32 shows the results of the moderating effect of age on the relationship between FC and UB 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 32

Moderation Effects of Age on the Relationship: FC → UB

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
AGE	Young	Old	Young	Old	Young + Old	Young + Old
	0.17	0.27	.002*	.001*	2.90	.002*

* Denotes significance at $p \leq .10$

The results in Table 32 show that age is a significant moderator of the relationship between FC and UB (p = 0.002*). This effect is significant for both “young” and “old” students (p = 0.002*for “young”; p = 0.001* for “old”). Thus, the relationship between FC and UB is significantly moderated equally by students of all ages (young and old).

4.6.12 The Moderating Effect of Internet Experience on FC → UB

Table 33 shows the results of the moderating effect of internet experience on the relationship between FC and UB 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 33

Moderation Effects of Internet Experience on the Relationship: FC→ UB

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
IXP	Inexp	Exp	Inexp	Exp	Inexp + Exp	Inexp + Exp
	0.38	0.12	.001*	.045*	2.15	.016*

* Denotes significance at $p \leq .10$

The results in Table 33 show that internet experience is a significant moderator of the relationship between FC and UB (p = 0.016*). The moderation effect is significant for both categories of internet experience (p = 0.001* for inexperienced internet users; p = 0.045* for experienced internet users). Thus, the relationship between FC and UB is moderated equally at all levels of internet experience (experienced and inexperienced internet users).

4.6.13 The Moderating Effect of Gender on BI → UB

Table 34 shows the results of the moderating effect of gender 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 34

Moderation Effects of Gender on the Relationship: BI→UB

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
GND	Male	Female	Male	Female	Male + Female	Male + Female
	-0.21	0.50	.001*	.001*	3.18	.001*

* Denotes significance at $p \leq .10$

The results in Table 34 show that gender is a significant moderator of the relationship between BI and UB (0.001*). The moderation effects are significant, but not different for male and female (p = 0.001* for “male”; p = 0.001* for “female”). Thus, the relationship between BI and UB is significantly moderated by gender; the moderating effect being equally strong for both male and female students.

4.6.14 The Moderating Effect of Age on BI → UB

Table 35 shows the results of the moderating effect of age on the relationship between BI and UB 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 35

Moderation Effects of Age on the Relationship: BI→UB

Moderator	Path coefficient	Path coefficient	p-value	p-value	t-value	p-value
AGE	Young	Old	Young	Old	Young + Old	Young + Old
	0.276	-0.32	.001*	.001*	0.67	.253

* Denotes significance at $p \leq .10$

The results in Table 35 show that age is not a significant moderator of the relationship between BI and UB (p = 0.253). Interestingly, the moderation effects are equally significant for male and female (p = 0.001* for both “male” and “female”). Thus, the relationship between BI and UB is moderated by age; the moderating effect being strong for both young and old students.

4.6.15 The Moderating Effect of Internet Experience on BI → UB

Table 36 shows the results of the moderating effect of internet experience on the relationship between BI and UB 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 36

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*

* Denotes significance at $p \leq .10$

The results in Table 36 show that internet experience is a significant moderator of the relationship between BI and UB (p = 0.017*). The moderation effects are significant, but not different for both categories of internet experience (p = 0.001* for both inexperienced and experienced internet users). Thus, the relationship between BI and UB is moderated by internet experience of the students; the moderating effect being equally strong for students at all levels of internet experience (experienced and inexperienced).

4.7 The Final E-learning Adoption Model (with moderation)

Figure 7 presents the final e-learning adoption model for undergraduate students in Kenya's public universities.

Figure 7

The University Students E-learning Adoption Model

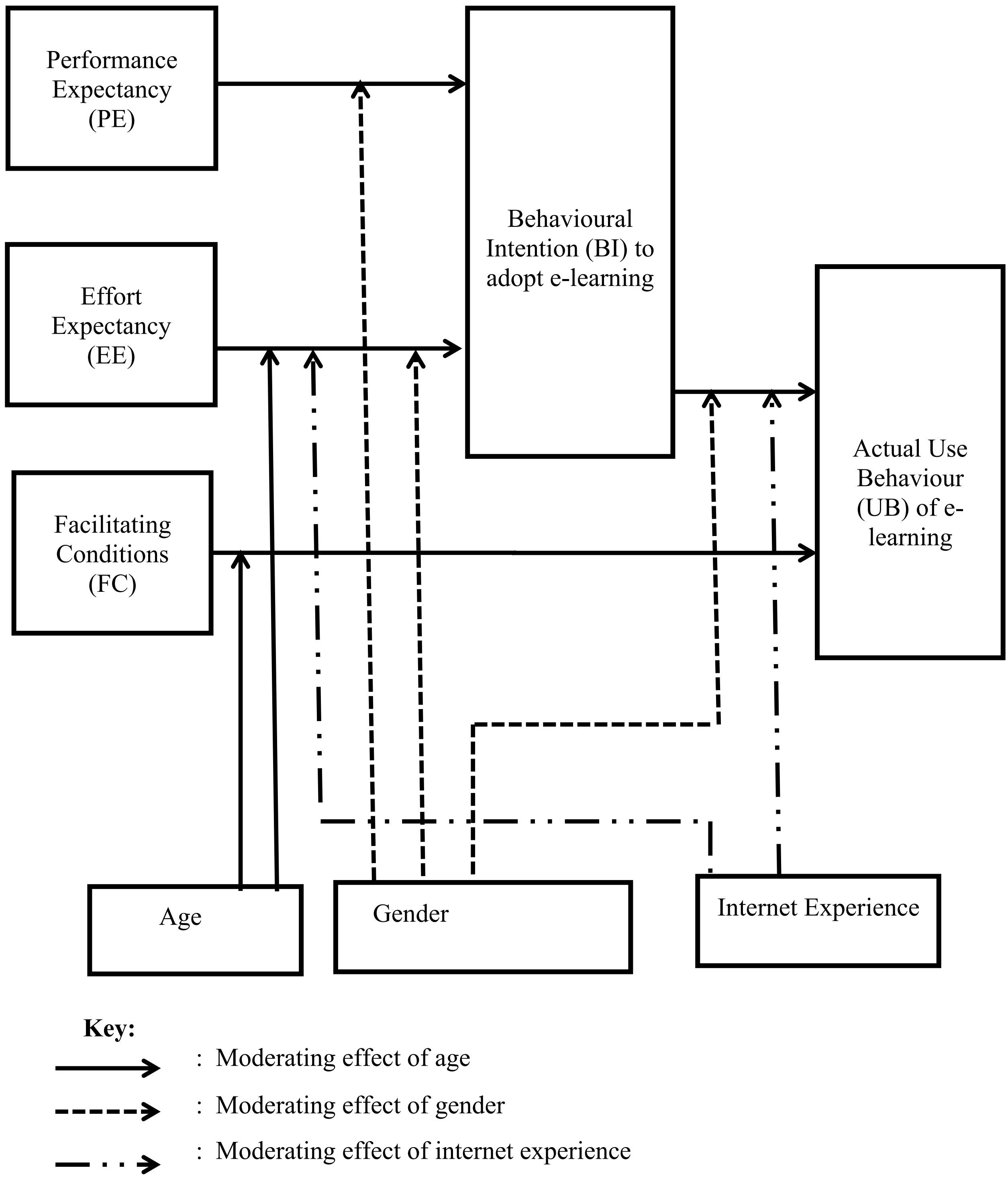


Figure 7 shows the direct relationships between predictors and outcomes of e-learning as well as the effect of moderators on the direct relationship between the predictors and outcomes. This is the final study model and is named; the University Students E-learning Adoption Model (USeLAM).

4.8 Summary of Results

Overall, the USeLAM accounted for 24% of the variance in intention to use e-learning and 15 % of the variance in actual use of e-learning. These values of variance are characteristically low compared to other studies. For example, Venkatesh (2003) established that the UTAUT model explained 69% of the variance in user intentions to use IT.

Table 37 is a summary of the results of the mean scores and S.D. for each of the indicators of the latent variables (predictors) in the study. The mean scores show the relative strength of the indicators for a given latent variable. A higher mean for an indicator implies that the strength of the indicator is higher than the rest.

Table 37

Means and S.D. of Indicators of the Latent Variables

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
Effort Expectancy	EE			
	EE_1	Easy to understand	5.70	1.62
	EE_2	Easy to acquire skills	5.92	1.47
	EE_3	Easy to use	5.59	1.66
	EE_4	Easy to learn	5.54	1.73
Social Influence	SI			
	SI_1	Influence of role models	4.84	2.26
	SI_2	Influence of peers	4.65	2.13
	SI_3	Support from course instructors	5.58	1.75
	SI_4	Support from the university	5.70	1.87
Facilitating Conditions	FC			
	FC_1	Possession of resources	5.80	1.52
	FC_2	Compatibility with other modes of learning	5.59	1.63
	FC_3	Knowledgeable in use the e-learning	5.89	1.49
	FC_4	Availability of assistance	4.86	2.12
Behavioural Intention	BI			
	BI_1	Improved academic productivity	6.47	0.91
	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
Actual Use Behaviour	UB			
	UB_1	Login	6.01	1.60
	UB_2	Reading	5.64	1.66
	UB_3	Downloading	5.09	2.02
	UB_4	Printing	4.20	2.20

(n = 388)

Table 37 shows that the strongest indicator (highest mean) for PE is the usefulness of e-learning. This is followed by quick accomplishment of tasks, increased academic productivity and increased chances of obtaining a high grade in that order. As far as EE is concerned, the strongest indicator is the ease of acquiring skills followed by ease of understanding. The other indicators were; ease of use and learning the e-learning mode of study. Support from the university was the strongest indicator of SI. This was followed by support from instructors, influence of role models and lastly those who influence the students' behaviour (friends, relatives and peers). The strongest indicator for FC was the knowledge students had of e-learning, possession of resources to undertake their studies, compatibility with other modes of learning and availability of assistance. Increased academic productivity was the strongest indicator of BI. The next indicator was "if e-learning would be easy to use", "approved by role models" while availability of assistance with e-learning was the least preferred indicator for BI. For UB, the indicator, from the strongest to the weakest were; daily login, reading online materials, downloading and printing e-learning materials in that order.

Table 38 presents the summary of the overall results and model of the study that include the direct relationships and the effects of moderators.

Table 38

Summary of Moderation Results

	PE → BI		EE → BI		SI → BI		FC → UB		B I → UB	
Moderator: AGE										
p-value (direct)	0.116		.001*		.001*		.002*		.253	
	Young	Old	Young	Old	Young	Old	Young	Old	Young	Old
p-value (moderated)	.001*	.179	.001*	.001*	.114	.001*	.002*	.001*	.001*	.001*
Moderator: GENDER										
p-value (direct)	.001*		.081*		.379		.230		.001	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
p-value (moderated)	.005*	.001*	.035	.001*	.001*	.207	.001*	.042*	.001*	.001*

	PE → BI		EE → BI		SI → BI		FC → UB		B I → UB	
Moderator: INTERNET EXPERIENCE										
p-value (direct)	.105		.048*		.003*		.016*		.017	
	Exp	Inexp	Exp	Inexp	Exp	Inexp	Exp	Inexp	Exp	Inexp
p-value (moderated)	.211	.001*	.001*	.005*	.001*	.040*	.045*	.001*	.001*	.001*

* Denotes significance at $p \leq .10$

Table 39 shows the moderation effects of age (AGE), gender (GND) and internet experience (IXP) on the four direct relationships (PE→BI; EE→BI, FC→UB and BI→UB) in the study. The relationships that were found to be significant were those between PE→BI, EE→BI, FC→UB and BI→UB while the moderators were; AGE, GND and IXP. A tick (√) indicates significant moderation of a significant direct relationship.

The relationships as presented in Figure 7 are summarized in Table 38. From the table, it is evident that the significant relationships are such that:

i) Age (AGE) moderates the relationships between PE and BI (PE→BI**)**, and between FC and UB (FC→UB**)**;

ii) Gender (GND) moderates the relationships between PE and BI (PE→BI), EE and BI (EE→BI**)** and between BI and UB (BI→UB**)**;

iii) Internet experience (IXP) moderates the relationships between EE and BI (EE→BI**)** and between BI and UB (BI→UB**)**.

In conclusion, the results in Table 39 present a summary, including the relative strength of each of the moderators.

Table 39

Relative Strength of the Moderators

Moderator/ Relationship	PE → BI	EE→ BI	SI → BI*	FC → UB	B I → UB
AGE	No Effect	X (Same for Young/Old)	X (Stronger for Old)	X (Same for Young/Old)	No Effect
GND	X (Same for Male/Female)	X (Stronger for Female)	No Effect	No Effect	X (Same for Male/Female)
IXP	No Effect	X (Same for experienced/ inexperienced)	X (Same for experienced/ inexperienced)	X (Same for experienced/ inexperienced)	X (Same for experienced/ inexperienced)

Note: * denotes exclusion from the final model; X denotes presence of moderation effect

To summarize, the relationships examined within this research are outlined below, along the influence of moderators on these relationships:

i) The relationship PE → BI is confirmed to exist, is significant and is moderated by gender only. The strength of moderation is the same for males and females.
ii) The relation EE → BI is confirmed to exist, is significant and is influenced by age, gender and internet experience. The strength of moderation is the same for young and old, and experienced and inexperienced leaners but is stronger for females compared to their male counterparts.
iii) The link SI → BI is confirmed to exist, but is not significant. However, it is moderated by age and internet experience. The moderation effect is stronger for older people but is the same for experienced and inexperienced internet users.
iv) The relationship FC → UB is confirmed to exist, is significant and is moderated by age and internet experience. The moderation effect is the same for young and old students and; experienced and inexperienced users of the internet.
v) The relationship BI → UB is confirmed to exist, is significant and is moderated by gender and internet experience. The moderation effect is the same for male and female students; and also, for experienced and inexperienced users of the internet.

CHAPTER FIVE
DISCUSSION

5.1 Introduction

This section provides an in-depth interpretation and analysis of the principal results derived from the preceding sections and sub-sections. The discussion is organized around the central themes, aligned with the literature review as well as the theoretical and conceptual framework guiding this research. The presentation proceeds systematically, consistent with the hypotheses proposed in the study. The initial focus is on the outcomes concerning PE as a direct determinant of BI. This is followed by an examination of EE as a direct determinant of BI, and subsequently SI as a predictor of BI. Thereafter, the findings addressing FC as a determinant of UB, together with BI as a predictor of UB, are presented in sequence. In addition, attention is given to the role of moderators in shaping the direct associations between predictors and outcomes in e-learning adoption. Finally, the analysis evaluates the overall strength of the model in accounting for patterns of e-learning adoption.

5.2 PE as a predictor of BI

Venkatesh et al. (2003) originally conceptualized PE as the degree to which an individual believes that using a new technological system will help to attain gains in job performance. This definition has received various modifications that are context specific. For example, Sewandono et al. (2022) define PE as the extent to which the use of e-learning is believed to enhance faculty research productivity. In this study, PE is defined as the degree to which a student believes that using the e-learning mode of study will lead to improvements in their academic performance.

To operationalize the definition of PE in this study, it refers to the fact that using the e-learning mode of study is useful; will enable a student to accomplish tasks more quickly; increase academic productivity and; increase chances of students scoring higher grades in the courses they are pursuing. From the results, it was observed that the strongest indicator (highest mean) for PE is the usefulness of e-learning as a mode of study for the course a student is pursuing. This is followed by quick accomplishment of tasks, increased academic productivity and increased chances of obtaining a high grade; in that order.

The results of the study show that the relationship between PE and BI is confirmed to exist, significant and is moderated by gender only; where the strength of moderation is the same for both male and female students. However, this relationship is not moderated by age or internet experience. Among the two significant predictors of BI, that is; PE and EE, PE explained 15.2%

of the variance in BI compared to 17.8% explained by EE. This implies that PE is a determinant of e-learning acceptance and adoption.

Though in a different context, these results agree with those obtained by Abbad (2021) and Bellaaj et al. (2015) who found that PE determines the intention of continued use of an e-learning system. They also established that with more internet experience, the effect of PE increases. This finding implies that as the degree to which a student believes that using an e-learning mode of study will help him or her to attain gains in academic performance increases, the student's likelihood of using the e-learning mode of study also increases. The findings are consistent with previous research that showed that PE had a direct effect on BI (Bellaj et al., 2015; Chao, 2019; Mahande & Malago, 2019).

With regard to gender, the results revealed that PE significantly positively influenced BI among both male and female students. This finding shows an interesting fact that the intention to use of e-learning among male and female students did not differ. This finding is contrary to what is considered ordinary; that there are indeed differences regarding acceptance and adoption of e-learning among male and female students. According to Adams et al. (2018), female students are perceived to be more proficient in Microsoft Office software and use mobile gadgets more frequently to communicate. Hence their intention to use e-learning is expected to be higher given that they possess complementary skills and a propensity towards e-learning compared to their male counterparts.

5.3 EE as a predictor of BI

The results of the study show that the relationship between EE and BI is confirmed to exist, significant and is moderated by age, gender and internet experience. The moderation effect is the same for both young and old students as well as experienced and inexperienced users of the internet. The moderating effect is however, stronger for female students compared to their male counterparts. Among the predictors of BI, EE contributed the higher variance in BI (17.8%) as compared to PE.

In this study, EE refers to the degree of ease associated with the use of the e-learning mode of study. It has been operationalized to mean that the e-learning mode of study would be easy to understand, acquire skills, easy to use and easy to learn to use. The EE predictor used had four indicators and was subjected to three levels of analysis; descriptive analysis, SEM and MGA. The results in Chapter Four showed that the respondents viewed their interaction with the e-learning mode of study as; easy to understand, acquire skills, easy to use and easy to learn to use. These finding imply that undergraduate students find it easy to navigate through the e-learning platforms. A possible explanation for this is that the students are savvy with the use of ICT tools and the internet which is a precursor of the ease of use of e-learning.

These findings agree with those obtained by Abbad (2016), Bellaaj et al. (2015) and Venkatesh et al. (2003) who found that EE determines the intention of continued use of an e-learning system. The result that EE had a positive relationship with the BI to use the e-learning mode of study implies that as the degree of ease associated with the use of the e-learning mode of study increases, the student's likelihood of using the e-learning mode of study also increases. This means that students' adoption of e-learning mode of study depends on the expected ease of use of the platforms. This study proves that EE theoretically and empirically effects BI and therefore is a precursor of e-learning acceptance among undergraduate students in Kenya. These findings are consistent with previous research (Abbad, 2021; Jameel et al., 2020), that showed that EE had a direct positive effect on BI to adopt e learning.

Regarding the moderating effect of age on the direct relationship between EE and BI, it was established that EE significantly and positively influenced BI among both young and older students. This study, therefore, supports the fact that age is an important factor in human learning and development. Therefore, 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. On the contrary, a study by Fleming et al. (2017) on employees' overall acceptance, satisfaction and future use of e-learning suggest that, despite the often-espoused stereotype, age is not a significant factor impacting either future use intentions or satisfaction with e-learning.

From the foregoing arguments, age tends to affect e-learning adoption differently depending on the context in which it is applied. For example, increased age has been associated with greater difficulty in processing complex stimuli and allocating attention to job-related information (Plude & Hoyer 1985), both of which may be necessary when using software systems. Further, Morris and Venkatesh (2000), argue that age differences are applicable in technology adoption contexts. On a different note, Levy (1988), interestingly suggests 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, this study included age as a moderating factor.

Regarding the moderating effect of internet experience on the direct relationship between EE and BI, EE significantly and positively influenced BI among students with internet experience and those without. Further, it was established that with more internet experience, the influence of EE on BI increased. An explanation for this finding is that the proliferation of computers and the use of electronic means of communication in everyday life have inadvertently made e-learning a preferred mode of study. Therefore, students who consider themselves as not being experienced with the use of internet will adopt e-learning in much the same way as those experienced with the internet. In conclusion, therefore, the ease associated with the use of the e-learning mode of study is the same whether a student is experienced with the use of the internet or not.

The moderating effect of gender on the direct relationship between EE and BI is stronger for female students compared to their male counterparts. This finding implies that expected ease of use of e-learning platforms explained BI to adopt the e-learning mode of study among all students' age groups. A plausible explanation of this is that due to the integration of basic computer skills in universities' syllabi, the computer self-efficacy of all students' age groups is high hence the students' confidence in their ability to navigate the e-learning platforms increases their intention to use this mode of study.

5.4 SI as a predictor of BI

The results of the study show that the relationship between SI and BI is confirmed to exist, but is not significant. However, it is moderated by age and internet experience and not by gender. The moderation effect is stronger for older students as compared to the younger ones but is the same for experienced and inexperienced internet users. Among all the predictors of e-learning SI explained only 0.4% of the variance in BI. Abbad (2021) conducted a similar study in Jordan and found similar results. He investigated learners' intentions to use the Learning Management System MOODLE by applying all the predictors of e-learning as used in this study, namely; PE, EE, SI and FC. Among all the predictors, the results indicated that SI had no influence on students' intention to use MOODLE.

Gass (2015) defines SI as involving intentional and unintentional efforts to change another person's beliefs, attitudes, or behaviour. He further distinguishes it from persuasion, which is intentional and requires some degree of awareness on the part of the target. Venkatesh et al. (2003), in formulating the UTAUT defined SI as the degree to which an individual perceives that important others believe he or she should use the new system. From these definitions, two terms emerge, namely; "another person" (Gauss, 2015) and "important others" (Venkatesh et al., 2003). In operationalizing these terms, and by extension SI, this study refers to SI as involving; influence of role models, influence of peers, support from course instructors and support from the university.

The SI predictor used had four indicators and was subjected to three levels of analysis; descriptive analysis, SEM and MGA. The descriptive analysis results showed that the respondents' role models and behavior influence did not positively perceive the e-learning mode of study. However, the analysis also showed that the programme instructors and the university in general supports the students in use of the e-learning mode of study. This finding indicates that even though learning institutions are investing in e-learning mode of study and instructors have also adopted the pedagogy delivery medium, there is still a poor perception of the medium among students' peers and this might constrain uptake. This finding is consistent with Abbasi et al. (2020) who found that majority of students have a poor perception of e-learning as they prefer face-to-face learning. This finding is associated with the fact that most students come from rural areas where there is poor network reception and internet access is expensive. Moreover, online learning receptibility is significantly higher for respondents who are more than 30 years of age; and who are the minority in university undergraduate programmes.

These findings contradict those obtained by Abbad (2021) and Bellaaj et al. (2015) who found that SI determines the intention of continued use of an e-learning system. They also established that with more internet experience, the influence of SI on intention of continued use of e-learning seems to be stronger for women than for men.

The SEM analysis found that social influence did not influence the behavioral intention to use the e-learning mode of study. This finding implies that as the degree to which an individual perceives that others believe he or she should use the e-learning mode of study has no influence on the likelihood of students using the e-learning mode of study. This implies that, generally, students will not use e-learning system because their peers or role models recommend it. This finding, though contrary to expectations, is consistent with other studies who found similar results (Bellaaj et al., 2015; Martins et al., 2015; Riffai et al., 2012).

The MGA of social influence with regard to gender revealed that social influence significantly positively influenced behavioral intention among male students. This finding shows an interesting fact that the use of e-learning among female students was not directly influenced by the opinion of their peers about e-learning. The implication of this finding is that the behavioral intention to use the e-learning mode of study for female students is predicted by other factors but not on the degree to which an individual perceives that others believe that they should use the e-learning mode of study. This difference in the gender implication on social influence is contrary to the current body of literature that generally postulate that social influence is a significant predictor of e-learning behavioral intention among female students. Wut and Lee (2021), argue that social influence affects female students' behavioral intention but not male students. Bellaaj et al. (2015), discovered that social influence had a greater impact on women's intentions to continue using e-learning. This indicates that when it comes to deciding whether or not to use an electronic learning system, Saudi Arabian female students are more sensitive to the opinions of others.

The MGA of social influence with regards to age groups revealed that social influence significantly positively influenced behavioral intention among students above 30 years of age. This finding implies that peers' opinions of e-learning platforms explained behavioral intention to adopt the e-learning method of study among students above 30 years of age. Prior research has indicated that social impact predicts e-learning intention more strongly in older persons than in younger people (Venkatesh et al., 2003; Wang et al., 2008). This could be because younger people have more self-esteem than older people, and hence are more likely to decide for themselves whether to use an advanced m-learning system without being influenced by others.

The MGA of social influence with regards to internet experience revealed that social influence significantly negatively influenced behavioral intention among students both with less than 3 years and positively influenced behavioral intent for students with more than 3 years of internet experience. This finding implies that students with more years of internet use are more likely to develop intent of use of e-learning if their peers have a favorable opinion of the learning mode than their colleagues with fewer years of internet experience. A plausible explanation for this trend is that students with more years of internet experience have higher self-efficacy in use of e-learning platforms hence can easily adopt the platforms due to peer influence as compared to their less internet savvy students who will not adopt e-learning due to peer influence as they are not proficient enough with the systems.

5.5 FC as a predictor of UB

The relationship FC → UB is confirmed to exist, is significant and is moderated by age and internet experience. The moderation effect is the same for young and old and; experienced and inexperienced users of the internet. Gender has no moderating effect on this relationship. Among all the predictors of e-learning FC contributed – 10.9% of the variance of in UB.

The Facilitating conditions predictor used had four indicators and was subjected to three levels of analysis; descriptive analysis, SEM and MGA. The descriptive analysis results show that the respondents acknowledged that; they have the resources necessary to use the e-learning mode of study, e-learning mode of study is compatible with other modes of study they use and they are knowledgeable in use the e-learning mode of study. However, the students did not have a specific person (or group) is available for assistance with e-learning difficulties. This finding indicates that even though learning institutions have invested in e-learning mode of study resources, customizing the mode of study to be compatible with study programs and students have also acquainted themselves with the learning medium, there is still a poor personal support system.

The SEM analysis revealed that facilitating conditions negatively influence the actual use of the e-learning mode of study. This suggests that a student's belief in the availability of technical infrastructure to support e-learning does not significantly affect their likelihood of using the system. In other words, students tend to use e-learning regardless of the availability of necessary resources or knowledge. The analysis also suggests that students find e-learning compatible with other study methods and that they will use the system particularly if support is available to help them with any challenges they encounter.

This finding, though contrary to expectations, agrees with Kibuku et al. (2020) who found that e-learning is being rolled out and adopted by learners despite a myriad of national, organizational, technical and social challenges. Some of the challenges include: Lack of adequate e-learning policies, insufficient ICT infrastructure, ever-evolving technologies, lack of technical and pedagogical competencies and training for e-tutors and e-learners, lack of an e-learning theory to underpin the e-learning practice, budgetary constraints and sustainability issues, negative perceptions towards e-learning, and quality issues.

The MGA of facilitating conditions with regards to gender revealed that facilitating conditions significantly positively influenced actual use among both male and female students. This finding implies that for the individual groups, their adoption of e-learning is dependent on the availability of necessary resources and knowledge to participate in e-learning; that e-learning is compatible with other modes of study they use and that there is a specific person (or group) available to support students with any difficulties arising from the use of e-learning mode of study.

The MGA of facilitating conditions with regards to age groups revealed that facilitating conditions significantly positively influenced actual use behaviour among students of both under and above 30 years of age. This finding implies that the availability of necessary resources and knowledge to participate in e-learning; that e-learning is compatible with other modes of study they use and that there is a specific person (or group) available to support students with any difficulties arising from the use of e-learning mode of study explained adoption of the e-learning method of study among all students age groups.

The MGA of facilitating conditions with regards to internet experience revealed that facilitating conditions significantly positively influenced actual use behaviour among students of both under and above 30 years of age. This finding implies that the availability of necessary resources and knowledge to participate in e-learning; that e-learning is compatible with other modes of study they use and that there is a specific person (or group) available to support students with any difficulties arising from the use of e-learning mode of study explained adoption of the e-learning method of study among all students of varying experience in use of the internet. This finding implies that varying levels of proficiency with digital technology needs to be complemented with support infrastructure to facilitate successful adoption of e-learning.

5.6 BI as a predictor of UB

The relationship between behavioural intention (BI) and use behaviour (UB) was found to be statistically significant and influenced by gender and level of internet experience. However, the moderating influence was consistent across both male and female learners, as well as among those who were digitally experienced and those who were not. Conversely, age did not exhibit any moderating role in the connection between intention to adopt and actual utilization of digital learning environments. Overall, BI accounted for approximately 8.3% of the total variance in UB.

The construct representing behavioural intention comprised four indicators and was analyzed at three stages: descriptive analysis, structural equation modelling (SEM), and multi-group analysis (MGA). The descriptive results showed that most students intend to continue using digital learning systems within the next academic term, particularly when these systems enhance their learning efficiency, are user-friendly, receive approval from peers or mentors, and offer reliable support mechanisms. These observations reveal that a substantial proportion of learners' do actually plan to sustain or expand their engagement with virtual learning platforms throughout the academic semester and beyond.

Findings from the SEM analysis demonstrated that behavioural intention exerts a positive influence on actual engagement with online learning systems. This suggests that the extent to which a learner intends to begin or maintain participation in digital learning—especially from the start to the end of the academic term and into subsequent periods—directly increases their likelihood of actual adoption. These outcomes reinforce the well-established assumption that intention serves as a reliable predictor of human action (Marandu et al., 2019). Extensive theoretical literature supports the existence of a direct link between intention and behaviour, as shown in the Technology Acceptance Model (Davis, 1989) and the Theory of Planned Behaviour (Ajzen & Madden, 1986). In alignment with these perspectives, both TAM and TPB draw from the Theory of Reasoned Action (TRA), which posits that a strong and consistent relationship exists between behavioural intention and subsequent action.

This outcome suggests that for learners above 30 years of age, their engagement with online learning systems does not necessarily stem from a pre-planned intention to utilize the technology. One possible reason for this observation could be that most students in this age group balance their studies with employment and are therefore enrolled in hybrid or mixed-mode programmes, prompting regular interaction with virtual learning environments.

The multi-group analysis (MGA) on behavioural intention in relation to internet experience revealed that behavioural intention significantly and positively affected actual system use among learners with fewer than three years of internet exposure, but had a negative association among those with between four and six years of experience. This implies that students who have been online for more than three years do not necessarily rely on advance planning when engaging with virtual learning platforms. This outcome differs from what might be anticipated, as students with greater digital experience tend to possess stronger awareness regarding the advantages of technology-enhanced learning and demonstrate higher proficiency in navigating such systems, which would normally correspond with stronger behavioural intentions.

CHAPTER SIX
CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This study serves to confirm that predicting undergraduate students' preference for online learning in public HEIs is a worthwhile yet complex process. This is because of the several variables involved in the analysis. Similarly, direct observation of constructs is seldom possible and unlikely to provide dependable relationships for model development. Therefore, effort must be expended to craft "latent" variables and operationalize them by using indicators that represent the variables. To put this in context, there were six latent variables in this study; with each latent variable represented by four indicators, making a total of 24 indicators. Moreover, five direct relationships linking predictors and outcomes of e-learning adoption were analyzed. Further, each direct relationship was moderated by age, gender and internet experience. Thus, 15 moderation effects were analyzed in developing the USeLAM.

Although relationships will always exist between any set of variables in a study, establishing these relationships is only important if they yield practical applications that will improve a particular process. In this case, the USeLAM shall improve planning and future forecasting for e-learning in public universities. In conclusion therefore, researchers ought to be cautious with the prediction process; particularly in the selection of an optimum number of variables to include and focus on an in-depth analysis of the variables that will afford the achievement of specific study outcomes. Care needs to be taken, for example, in the simplification process so that over-simplification does not trivialize the outcomes of the study. On the other hand, a very complex model will result into a model that is unlikely to have any practical applications. A balance is therefore needed between analytical complexity – brought about by including many variables under consideration, on the one hand; and the practical applications of the model on the other. The USeLAM therefore, becomes the first model of its kind in Kenya and forms the basis of future prediction of undergraduate students' online learning preferences. It is particularly useful where the predictors and moderators change over time.

It is noteworthy to point out that the USeLAM is not only applicable to science education, but can be used across many areas of study in both public or private universities, foreign or local universities, or at undergraduate or postgraduate levels. It is however inconclusive to assert that studies on e-learning adoption should be discipline-specific or applicable to a specific university course or discipline. This is because the distinction between and within disciplines in undergraduate studies in Kenya is becoming increasingly obscured. For example, the categorization of degree programmes in public universities into science, arts or business is no longer an indication of anything more than a nomenclature.

In this study, gender moderates four of the five relationships while internet experience moderates three relationships. Age, on the other hand, moderates only two of the relationships in the study. Therefore, among all the moderators, gender is the most important moderator, followed by internet experience and age in that order. This is consistent with an argument by Harris and Gibson (2006) and Maritim and Getuno (2018) that prior experience with computers and the internet is positively correlated with the acceptance of e-learning courses. Further, age, gender and internet experience significantly influence students' e-learning adoption albeit in different ways. The following are specific conclusions of the study according to the five relationships and three moderators that were analyzed:

i) The USeLAM outlines a clear and meaningful link between performance expectancy (PE) and behavioural intention (BI). This association is affected solely by gender, with the moderating influence remaining consistent among both male and female learners. Consequently, performance expectancy serves as a key determinant in shaping undergraduate students' engagement with digital learning platforms. It would therefore appear that a prominent aspect of e-learning adoption is "learning-for-life" or life-long-learning as depicted by the usefulness indicator. Therefore, the focus of e-learning ought to be on students' personal learning environments (Maria Paz et al. (2016); Rocha et al. (2024; Zhang et al., 2023) which encompass the totality of a students' socio-cultural and economic circumstances and how they impact learning.

ii) The USeLAM establishes that a positive association exists between effort expectancy (EE) and behavioural intention (BI), which is both statistically meaningful and influenced by demographic variables such as age, gender, and internet exposure. The moderation pattern remains consistent across both younger and older learners, as well as between students with advanced or limited internet proficiency. However, the influence of gender on the connection between EE and BI appears more prominent among female students than among their male peers. Consequently, EE emerges as a significant determinant of undergraduate students' willingness to embrace digital learning platforms. The inference derived from this outcome regarding effort expectancy in e-learning indicates that learners generally do not perceive mastering the technical aspects of online study as a barrier to adopting such systems. Hence, the effectiveness and appeal of an e-learning interface primarily depend on its structural design—particularly its ease of navigation and adaptability to learner needs. This reflects the principles of human-centred design, as articulated by Landry (2020).

iii) The USeLAM affirms the presence of an insignificant link between social influence (SI) and behavioural intention (BI). This association is influenced by both age and internet familiarity, but not by gender. The influence tends to be more evident among mature learners than among their younger peers. Nevertheless, the pattern of influence remains consistent between users with high and low levels of internet experience. Hence, SI does not serve as a key determinant of undergraduate students' willingness to embrace digital learning technologies, and therefore is excluded from the final USeLAM framework. In summary, these results imply that, although learners receive limited encouragement and assistance from their institutions, instructors, mentors, friends, family members, and peers, there is a gradual rise in the utilization of digital learning platforms among undergraduate students. This growing engagement is expected to strengthen and sustain the broader adoption of e-learning practices within higher education institutions.

iv) The USeLAM describes a reverse relationship involving FC and UB**.** This relationship is significant and is affected by age and internet experience. The strength of moderation is the same for young and old students and; experienced and inexperienced internet users. Gender has no moderating effect on this relationship. Thus, UB is, in fact, the predictor of FC and not the other way round. This is an interesting conclusion given that actual use of technology seems to influence the conditions under which the technology is used and not vice-versa. In context, this means that despite there being inadequate resources available for students' use or inadequate preparations, e-learning is still being rolled out in public universities anyway. This leads to the conclusion that roll out of e-learning appears to precede sufficient planning on the part of the students to undertake e-learning. In re-affirming support for this conclusion, the study established that the most plausible reason for this situation is that university students already have some knowledgeable of e-learning even before engaging in it.

v) The USeLAM describes a relationship between BI and UB that is significant and influenced by one's gender and internet experience. This influence is the samilar for female and male students and also for those experienced and inexperienced in the use of the internet. These findings serve to confirm that, regardless of age, intention precedes usage of technology in HEIs. Furthermore, a most salient precursor of technology usage emanating from intention is increased academic productivity. Thus, public university students believe that they can accomplish more work academically through the e-learning mode of study. Accomplishing more work in an academic environment is one of the key performance indicators in e-learning adoption (Wei et al., 2022).

vi) Overall, the USeLAM explains 24% and 15% of the variance in BI and UB respectively. These values suggest that the influence of USeLAM on BI and UB is much lower than that of the UTAUT which accounted for 69% of the variance in technology adoption (Venkatesh et al., 2003). However, USeLAM will still find useful application in e-learning adoption studies because no other model exists for predicting the adoption of e-learning in Kenya's HEI's. This is particularly true because it forms the basis or the starting point for investigating predictors and outcomes of e-learning adoption.

6.2 Recommendations

This study identified two types of recommendations; for practice and further research:

6.2.1 Recommendations for Practice

The following are the study's recommendations for practice:

i) The findings of this study dispel the often-hyped notion that academic performance is the most important basis for practical intervention in educational studies involving students. Managers of public universities in Kenya need to focus on how e-learning complements students' lives and less on other indicators such as accomplishment of tasks, academic productivity or attaining higher grades. This paradigm shift necessitates moving beyond a narrow, metrics-driven view of education. Instead of solely valuing end-results like grades and task completion, university leadership should champion e-learning initiatives that seamlessly integrate into the students' daily routines, reduce their cognitive load, and address real-world challenges such as time constraints, remote access, and flexible scheduling. By prioritizing the student's holistic experience and well-being, institutions can foster deeper, more intrinsic motivation for learning. This approach ultimately leads to more sustainable engagement and long-term success, where academic achievement becomes a natural byproduct of a supportive and complementary learning ecosystem, rather than a pressured and isolated goal.

ii) The findings of this study show that it is relatively easier for undergraduate university students to acquire online learning skills. We therefore recommend the design of online learning platforms that are inherently manipulable through self or personalized learning. Such platforms lend themselves amenable to self-learning, are based on human-centred design and would employ a mix of pure online and blended learning formats. To capitalize on this student adaptability, e-learning systems must be architected for intuitive use and personalization. This means adopting a human-centred design philosophy that involves students in the development process, ensuring platforms are not just functional but also psychologically and ergonomically supportive. Features like customizable dashboards, adaptive learning paths that respond to individual performance, and a variety of content delivery methods (video, text, interactive simulations) are essential. Furthermore, a strategic blend of fully online and blended formats can cater to diverse learning preferences and logistical needs, allowing students to choose the mode that best suits their circumstances while still benefiting from valuable face-to-face interactions and support when needed.

iii) Neither the institution, the instructors, role models, friends, relatives nor peers dictate undergraduate university students' preference for online study. This means that it is the students' personal agenda, devoid of any social influence around them, that is important in e-learning adoption. Thus, this study recommends more engagement of the university in providing direct or indirect support for students enrolled in their e-learning programmes. Recognizing that the driving force for e-learning is internal and personal underscores a critical opportunity for universities. Since students are making a self-directed choice, the institution's role evolves from one of persuasion to one of empowerment. Direct support should include robust, easily accessible technical help desks, dedicated e-learning tutors, and comprehensive online orientation programs. Indirect support is equally vital and involves creating a strong sense of online community through discussion forums and group projects, fostering clear and consistent communication from instructors, and ensuring that administrative processes are fully integrated and streamlined for the online learner. This holistic support framework validates the student's personal decision to learn online and provides the scaffolding necessary for them to succeed on their own terms.

iv) The confidence with which the students, regardless of gender, approach e-learning even before having sufficient background knowledge and resources about e-learning could be misplaced. In fact, this "unpreparedness" for e-learning probably explains the high drop-out rate among e-learning students in HEI's (Rahmani et al., 2024). Therefore, public universities in Kenya should develop adequate mechanisms to create facilitative conditions to support e-learning adoption by students through; furnishing them with adequate knowledge – through training - on e-learning, provision of adequate resources to undertake learning, and providing sufficient all-rounded learner-support services. This initial student optimism, while positive, can be a liability if not met with concrete institutional preparation. To bridge this gap between confidence and competence, universities must implement proactive and mandatory pre-enrollment readiness programs. These programs would demystify e-learning by realistically outlining its demands, teaching essential digital literacy and time management skills, and familiarizing students with the specific LMS platform. Beyond knowledge, facilitative conditions require tangible resource provision, which could include subsidized internet data, loaner devices for students in need, and ensuring all digital library resources are fully accessible off-campus. Finally, all-rounded learner-support must extend beyond academics to include wellness checks, career advising, and counselling services delivered through online channels, thereby creating a safety net that addresses the multi-faceted challenges of the e-learning journey and directly combats attrition.

v) Age is not a determinant of undergraduate university students' belief in their ability to accomplish more academic work. Therefore, the study recommends designing e-learning courses that appeal to the range of ages of 18 – 60-year-olds in this study. These courses must include assessment exercises that provide opportunities for learners to increase the amount of work a learner accomplishes in order to quantify the amount of work and help determine the level of students' work accomplishment. The age-inclusive nature of self-efficacy beliefs means that course design must be universally appealing and not inadvertently favour one age demographic over another. This involves using a variety of teaching materials that resonate with different generational experiences and learning habits, from traditional scholarly articles to contemporary multimedia case studies. Furthermore, to cater to this diverse age-set's desire to demonstrate their capability, assessments should be designed with scalability and measurable output in mind. This can be achieved through a portfolio-based approach, where students compile a body of work throughout the course, or through tiered assignments that allow learners to opt for additional, challenging tasks for extra credit or deeper mastery. Such a system not only quantifies accomplishment objectively but also empowers students of all ages to visibly chart their own productivity and growth.

6.2.2 Recommendations for Further Research

Similarly, for further research, we recommend:

i) A study about what learners in HEIs consider useful in e-learning and research these aspects with a view to unraveling their relative importance. For example, an investigation involving different modes of delivery, ranging from purely online to various versions of blended learning. A deeper, more granular investigation is needed to move beyond simply identifying useful e-learning features and to instead rank their priority from the student perspective. This research could employ advanced statistical methods like conjoint analysis or discrete choice experiments to determine the trade-offs students are willing to make. For instance, how much value do they place on live virtual lectures versus asynchronous discussion boards? Does round-the-clock platform access outweigh having a dedicated human tutor? By systematically comparing different delivery models—synchronous online, asynchronous online, hybrid, and flipped classrooms—this research can provide evidence-based hierarchy of student needs, offering invaluable, data-driven guidance for institutions seeking to allocate resources effectively and design programs that students truly value and utilize.

ii) A study on e-learning platforms used by public universities in a bid to determine how human-centred design has been incorporated. For instance, some public universities use proprietary LMS' while others customize and use the free and open-source software (FOSS) with different levels of interactivity features. This is because each university had its own e-learning mode of study. A comprehensive audit and comparative analysis of the various Learning Management Systems (LMS) in use across the public university sector is crucial. This study should go beyond a feature checklist to conduct a rigorous heuristic evaluation and user-testing with actual students and instructors to assess the usability, accessibility, and overall user experience (UX) of these platforms. It should investigate whether the choice of a proprietary system (like Blackboard) versus a customized open-source solution (like

Moodle) leads to significant differences in pedagogical flexibility, student engagement, and satisfaction. The findings would reveal best practices in LMS design and implementation specific to the Kenyan context, providing a benchmark for universities and informing future procurement and development decisions to ensure technology serves the user, not the other way around.

iii) Further research is recommended on the kind of social support needed by e-learning students in public universities from the universities themselves, the instructors, their role models, friends, family, relatives and peers. This support is in relation to what would make e-learning a worthwhile endeavour for the students. While this study found that social influence doesn't dictate the initial preference for e-learning, the role of social support post-enrollment is a critical and unexplored area. Qualitative, in-depth research is needed to map the entire ecosystem of support for an e-learning student. This involves understanding the specific forms of encouragement needed from family, the mentorship role of instructors in a virtual space, and how peers can form effective virtual study groups. The research should aim to develop a typology of social support—emotional, informational, and instrumental—relevant to e-learning. The ultimate goal is to create evidence-based models for building "support webs" around online learners, making the often-isolating endeavour of e-learning a socially embedded and therefore, a more sustainable and rewarding experience.

iv) A study is recommended to establish the direction of causality between FC and UB. Whereas this study suggests that UB actually influences FC, previous research suggests otherwise. This contradiction is worth investigating in different technology settings in order to validate or refute the current findings within the higher education sector. The discovered contradiction regarding the relationship between Facilitating Conditions and actual Usage Behaviour presents a compelling theoretical puzzle. Does a well-resourced environment (FC) lead to greater use (UB), or does persistent use (UB) force an institution to improve its support structures (FC)? To resolve this, a longitudinal or experimental research design is recommended. This could involve tracking a cohort of e-learning students over time to see how changes in FC impact their UB, or conducting intervention studies where FC are deliberately enhanced in one group and not another. Extending this investigation beyond e-learning to other educational technologies within HEIs (like library databases or research software) would help determine if this reversed causality is a unique phenomenon of e-learning platforms or a broader pattern in technology adoption, thereby contributing significantly to academic theory and institutional strategy.

v) An investigation on learning analytics regarding the quantity of work students can accomplish within an e-learning course of study. This metrics can then be used to determine actual measures instead of students' self-reported measures as used in the present study. To move from subjective perception to objective measurement, future research must leverage the power of learning analytics. This involves a detailed, data-driven investigation that mines LMS data logs to track concrete metrics of student accomplishment. Key performance indicators (KPIs) could include the average time spent on the platform per week, frequency of logins, completion rates for individual modules, participation levels in forums, and scores on formative assessments. By correlating these behavioural metrics with final grades and completion status, researchers can establish reliable, objective benchmarks for what constitutes "productive" engagement in an e-learning environment. This would replace the potentially biased self-reported data with hard evidence, enabling educators to identify at-risk students early, personalize interventions, and accurately evaluate the effectiveness of different course designs and pedagogical approaches based on tangible outcomes.

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APPENDICES

Appendix A: Students' E-Learning Adoption Questionnaire (SeLAQ)

Instructions:

I am collecting data for a study on e-learning adoption by new undergraduate students recently registered in e-learning programmes in public universities in Kenya. To be eligible to respond to this questionnaire you should be registered for the e-learning mode of study at your university. The questionnaire has 5 items in Section A and 24 items in Section B. It will take about 10-15 minutes of your time. Kindly respond to each question by filling in, marking against your preferred choice using a tick (√) or a cross (X) among the responses from, SD= Strongly Disagree to SA= Strongly Agree. The results of the study will be reported in general terms and no responses shall be attributed to you as an individual. Participation in this study is voluntary. Do NOT write your name.

Section A

1. **Name of University:** KU ☐ EGU ☐ JKUAT ☐
2. **Gender:** Male ☐ Female ☐
3. **Age:** 18 – 19 ☐ 20 – 24 ☐ 25 – 29 ☐ 30 – 34 ☐ 35 – 39 ☐ 40 - 60 ☐
4. **What is your level of experience with using the internet?** 0 - 1 year ☐ 1 – 2 years ☐ 3 – 4 years ☐ 5 – 6 years ☐
5. **Academic Programme:** Arts ☐ Science ☐ Business ☐ Other ☐

Section B

Kindly respond to each question by ticking (√) against your preferred choice where; 1 = Strongly Disagree; 2 = Disagree; 3 = Somewhat Disagree; 4 = Neither Agree nor Disagree; 5 = Somewhat Disagree; 6 = Disagree; 7 = Strongly Agree.	Strongly Disagree						Strongly Agree
	1	**2**	**3**	**4**	**5**	**6**	**7**
Performance Expectancy							
1. The e-learning mode of study is useful for the degree programme I am pursuing.							
2. Using the e-learning mode of study enables me to accomplish tasks more quickly.							
3. Using the e-learning mode of study has increased my academic productivity.							
4. Using the e-learning mode of study has increased my chances of getting a high grade.							
Effort Expectancy							
5. My interaction with e-learning is understandable.							
6. It has been easy for me to become skilful at using the e-learning mode of study.							
7. The e-learning mode of study was easy to use.							
8. Learning to use the e-learning mode of study is easy for me.							
Social Influence							

Kindly respond to each question by ticking (√) against your preferred choice where; 1 = Strongly Disagree; 2 = Disagree; 3 = Somewhat Disagree; 4 = Neither Agree nor Disagree; 5 = Somewhat Disagree; 6 = Disagree; 7 = Strongly Agree.	**Strongly Disagree**					**Strongly Agree**
	1	**2**	**3**	**4**	**5**	**6**	**7**
9. My role models think that I should follow the e-learning mode of study.							
10. People who influence my behaviour think that I should use the e-learning mode of study.							
11. The instructors of this degree programme are helpful in the use of the e-learning mode of study.							
12. The university supports me in the use of the e-learning mode of study.							
Facilitating Conditions							
13. I have the resources necessary to use the e-learning mode of study.							
14. The e-learning mode of study is compatible with other modes of study I use.							
15. I am knowledgeable in use the e-learning mode of study.							
16. A specific person (or group) is available for assistance with e-learning difficulties.							
Behavioural Intention							
17. I intend to use the e-learning mode of study in the next three months if it will improve my academic productivity.							
18. I intend to use the e-learning mode of study in the next three months if it would be easy to use.							
19. I intend to use the e-learning mode of study in the next three months if my role models approve of it.							
20. 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							
Actual Use Behaviour							
21. I have logged onto the e-learning platform a lot since my admission into this university							
22. I have read the online learning materials a lot since my admission into this university							
23. I have downloaded the online learning materials a lot since my admission into this university							
24. I have printed the online learning materials a lot since my admission into this university							

Appendix B: List of Universities in Kenya

a) Accredited Universities

		Year of Establishment	Year of Award of Charter
	Public Chartered Universities		
1.	University of Nairobi (UoN)	1970	2013
2.	Moi University (MU)	1984	2013
3.	Kenyatta University (KU)	1985	2013
4.	Egerton University (EGU)	1987	2013
5.	Jomo Kenyatta University of Agriculture and Technology (JKUAT)	1994	2013
6.	Maseno University (Maseno)	2001	2013
7.	Dedan Kimathi University of Technology	2007	2012
8.	Chuka University	2007	2013
9.	Technical University of Kenya	2007	2013
10.	Technical University of Mombasa	2007	2013
11.	Pwani University	2007	2013
12.	Kisii University	2007	2013
13.	Masinde Muliro University of Science and Technology (MMUST)	2007	2013
14.	Maasai Mara University	2008	2013
15.	South Eastern Kenya University	2008	2013
16.	Meru University of Science and Technology	2008	2013
17.	Multimedia University of Kenya	2008	2013
18.	Jaramogi Oginga Odinga University of Science and Technology	2009	2013
19.	Laikipia University	2009	2013
20.	University of Kabianga	2009	2013
21.	University of Eldoret	2010	2013
22.	Karatina University	2010	2013
23.	Kibabii University	2011	2015
24.	Kirinyaga University	2011	2016
25.	Machakos University	2011	2016
26.	Murang'a University of Technology	2011	2016
27.	Rongo University	2011	2016
28.	Taita Taveta University	2011	2016
29.	The Co-operative University of Kenya	2011	2016
30.	University of Embu	2011	2016
31.	Garissa University	2011	2017
32.	Alupe University	2015	2022
33.	Kaimosi Friends University	2015	2022
34.	Tom Mboya University		2022
35.	Tharaka University		2022

b) Public University Constituent Colleges

36.	Turkana University College	2016
37.	Bomet University College	2017
38.	Koitalel Samoei University College	2018
39.	National Intelligence Research University College	2021
40.	Mama Ngina University College	2021

c) Private Chartered Universities

		Year of Establishment	Year of Award of Charter
41.	University of Eastern Africa, Baraton	1989	1991
42.	Catholic University of Eastern Africa (CUEA)	1989	1992
43.	Daystar University	1989	1994

d) Accredited Universities

		Year of Establishment	Year of Award of Charter
44.	Scott Christian University	1989	1997
45.	United States International University	1989	1999
46.	St. Paul's University	1989	2007
47.	Pan Africa Christian University	1989	2008
48.	Africa International University	1989	2011
49.	Kenya Highlands Evangelical University	1989	2011
50.	Africa Nazarene University	1993	2002
51.	Kenya Methodist University	1997	2006
52.	Strathmore University	2002	2008
53.	Kabarak University	2002	2008
54.	Great Lakes University of Kisumu	2006	2012
55.	KCA University	2007	2013
56.	Mount Kenya University	2008	2011
57.	Adventist University of Africa	2008	2013
58.	KAG - EAST University	1989	2016
59.	UMMA University		2019
60.	Presbyterian University of East Africa		2020
61.	Aga Khan University		2021
62.	Kiriri Women's University of Science and Technology		2022
63.	The East African University		2022
64.	Zetech University		2022
65.	Lukenya University		2022

e) Private University Constituent Colleges

		Year of Establishment
66.	Hekima University College (CUEA)	1993
67.	Tangaza University College (CUEA)	1997
68.	Marist International University College (CUEA)	2002

f) Universities with Letters of Interim Authority

		Year of Establishment
69.	GRETSA University	2006
70.	Management University of Africa	2011
71.	Riara University	2012
72.	Pioneer International University	2012
73.	International Leadership University	2014
74.	RAF International University	2016
75.	AMREF International University	2017
76.	Uzima University	2020

g) Specialized Degree-Awarding University

		Year of Establishment
77.	National Defence University – Kenya	2021
78.	Open University of Kenya	2023

Appendix C: Means and Standard Deviations of Indicators

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
Effort Expectancy	EE			
	EE_1	Easy to understand	5.70	1.62
	EE_2	Easy to acquire skills	5.92	1.47
	EE_3	Easy to use	5.59	1.66
	EE_4	Easy to learn	5.54	1.73
Social Influence	SI			
	SI_1	Influence of role models	4.84	2.26
	SI_2	Influence of peers	4.65	2.13
	SI_3	Support from course instructors	5.58	1.75
	SI_4	Support from the university	5.70	1.87
Facilitating Conditions	FC			
	FC_1	Possession of resources	5.80	1.52
	FC_2	Compatibility with other modes of learning	5.59	1.63
	FC_3	Knowledgeable in use the e-learning	5.89	1.49
	FC_4	Availability of assistance	4.86	2.12
Behavioural Intention	BI			
	BI_1	Improved academic productivity	6.47	0.91
	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
Actual Use Behaviour	UB			
	UB_1	Login	6.01	1.60
	UB_2	Reading	5.64	1.66
	UB_3	Downloading	5.09	2.02
	UB_4	Printing	4.20	2.20

Appendix D: NACOSTI Research Permit

Official receipt

ORIGINAL

AC:

OFFICIAL RECEIPT 23215

Station: NAIROBI Date: 22/2/18

Received from: DANIEL MAKINI GETONO

Shillings: TWO THOUSAND KSH

cents

on account of: RESEARCH PERMIT

Vote Head: R-43

NACOSTI

USD

Kshs: 2000

AC No.

Item: A/A

Cash Cheque No.: DIRECT DEPOSIT

Signature of Officer receiving remittance

Research Permit - Page 1

THIS IS TO CERTIFY THAT:
MR. DANIEL MAKINI GETUNO
of EGERTON UNIVERSITY, 0-604
Nairobi,has been permitted to conduct
research in *Kisumu , Nairobi, Nakuru , Uasin-Gishu Counties*

on the topic: *A MODEL FOR PREDICTING UNDERGRADUATE STUDENTS ADOPTION OF E-LEARNING IN KENYA'S PUBLIC UNIVERSITIES*

for the period ending:
26th February,2019

Permit No : NACOSTI/P/18/52431/21466
Date Of Issue : 27th February,2018
Fee Recieved :Ksh 2000

Applicant's Signature

G.P. Kalerwa
Director General
National Commission for Science, Technology & Innovation

Research Permit - Page 2

CONDITIONS

1. The License is valid for the proposed research, research site specified period.
2. Both the Licence and any rights thereunder are non-transferable.
3. Upon request of the Commission, the Licensee shall submit a progress report.
4. The Licensee shall report to the County Director of Education and County Governor in the area of research before commencement of the research.
5. Excavation, filming and collection of specimens are subject to further permissions from relevant Government agencies.
6. This Licence does not give authority to transfer research materials.
7. The Licensee shall submit two (2) hard copies and upload a soft copy of their final report.
8. The Commission reserves the right to modify the conditions of this Licence including its cancellation without prior notice.

REPUBLIC OF KENYA

NACOSTI

National Commission for Science, Technology and Innovation

RESEARCH CLEARANCE PERMIT

Serial No.A 17698

CONDITIONS: see back page

Appendix E: NACOSTI Research Authorization Letter

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY AND INNOVATION

Telephone:+254-20-2213471,
2241349,3310571,2219420
Fax:+254-20-318245,318249
Email: dg@nacosti.go.ke
Website : www.nacosti.go.ke
When replying please quote

NACOSTI, Upper Kabete
Off Waiyaki Way
P.O. Box 30623-00100
NAIROBI-KENYA

Ref: No. **NACOSTI/P/18/52431/21466**

Date: **27th February, 2018**

Daniel Makini Getuno
Egerton University
P.O. Box 536-20115
EGERTON.

RE: RESEARCH AUTHORIZATION

Following your application for authority to carry out research on ***"A model for predicting undergraduate students adoption of E-Learning in Kenya's public universities,"*** I am pleased to inform you that you have been authorized to undertake research in **Kisumu, Nairobi, Nakuru and Uasin Gishu Counties** for the period ending **26th February, 2019.**

You are advised to report to **the County Commissioners and the County Directors of Education of the selected Counties** before embarking on the research project.

Kindly note that, as an applicant who has been licensed under the Science, Technology and Innovation Act, 2013 to conduct research in Kenya, you shall deposit **a copy** of the final research report to the Commission within **one year** of completion. The soft copy of the same should be submitted through the Online Research Information System.

GP Kalerwa
GODFREY P. KALERWA MSc., MBA, MKIM
FOR: DIRECTOR-GENERAL/CEO

Copy to:

The County Commissioners
Selected Counties.

The County Directors of Education
Selected Counties.

National Commission for Science, Technology and Innovation is ISO9001:2008 Certified

Appendix F: Egerton University Research Ethical Clearance

EGERTON UNIVERSITY

TEL: 051-2217808
Fax: 051-2217942
e-mail: dvcre@egerton.ac.ke
website: www.egerton .ac.ke

P. O. BOX 536-20115
EGERTON

RESEARCH ETHICS REVIEW COMMITTEE

EU/RE/DVC/009 **23rd January, 2019**
Approval No. EUREC/APP/076/2018

Mr. Daniel Makini Getuno,
Department of Curriculum, Inst and Educational Management,
P. O. Box 536-20115,
EGERTON
makinigetuno@gmail.com

Dear Mr. Getuno,

RE: Initial Submission - Ethical Clearance Approval of A model for predicting undergraduate students' adoption of e-learning in Kenya's Public Universities

Reference is made to your application for Ethical Clearance of your Research Project entitled:
A model for predicting undergraduate students' adoption of e-learning in Kenya's Public Universities.

It was observed that you addressed all the ethical issues that were raised in a Committee Meeting held on **29th November, 2018** through your response dated **14th January, 2019**. On the basis of this, your application is therefore granted ethical **Approval No.EUREC/APP/076/2018** for implementation effective for one year from **24th January, 2019** upon which you are expected to apply for renewal if the study will not have ended by time of expiry of this approval. Please further note that the Standard Operating Procedures (SOPs) requires that you submit progress reports twice in a year and a final report at the end of your study to the Committee.

Any unanticipated problems resulting from the implementation of this protocol should be brought to the attention of the Committee notifying them of any proposal change(s) or amendment(s), serious or unexpected outcomes or study termination for any reason. You are also required to inform the Committee when the study is completed or discontinued.

Your proposal has therefore been given ethical approval. You are required to obtain a Research License from NACOSTI by checking https://oris.nacosti.go.ke/guidelines.php and ensure that you comply with other regulations/ requirements e.g. MTA, Data transfer, access permit, export license etc. as and when applicable before commencement of your study.

Yours faithfully,

Prof. J. K. Kipkemboi
CHAIRMAN – RESEARCH ETHICS COMMITTEE

DEPUTY VICE CHANCELLOR
EGERTON UNIVERSITY
P. O. Box 536 - 20115
EGERTON
RESEARCH & EXTENSION

JKK/SK/sam
cc. DVC (R&E) - To note the file copy

Transforming Lives through Quality Education

Appendix G: Vice - Chancellor's Approval Letter to Collect Data From KU

KENYATTA UNIVERSITY

OFFICE OF DEPUTY VICE-CHANCELLOR, RESEARCH, INNOVATION AND OUTREACH

P. O. Box 43844 - 00100
Nairobi. Kenya
Tel. 254-20-810901 Ext. 026
E-mail: dvc-rio@ku.ac.ke

Ref: KU/DVCR/RCR/VOL.3/259

Daniel Getuno
Department of Educ. Management
EGERTON UNIVERSITY

17th December, 2018

Dear Mr. Getuno,

RE: **REQUEST TO COLLECT RESEARCH DATA AT KENYATTA UNIVERSITY**

This is in reference to your letter dated 16th November, 2018 requesting for authorization to collect research data at Kenyatta University on the topic "*A Model for Predicting Undergraduate Students Adoption of e-Learning in Kenya's Public Universities*" towards a PhD degree of Egerton University.

I am happy to inform you that the Vice-Chancellor has approved your request to collect data. It has been noted that your data will be collected from the Digital School.

The University requires that, upon completion of your research, you submit a hard copy of your project report to the Deputy Vice-Chancellor, Research who shall forward it to the University Library. Kindly therefore complete and sign Form RIO3 and return it to my office prior to the commencement of collection of data.

Yours Sincerely,

Prof. F. Q. Gravenir
Deputy Vice-Chancellor
Research, Innovation & Outreach
cc. Vice-Chancellor

Appendix H: Vice-Chancellor's Approval Letter to Collect Data From JKUAT

JOMO KENYATTA UNIVERSITY
OF
AGRICULTURE AND TECHNOLOGY
P.O. Box 62000-00200 Nairobi Kenya, Tel: +254-067-5870001-4, +254-67-53-52711,
Office of the Registrar (Administration)

JKU/ACA/3D **15TH OCTOBER, 2018**

David Makini Getuno
Egerton University
P.O. Box 536 - 20115
EGERTON

Dear Mr. Getuno

RE: PERMISSION TO COLLECT DATA

Reference is made to your letter dated 4th October, 2018, in which you sought permission to collect data for your PhD research project entitled ***"A model for predicting undergraduate students' adoption of e-learning in Kenya's Public Universities".***

Approval has been granted for you to collect data on the understanding that all the data collected will be for academic purpose only and will be kept confidential throughout the project and after completion of the project. This is on condition that the University Library will receive a copy of your final thesis for future reference.

Yours sincerely,

DR JOSEPH OBWOGI, PhD
REGISTRAR (ADMINISTRATION)

Copy to: - Deputy Vice Chancellor (Admin)
- Human Resource Manager

Setting Trends in Higher Education, Research and Innovation

Appendix I: Vice-Chancellor's Approval Letter to Collect Data From EGU

EGERTON UNIVERSITY

P.O. Box 536 -20115
Egerton, Kenya

Tel: +254-51-2217801/808
+254-51-2217891/2
Cell: 0708489256
0775015388
Fax: +254-51-2217942
E-mail: dvcre@egerton.ac.ke

OFFICE OF THE DEPUTY VICE - CHANCELLOR
RESEARCH AND EXTENSION

EU/DVCRE/089 9th October, 2018

Daniel Makini Getuno
Department of C. I. & E.M.
Egerton University

RE: AUTHORITY TO COLLECT DATA AT EGERTON UNIVERSITY

Reference is made to your letter dated 1st September, 2018 requesting for authority to collect data at Egerton University for the PhD study titled: '***A Model for Predicting Undergraduate Students' Adoption of E-Learning in Kenya's Public Universities.***'

Authority is hereby granted for you to collect data from E-Learning students at Egerton University.

It is noted that this research is purely for academic purposes and will not be used otherwise. Upon completion of the study please ensure that you provide a copy of the report for our retention.

Prof. Bockline O. Bebe, PhD
For: Ag. Deputy Vice-Chancellor [Research & Extension]

cc. DVC/AA
Director, CODL
Coordinator IMD/E-Learning

ACK/po

'Transforming Lives through Quality Education'
Egerton University is ISO 9001:2008 Certified

Appendix J: Informed Consent Form

Title of Study: A model for predicting undergraduate students' adoption of e-learning in Kenya's public universities

Principal Investigator

Daniel Makini Getuno
Department of Curriculum, Instruction & Educational Management
P.O. BOX 536 – 20115 EGERTON
Mobile phone: +254-723-803-662
Email: makinigetuno@gmail.com

Purpose of Study

You are invited to participate in a research study. Before making a decision, it is important that you understand the purpose of the study and what your participation will involve. Please read the information below carefully, and feel free to ask the researcher any questions if something is unclear or if you need additional details. The purpose of this study is to develop a model for predicting the adoption of e-learning among undergraduate students in Kenya's public universities. This study is being conducted as part of the requirements for the award of a PhD degree from Egerton University.

Study Procedures

The researcher will first contact you at the university and request you to fill a questionnaire. You will provide your telephone and/or e-mail that will be used to contact you in future. At a later date, the researcher will contact you through the contact information you provided in order to ask further questions.

Risks

There are no reasonably foreseeable risks associated with this study. However, should any risks arise during the study procedures, appropriate steps will be taken to minimize them. This may include allowing you to decline to answer any or all questions, and you are free to withdraw from the study at anytime if you choose.

Benefits

There will be no direct benefit to you for your participation in this study. However, we hope that the information obtained from this study may improve delivery of e-learning programmes in Kenyan universities. In addition, the study aims to contribute to knowledge in the field of e-learning adoption by way of minimizing the drop-out rates in e-learning programmes. Finally, the results of the study will ensure that the best e-learning practices are applied so that there is a return-on-investment for universities that have setup e-learning infrastructure and systems.

Confidentiality

The researcher will take every possible measure to protect your confidentiality, including:

- Assigning code names or numbers to participants, which will be used on all research notes and documents.
- Storing notes, interview transcripts, and any other identifying information in a password-protected file accessible only to the researcher.

Your data will remain confidential unless the researcher is legally required to disclose certain information. This may include, but is not limited to, instances of abuse or situations where the participant is exposed to risks of physical or psychological harm.

Contact Information

If you have questions at any time about this study, or you experience adverse effects as a result of participating in this study, you may contact the researcher whose contact information is provided on the first page. If you have questions regarding your rights as a research participant, or if problems arise which you do not feel you can discuss with the Primary Investigator, please contact the Egerton University Ethical Review Board by e-mail: eurec@egerton.ac.ke or telephone: +254-775-015388.

Voluntary Participation

Participation in this study is entirely voluntary. You have the choice to decide whether or not to participate. Should you choose to take part, you will be required to sign a consent form. Even after signing, you retain the right to withdraw from the study at any time and without needing to provide a reason. Your decision to withdraw will not impact your relationship with the researcher, if one exists. If you decide to withdraw before the data collection is finished, your data will either be returned to you or destroyed.

Consent

I have read and understood the provided information and have had the opportunity to ask questions. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving a reason and without cost. I understand that I will be given a copy of this consent form. I voluntarily agree to take part in this study.

Participant's signature ______________________________ Date __________

Investigator's signature ______________________________ Date __________

Appendix K: Executive Order No. 1 of 2023: Functions and Institutions of the State Department for Higher Education and Research

Functions:

§ University Education Policy and Standards;

§ University Education Management;

§ Management of Continuing Education (excluding TVETS);

§ Public Universities Management;

§ Education Research and Policy;

§ Policy and Standards on Science and Technology.

Institutions:

§ Commission for University Education

§ Kenya Universities and Colleges Placement Service (Universities Act, No. 42 of 2012)

§ National Commission for Science Technology and Innovation (Science, Technology and Innovation Act, No. 28 of 2013)

§ Higher Education Loans Board (Higher Education Loans Board Act, No. 3 of 1995)

§ National Research Fund (Science, Technology and Innovation Act, 2013)

§ Universities Funding Board

§ Kenyatta University (Universities Act, No. 42 of 2012)

§ University of Nairobi (Universities Act, No. 42 of 2012)

§ Jomo Kenyatta University of Agriculture and Technology (Universities Act, No. 42 of 2012)

§ Moi University (Universities Act, No. 42 of 2012)

§ University of Eldoret (Universities Act, No. 42 of 2012)

§ Karatina University (Universities Act, No. 42 of 2012)

§ Taita Taveta University (Universities Act No. 42 of 2012)

§ Kirinyaga University (Universities Act, No. 42 of 2012)

§ Muranga University of Technology (Universities Act, No. 42 of 2012)

§ Egerton University (Universities Act, No. 42 of 2012)

§ Maseno University (Universities Act, No. 42 of 2012)

§ Masinde Muliro University of Science and Technology (Universities Act No. 42 of 2012)

§ The Technical University of Kenya (Universities Act, No. 42 of 2012)

§ Technical University of Mombasa (Universities Act, No. 42 of 2012)

§ Pwani University (Universities Act, No. 42 of 2012)

§ South Eastern Kenya University (Universities Act, No. 42 of 2012)

§ Dedan Kimathi University of Technology (Universities Act, No. 42 of 2012)

§ University of Kabianga (Universities Act, No. 42 of 2012)

§ Masai Mara University (Universities Act, No. 42 of 2012)

§ University of Kibabii (Universities Act, No. 42 of 2012)

§ Jaramogi Oginga Odinga University of Science and Technology (Universities Act, No. 42 of 2012)

§ Laikipia University (Universities Act, No. 42 of 2012)

§ Meru University of Science and Technology (Universities Act, No. 42 of 2012)

§ Garissa University (Universities Act, No. 42 of 2012)

§ Machakos University (Universities Act, No. 42 of 2012)

§ Multi -Media University (Universities Act, No. 42 of 2012)

§ Kisii University (Universities Act, No. 42 of 2012)

§ Rongo University (Universities Act, No. 42 of 2012)

§ University of Embu (Universities Act, No. 42 of 2012)

§ Chuka University (Universities Act, No. 42 of 2012)

§ Tharaka University (Universities Act, No. 42 of 2012)

§ Co -operative University of Kenya (Universities Act, No. 42 of 2012)

§ Kaimosi Friends University (Universities Act, No. 42 of 2012)

§ Alupe University (Universities Act, No. 42 of 2012) § Mama Ngina University College (Universities Act, No. 42 of 2012)

§ Bomet University College (Universities Act, No. 42 of 2012)

§ Tom Mboya University (Universities Act, No. 42 of 2012)

§ Turkana University College (Universities Act, No. 42 of 2012)

§ Koitalel Arap Samoei University College (Universities Act, No. 42 of 2012)

§ University of Nairobi Enterprises (Companies Act, Cap. 486)

§ University of Nairobi Press

Appendix L: Publications

Building a Model for E-learning Adoption: Is Performance Expectancy a Predictor of Behavioural Intention to Adopt E-Learning in Higher Education?

Daniel Makini Getuno[1], Ezra Kiprono Maritim[2], Fred Nyabuti Keraro[3*]

[1] *Department of Curriculum, Instruction and Educational Management, Faculty of Education and Community Studies, Egerton University;* dmakini@egerton.ac.ke

[2] *Department of Psychology and Educational Foundations, Faculty of Education and Community Studies, Egerton University;* ekmaritim@yahoo.com

[3*] *Department of Curriculum, Instruction and Educational Management, Faculty of Education and Community Studies, Egerton University;* fkeraro@egerton.ac.ke

* *Correspondence author*

Abstract

The ultimate purpose of this study was to contribute to building a model for e-learning adoption among undergraduate university students in Kenya. The study contributes towards the development of the model by examining the relationship between Performance Expectancy (PE) and Behavioural Intention (BI) to adopt online learning among undergraduate students in Kenya's public universities. This study was based on a modified form of the Unified Theory of Acceptance and Use of Technology (UTAUT). A cross-sectional survey design was employed where stratified random sampling was used to select three public universities to participate in the study. A sample of 388 subjects was selected and data collected using a questionnaire with eight close-ended items on a 7-point Likert scale. The Cronbach – Alpha (CA) test was used to estimate the reliability of the questionnaire and yielded a CA coefficient of 0.78. The SmartPLS (Version 3.2 for Windows) software, applying the Partial Least Squares, Structural Equation Modelling (PLS-SEM) technique was used to test the hypotheses of the study. The tests of significance were performed above the 90% level of confidence ($p < .100$). The results indicate that there was a statistically significant relationship between PE and BI to adopt e-learning ($\beta = .15$, $t = 3.16$, $p = .002$). Further analysis of the effect of age (AGE), gender (GND) and internet experience (IXP) on the relationship between PE and BI was done using the Warp PLS software (version 7.0) applying the PLS-Multi Group Analysis (MGA). The results of testing the moderating effects indicate that of the three moderators, only students' GND significantly moderates the relationship between PE and BI to adopt e-learning, this effect being equally significant for both male and female students.

Keywords: model, e-learning adoption, performance expectancy, behavioural intention, higher education.

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