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ACCEPTANCE OF ONLINE LEARNING AMONG AFRICAN GRADUATES

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ABSTRACT

In the current globalized world, the pursuit of knowledge has progressed beyond the physical boundaries of educational institutions. The acquisition of education and the learning process take many different forms in the modern world which has granted members of the public easy access to educational opportunities. Among the numerous convenient forms available, online learning is the most acceptable and widely used method of advancing education utilized by reputed educational institutions across the globe. This research focuses on investigating factors that influence student utilization and adapting of online learning in some selected countries of Africa. The research is based on the Technology Acceptance Model (TAM) which is widely used as a theoretical paradigm for explaining students' acceptance of online learning. The factors under investigation include Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Cost (PC), Compatibility (COMP), Perceived Online Service Quality (POSQ), Infrastructure Enablers (IE) and Online Learning Acceptance and Satisfaction (OLAS). Data was collected through structured questionnaires from a sample of 310 students from different countries in Africa and analyzed using partial least squares - structural equation modelling (PLS-SEM) software to test the relationship between the factors. The results of this research show that PU, PEU, COMP, and POSQ have a positive and significant relationship with OLAS. In other words, these factors contribute positively and efficiently towards the acceptance and spread of online learning in selected African countries. However, PC and IE have an insignificant relationship with OLAS. In other words, African students perceive online learning as a high-cost option. Comparing the education costs in different African universities, this study has found that the International Open University (IOU), the Gambia, provides quality education with the lowest customized costs. The findings of this research are of great importance for educational institutions and policy makers in Africa and worldwide and may help them promulgate effective solutions for the challenges impeding the spread of online learning in Africa, in the hope of serving developing societies.

Keywords: Online learning, graduate students in Africa, Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Cost (PC), Compatibility (COMP), Perceived Online Service Quality (POSQ), Infrastructure Enablers (IE), Online Learning Acceptance and Satisfaction (OLAS), Technology Acceptance Model (TAM).

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1. INTRODUCTION

The advent of the twenty-first century has brought numerous significant changes in the world, out of which the information revolution is considered the most important breakthrough as it has changed the global socioeconomic and sociocultural milieu. Advancements in the fields of information and technology have not only brought global citizens on a common platform but have also opened several new ways of human interaction – including the mode of acquisition of education. With the advancement of technology, education can be obtained beyond the physical boundaries of educational institutions. This has enhanced educational choices for students and revolutionized the classroom experience, as through online education they can attend classes from the comfort of their homes. Online learning is a widely accepted method of promoting education utilized successfully by many institutions across the world (Ullah et al., 2017). It is a platform that allows for the use of technology to support and deliver learning among a group of people bound by the same identity features, values, beliefs, interests, and goals (Hramiak, 2010). Online learning has become more feasible technologically, economically, logistically as well as operationally. Incentives for universities for moving towards offering online programs are related to their financial constraints and rewards, e.g., reduced infrastructure for classrooms, offices, cafeterias, dorms, and libraries. It also includes an increase in non-traditional students who are working full time; and the modern advancement in technology facilitates the online acquisition of education for them (Palvia et al., 2018).

It is noteworthy that in underdeveloped countries of Africa, millions of students now complete their tertiary education without quitting their employment and this has only become possible because of the provision of online courses. Sub-Saharan Africa (SSA) is one of the world's largest geographical regions, with 48 nations and more than one billion people. In

2020, the gross tertiary education enrolment ratio was just 9.4%, far below the 38% average for the world. Naturally, there are significant regional variations in the rate. Gross tertiary enrolment, for instance, is 40% in Mauritius, 23.6% in Cabo Verde, 15% in Ghana and Togo, 10% in Lesotho, and 4.4% in Niger. The region spends around 21% of the whole government education budget on postsecondary education, 27% on secondary education, and 43% on elementary education (Gangwar & Bassett, 2020).

As a continent, Africa has emerged as the world's fastest-growing e-learning market owing to large numbers of aspiring students who seek higher education but encounter obstacles due to lack of access to infrastructure and resources, or the inability to take time off from their jobs. In recent years, Africa's development has been facilitated by fiber-optic connectivity, and more students, particularly those residing in urban areas, are now able to join online classes due to the expansion of internet access. This study focuses on comprehending factors that influence student utilization of online learning platforms in selected countries across Africa. The factors under investigation include a) Perceived Usefulness (PU), b) Perceived Ease of Use (PEU), c) Perceived Cost (PC), d) Compatibility, e) Perceived Online Service Quality (POSQ), f) Infrastructure Enablers (all independent variables); and, g) Online Learning Acceptance and Satisfaction (OLAS) (as a dependent variable).

The rationale for this study is based on three main factors. First, the available empirical information reflects that an e-learning system's effectiveness depends on its comprehensive implementation (Chinyamurindi & Shava, 2015; Chinyamurindi & Louw, 2010). Therefore, the present study is focused on ascertaining full utilization of an online learning opportunity by identifying the factors that influence student usage. This has the potential to benefit not only the student but also the lecturer designing the content on platforms such as online learning communities. Second, as online learning is expanding largely to become an alternative source of acquiring knowledge and education globally, statistical evidence on African graduates is still scarce. Therefore, the study is more focused on exploring African students' attitudes and intentions towards acquiring knowledge and uplifting their skills through online learning. Third, discussions on the potential of online learning industry in the African continent presents a promising picture. However, although the African continent has abundant natural resources, it is still far behind in the process of development when compared with other continents. Therefore, this study intends to explore the nature of the dimensions of various challenges faced in the development of online education in Africa. Thus, in the following pages, at first the concept of online learning in the context of innovation in technology is briefly discussed and then its theoretical dimensions are presented. This leads to the research hypotheses and aims of the study. Thereafter, the empirical research is contextualized to include a presentation of the background, research sample, research paradigm, data collection instrument, process and the analytical framework used in this work. Finally, the results and discussion conclude this paper.

2. REVIEW OF LITERATURE

In this section, the researchers briefly reviewed the literature related to online learning, technology acceptance model, online learning acceptance and satisfaction, factors affecting online learning acceptance and satisfaction, perceived usefulness, perceived ease of use, perceived cost, compatibility, perceived online service quality and infrastructure enablers.

2.1 Online learning

Online learning is a mode of education that provides education through the internet (Al-Syyed, 2015). For many students who cannot attend on-site classes, it is an easily manageable and affordable substitute. Online learning has been utilized in a variety of contexts (including industry and museums, etc.), as well as in higher education. The use of this mode increased tremendously during the recent Covid pandemic (Aguilera-Hermida, 2020; Ennes & Lee, 2021). Participants only require a device such as a computer, tablet or smartphone and internet connectivity. In synchronous classes, instructors and students meet at a set time electronically and then students are free to complete their assignments whenever and wherever it suits their schedules. In the case of mixed or hybrid formats, the majority of the course material is supplied online (Allen & Seaman, 2015; Gonzalez et al., 2020).

Online learning may enhance access to higher education for groups that would otherwise be excluded and can offer efficient learning processes where students achieve the desired learning goals when it is correctly structured (Ayodele et al., 2018). Higher education institutions began providing lessons in various and novel modalities throughout the pandemic (e.g., some students remotely and some students in the classroom in real-time). Each institution must adapt to its specific requirements and conditions (Affouneh et al., 2020; Maphalala et al., 2021). This new teaching method is called “emergency remote teaching” (Hodges et al., 2020).

Online education demands greater self-discipline from students than traditional classroom instruction (Jung et al., 2017). Additionally, educators must exert more effort than they would in a typical classroom setting to sustain student engagement, which is crucial for learning results (Panigrahi et al., 2018). Furthermore, online learning provides particular online pedagogical techniques and resources created to draw learners into a distinctive online learning culture that improves students' performance (Bower, 2019; Jung, 2014). The potential for effective online higher education is more dependent on faculty and institutional practices and efforts than on technology (Bower, 2019; Jung & Lee, 2020). There are now various cutting-edge methods available to improve students’ participation in online environments. These materials can be located and accessed as “open educational resources” (OERs).

In the case of underdeveloped continents such as Africa, studies revealed a high potential for online learning expansion due to several reasons. To name but a few: a large youth population; abundant untapped wealth and natural resources; the need for self-development to meet evolving opportunities; high rates of poverty; the need to work and study simultaneously; and so on. Exploring the reasons hindering African students from using online learning as an alternative means of gaining knowledge is a motivational factor behind undertaking this study.

Technology usage, behavior adoption, and acceptability factors have recently attracted a lot of attention. Technology acceptance models have evolved into a theoretical framework for the use and acceptance of online technologies as a result of the rise in usage (Jung et al., 2017). The TAM model (Davis, 1989), the AIUTA-2 model (Venkatesh et al., 2012), and the GETAMEL model are the most popular models (Abdullah & Ward, 2016) in this regard. These models' elements are based on a variety of theories, including those that address information adoption, PC usage, cognitive theory, unified theory of acceptance, and use of technology (Aldholay et al., 2018; Chen & Hwang, 2019; Kemp et al., 2019; Venkatesh et al., 2016). Many researchers have used these models to analyze the use and acceptance of specific educational technologies such as OER (Jung & Lee, 2020), e-learning systems (Pham & Tran, 2020; Yakubu & Dasuki, 2019), online learning blogs (Ifinedo, 2018), and other technological educational tools.

Nevertheless, numerous researchers have also built their own learning models and created their instruments by customizing to the particular technology they were studying. They frequently suggest new models or add new constructions to the existing models (Aldholay et al., 2018; Martinho et al., 2021). Furthermore, the variables that the researcher uses to study variability are crucial to structural equation modeling. The structures used to gauge the use and acceptability of technology as a consequence have a wide range. According to Kemp et al. (2019), the fact that measuring methods and conceptions differ greatly results in inconsistent findings. They built a modular taxonomy with metrics tailored expressly for educational technologies.

2.2 Technology Acceptance Model (TAM)

The factors influencing technology acceptance among user populations are explained by Technology Acceptance Models (TAM) (Abdullah & Ward, 2016; Kemp et al., 2019). Cognitive theories that describe the process of behavior adoption served as the foundation for the first technology acceptance model (TAM). The willingness and ongoing usage of technology by the user is implied by technology adoption. Researchers utilize TAM to analyze the adoption and usage of mobile learning; however, the initial model had flaws and underwent several modifications (García Botero et al., 2018). Kemp et al. (2019). For instance, introduction of a taxonomy of characteristics that influence attitudes regarding the usage of educational technologies by students or instructors in higher education institutions based on several technology acceptance models. This taxonomy was divided into seven major groups: a) attitude, affecting factors, and motivation; b) social factors; c) usefulness and visibility; d) instructional attributes; e) perceived behavioral control; f) cognitive engagement; and g) system attributes. Even though all the factors are influential for adopting technology, this research will focus on the factors which are mainly related to students' behavior or attitude. The factors that will be considered in this study are perceived usefulness (PU), perceived ease of use (PEU), perceived cost (PC), compatibility (CO), perceived online service quality (POSQ), infrastructure enablers (IE), and online learning acceptance and satisfaction (OLAS). Most of the factors considered for this study focus on the personal and behavioral aspects of the learner, taking into account the enabling factors and some external circumstances that affect the learner's intention to enroll in online learning or not, particularly in Africa.

2.2.1 Online learning acceptance and satisfaction (OLAS)

Previous studies on technology adoption revealed many factors as important for acceptance behavior in the online learning industry (Aguilera-Hermida, 2020; Aguilera-Hermida et al., 2021; Aldholay et al., 2018; Azhar et al., 2021; Md Yunus et al., 2021; Peñarroja et al., 2019). Bhattacherjee and Sanford (2009) proved that attitude will result in a positive intention to accept new conditions and environments. Attitude is assumed to influence acceptance behavior (Khan et al., 2017). According to another study by Aguilera-Hermida (2020), students prefer face-to-face learning over online learning. Furthermore, students who favored face-to-face learning found it difficult to adjust to online learning. In the same vein, Ullah et al. (2017) investigated undergraduate students' attitudes toward online learning at the University of Peshawar. They found a lack of positive attitude as a result of the high difficulty level in comprehending and using an online learning tool without proper assistance.

On the other hand, previous studies indicated that students' familiarity with technology usage and their perceptions of how they benefit from online learning systems influence student satisfaction (Hammoud et al., 2008; Liu et al., 2009; Changchit & Klaus, 2012). According to Mitchell et al. (2005), users with more computer knowledge are more likely to enjoy web-based learning. Students perceive online education positively, according to Liu et al. (2009), because of the Internet-enabled and tactile user interface. WebCT, chat rooms, and message boards according to Changchit and Klaus (2012), were among the most useful technologies that contributed to better satisfaction of online learning. According to Hammoud et al. (2008), students often have a positive perception of WebCT usage. The study revealed a significant impact of WebCT on students' achievements and learning outcomes. As a result, learning technologies and communication tools are posited to play deterministic roles in determining students' acceptance behavior and satisfaction towards online learning.

2.2.2 Factors affecting online learning acceptance and satisfaction

This study focuses on six main factors affecting online learning acceptance and satisfaction, i.e., perceived usefulness, perceived ease of use, perceived ease of cost, compatibility, perceived online service quality, and infrastructure enablers. A brief overview of these factors along with their respective hypotheses is given hereunder.

a) Perceived usefulness (PU)

Perceived usefulness has been defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989, p. 320). Perceived usefulness is the primary precursor that determines the behavioral aim to use a computer system (Venkatesh et al., 2003). Recent research has shown that perceived usefulness directly influences behavior intention and acceptance of online learning (Azhar et al., 2021; Lazim et al., 2021; Lee, 2010). Once students and knowledge seekers realize the importance of technology based alternative method of learning, the intention to utilize such service would increase. Nguyen et al. (2020) researched the elements that affected learners’ use of networked pedagogical systems. Twenty universities in Vietnam contributed a total of 246 students to the research. The findings of this research showed that factors such as computer self-efficacy, computer experience, perceived ease of use, perceived usefulness, enjoyment, and subjective norm positively influenced students’ approval of networked pedagogical systems, whereas factors such as system characteristics did not. Based upon this study, we posited the following hypothesis:

H1: Perceived usefulness significantly and positively affects online learning acceptance and satisfaction of African students.

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b) Perceived ease of use (PEU)

Widespread research has provided support that perceived ease of use had a significant effect on usage intention. It is an important forecaster of online learning acceptance. This study seeks to revalidate such relationships in the perspective of online learning industry in Africa. Perceived ease of use refers to the degree to which a person believes that using a particular system would be free of some sort of effort (Davis, 1989). In recent research conducted by Ayodele et al. (2018) regarding factors hindering the adoption of online learning in Nigeria, perceived ease of use had significant effect on users' acceptance of online learning. In another research by Farahat (2012), perceived ease of use was found positively related with the intention to adopt online learning in the Egyptian universities. Al-Gahtani (2016) investigated the factors which contribute towards the acceptance of e-learning in Saudi Arabia. A survey was distributed among 286 university students in which among other determinants, perceived ease of use was one of the significant factors in usage intention. Based upon this study posited the following hypothesis:

H2: Perceived ease of use significantly and positively affects online learning acceptance and satisfaction of African students.

c) Perceived cost (PC)

Perceived cost is defined as the extent to which a person believes that using technology will cost money (Luarn & Lin, 2005). The cost may include the transactional cost in the form of course subscribing charges, mobile network charges for accessing online lessons and mobile device, tablets, computers and laptops device costs. According to Wu and Wang's (2005) study on the adoption of mobile commerce, perceived cost was not as important as other factors including perceived risk, compatibility, and perceived usefulness. A further qualitative investigation on the same study was conducted, which revealed that perceived cost is normally a major concern when a technology

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is first introduced. However, in times of crisis or unexpected necessity, as the COVID-19 outbreak, the utility advantages exceed the financial concerns. This was evidenced by Sarosa (2022), who found perceived costs to have no influence over online learning in Indonesia. The researcher attributed the reason to government support in providing internet coverage to support students in shifting towards distance learning at the time of the pandemic, as well as the availability of the internet in the country and low subscription prices. Based upon this, this study posited the following hypothesis:

H3: Perceived cost significantly and positively affects online learning acceptance and satisfaction of African students.

d) Compatibility (CO)

Compatibility is viewed as the degree to which an innovation is perceived as being consistent with the existing values, past experiences and the needs of potential adopters. Hence, it is a measure of the values and beliefs of the customers, the ideas they have adopted in the past as well as the ability of an innovation to meet their needs (Ifinedo, 2018; Rogers et al., 2014). It is suggested that compatibility has a positive influence on the behavioral intention of students towards online learning. In this regard, Aldholay et al. (2018) suggested in their model that compatibility would have a positive and significant influence on the actual use of online learning for students in Yemen. This was supported by the findings of Changchit and Klaus (2010), who confirmed that students with employment status prefer online courses as they perceive greater flexibility in terms of accessing class materials and studying at their own pace. Therefore, the following hypothesis is posited:

H4: Compatibility significantly and positively affects online learning acceptance and satisfaction of African students.

e) Perceived online service quality (POSQ)

Service quality in online education refers to the quality of personal support services provided through the online learning system, such as assistance with online registration, course selection, and financial aid by institutions, online technical support services, timely feedback by faculty and so on. This suggests that the student support services supplied by online education service providers (i.e., institutions), online student service coordinators, and instructors are used to assess the service quality of online education (Larmuseau et al., 2019; Thongsri et al., 2019). There is a considerable body of evidence demonstrating that service quality is a crucial driver of customer satisfaction in the educational context (Lee, 2010). According to Helgesen and Nesset (2007), service quality is a reliable predictor of student satisfaction. According to Al Mulhem (2020), website technical quality, website content quality, website design quality, and website access are crucial for boosting the utilization of e-learning systems. Eze et al. (2020) explored factors influencing students' usage of e-learning in private HEIs in Nigeria using a qualitative approach. They researched Landmark University students and discovered that ease of use, speed, accessibility, and service delivery were among other factors that influenced the students' adoption of online learning. As a result, the quality of technical support services is quite likely to play an essential part in online learning acceptance and student satisfaction. Based upon this, we posited the following hypothesis:

H5: Perceived online service quality significantly and positively affects online learning acceptance and satisfaction of African students.

f) Infrastructure enablers (IE)

Infrastructure enablers (facilitating conditions) can be characterized in the context of technology utilization studies as organizational support for technology users can impact the system use (Qiao et al., 2021; Venkatesh et al., 2016). According to Venkatesh et al. (2003), it is the degree to which users

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perceive that an organizational and technological infrastructure exists to enable the use of information technology. Infrastructure enablers (IE) are environmental elements that impact a person's motivation to complete a task. According to Groves and Zemel (2000), facilitating supports (e.g., skills training, available information or resources, and administrative assistance) are extremely important elements influencing the usage of instructional technology in teaching. Earlier research on students' adoption of various technologies (Ullah et al., 2017) shown that IE is an important component in promoting user acceptance of technology. According to Al Mulhem (2020), students at Saudi Arabia's King Saud University evaluated system functioning, system dependability, top management support elements, and enabling conditions as key variables influencing perceived utility, ease of use, and actual usage of online learning. Adarkwah (2021) identified discrepancies in access to digital infrastructure as a key hindrance to online learning in Sub-Saharan Africa. In Ghana, Asampana et al. (2017) attributed the low level of online learning acceptance at the tertiary level to poor IT infrastructure, inadequate training, and the relevance of the system to quality lecture delivery. Although students' perception of the system's usefulness was high, particularly among higher levels, because of low internet availability, Ngalomba (2020) saw online learning as a barrier in Africa. He said that just around one-third of the population has access to broadband internet. In terms of South Africa, which is regarded as an advanced African country, Clement (2020) indicated that the country had 36.54 million internet users, of whom 34.93 million were mobile internet users as of January 2020. According to StatsSA's statistics, only 9.5% of the SA population has home internet connection (StatsSA, 2016). Based on it, it is worth posing the following hypothesis:

H6: Infrastructure enablers significantly and positively affects online learning acceptance and satisfaction of African students.

2.3 Conceptual Framework

Various factors have been taken into consideration as potential variables in building a conceptual framework for the present research model. As shown in Figure 1, the dependent variable for this study is online learning acceptance and satisfaction (OLAS). Six independent variables were identified as factors impacting the OLAS namely perceived usefulness (PU), perceived ease of use (PEU), perceived cost (PC), compatibility (CO), perceived online service quality (POSQ) and infrastructure enablers (IE). Two variables (PU, PEU) are described as factors provided by TAM theory in terms of measuring the acceptance of services and products acceptance by clients.

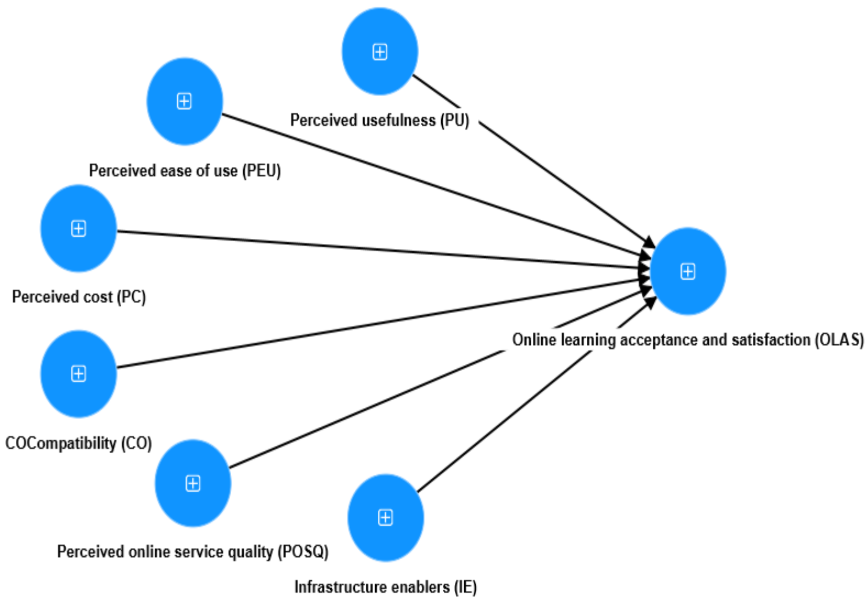

Figure 1. Research Framework

3. Methodology

This research consists of two parts. The first part deals with student's perception and acceptance of online learning. A primary survey was carried out for this purpose. The second part deals with the comparative education costs among the sample African universities and data was obtained from the respective universities' websites.

3.1 Data collection and sampling procedures of first phase of the research

The purpose of the research is to investigate factors that influence student utilization of online learning platforms in selected countries across Africa. In this study, questionnaires were distributed to students from seven countries in Africa, i.e., Nigeria, Gambia, Zimbabwe, Mozambique, Rwanda, Ivory Coast and Uganda. Students were selected randomly through a random sampling technique. A total 310 questionnaires were distributed to the targeted respondents through online distribution technique. Out of the total, 272 questionnaires were considered for further analysis with a response rate of 88%. The remaining 38 questionnaires were excluded due to incomplete answers and detection of potential outliers which can affect and distort the accuracy of the analysis (Hair et al., 2010). The questionnaire for this study was divided into three sections (i.e., A, B and C). Section A contains respondents' demographic data, including gender, age, nationality, level of education, income and experience in online learning. Section B contains 37 items pertaining to six factors which supposedly influence the acceptance of online learning among students in Africa. In Section C, eight questions were posed to gather data on acceptability and satisfaction with online learning.

3.2 Measurement of variables

In this study, the factors that are supposed to influence student utilization of an online learning platforms (PU, PEU, PC, CO, POSQ, IE) were tested as independent variables of OLAS. This study is quantitative in nature, based on cross-sectional research design, whereby the data for the whole study was collected at one point in time. The measurements used in this study were originally developed and adapted from past literature (see Table 1). Prior to data collection, the study's measurements were screened and validated by academics having expertise in online education and learning. The five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), was the choice for answering most questions.

Table 1. Measurement Scales (Items, Reliability and Sources)

Scale	Total items	Source
Perceived usefulness (PU)	8	Adapted from Davis (1989); Lee (2010)
Perceived Ease of Use (PEOU)	7	Adapted from Davis (1989); Lee (2010)
Perceived cost (PC)	4	Adapted from Luarn and Lin, (2005); Wu and Wang (2005)
Compatibility (CO)	6	Adapted from Wu and Wang (2005)
Perceived online service quality (POSQ)	7	Adapted from Farahmandian et al. (2013); Lee (2010)
Infrastructure enablers (IE)	5	Adapted from Park et al. (2011); Venkatesh et al. (2016)
Online learning acceptance and satisfaction (OLAS)	8	Adapted from Lee (2010)

3.3 Analytical method

In the first part of the study, IBM SPSS Statistics version 22.0 and Smart PLS version 4 were used to analyze the data. The choice of PLS was based on its capacity to assess causal relationships across all latent constructs while coping with measurement errors in the structural model (Hair et al., 2017). As this study is analytical and explanatory in nature, PLS appears to be the best fit for the current investigation (Hair et al., 2017). According to Hair et al. (2017), measurement models were tested individually before the structural model was evaluated. All aspects of data and research must guarantee that there is no Common Method Bias before conducting measurement models. Common Method Bias suggests that the variance in the questionnaire is represented in the measuring method rather than the concept itself. In the second part of the research, a comparative analysis of tuition fees of reputed African universities was carried out. Here, the eight leading African universities from seven different countries were taken as sample organizations and their tuition fees (2022-23) were obtained from their websites.

4. RESULTS

In this section, analysis is made with regard to countries' demographic profiles, assessment of measurement model and assessment of structural model.

4.1 Demographic profiles

The demographic profiles considered in this study are nationality, gender, age, education and income. As presented in Table 2, 88.5% of the sample respondents were from Nigeria, 9% from the Gambia, 2.2% from Zimbabwe, 1.6% from Mozambique, 7.1% from Rwanda, 2.2% from Ivory coast and 2.5% were from Uganda. Most respondents of the study sample (57%) were female, while 47% were male. In terms of age distribution, the largest group of students was between 20 and 24 years old, followed by students aged between 25 and 29 years, students aged between 30 and 34, students aged between 35 and 39, students over 45 years, and lastly students aged between 40 and 44 years. In terms of education level, the majority of the students held a certificate (48.5%) and a diploma (35.2%), whereas 0.4% of the students held PhDs, 3.6% held masters, and 12.1% of the students held bachelor's degrees. With regard to the level of income, the majority of students (82.7%) earn less than $250 per month. The second largest group (6.6%) earns between $251 and $500 per month. In contrast, 1.8% of students earn more than $2,000 per month.

Table 2. Demographic profiles

Variables	***N***	**(%)**
Nationality		
Nigeria	223	88.5
Gambia	8	9
Zimbabwe	6	2.2
Mozambique	4	1.6
Rwanda	18	7.1
Ivory coast	6	2.2
Uganda	7	2.5
Gender		
Male	117	43
Female	155	57
Age		
20-24 years	90	33.1
25-29 years	66	24.2
30-34 years	49	18.1
35-39 years	41	15.1
40-44 years	10	3.7
>45 years	16	5.8
Education		
Certificate	132	48.5
Diploma	96	35.2
Bachelor	33	12.1
Master	10	3.6

PhD	1	.4
Income		
0-250$	225	82.7
251-500$	18	6.6
501-750$	7	2.6
751-1000$	7	2.6
1001-1500$	4	1.5
1501-2000$	6	2.2
>2001$	5	1.8

4.2 Assessment of Measurement Model

In the beginning of this process, the convergent validity was tested. During the convergent validity test, the indicator or item loadings, average variance extracted (AVE), and composite reliability (CR) were all taken into account. According to the results in Table 3, item loading surpassed 0.8 for items that met the recommended value provided by Hair et al. (2019). Hair et al. (2019) proposed an AVE threshold or requirement of more than 0.5. AVEs in the current research ranged from 0.713 to 0.873. The CR value varied from 0.882 to 0.932, which corresponded to Hair et al. (2019) recommended value of 0.7. The findings of the measuring model are shown in Table 1.

Table 3. Results of Measurement Model

Construct	Items	Loadings	VIF	CR	AVE
Perceived usefulness (PU)	PU4	0.901	2.513	0.928	0.811
	PU6	0.903	2.566		
	PU8	0.898	2.396		
Perceived ease of use (PEU)	PEU3	0.916	1.749	0.905	0.827
	PEU5	0.903	1.749		

Perceived cost (PC)	PC1	0.871	2.083	0.919	0.791
	PC3	0.917	2.743		
	PC4	0.880	2.262		
Compatibility (CO)	COMP1	0.869	2.560	0.920	0.742
	COMP2	0.857	2.315		
	COMP3	0.862	2.601		
	COMP5	0.857	2.433		
Perceived online service quality (POSQ)	POSQ5	0.933	2.255	0.932	0.873
	POSQ7	0.935	2.255		
Infrastructure enablers (IE)	IE2	0.858	1.840	0.882	0.713
	IE4	0.849	1.883		
	IE5	0.825	1.531		
Online learning acceptance and satisfaction (OLAS)	OLAS2	0.870	2.054	0.917	0.787
	OLAS5	0.881	2.241		
	OLAS6	0.910	2.521		

Following the preceding test of convergent validity, the discriminant validity must be assessed. To assess discriminant validity, Fornell and Larcker (1981) criteria was previously utilized. However, the Fornell and Larcker (1981) criteria has been criticized for not reliably detecting the lack of discriminant validity in frequent study contexts (Henseler et al., 2015). Thus, Henseler et al. (2015) proposed an alternate method for determining discriminant validity based on the Heterotrait-Monotrait correlation ratio. Henseler et al. (2015) used Monte Carlo simulation research to illustrate the higher performance of this technique. As a consequence, we examined the discriminant validity using this new proposed approach, and the results are displayed in Table 5. If the HTMT value is more than 0.85 HTMT0.85 (Kline, 2015) or HTMT0.90 (Gold et al., 2001), then discriminant validity is a concern. As demonstrated in Table 5, all of the values passed the HTMT0.90 (Gold et al., 2001) and

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HTMT0.85 (Kline, 2015) tests, suggesting that discriminant validity has been established. Based on these findings, the measurement model has appropriate convergent and discriminant validity.

Table 4. Discriminant validity using Fornell and Lacker criterion

	CO	IE	OLAS	PC	PEU	POSQ	PU
CO	*0.861*						
IE	0.744	*0.844*					
OLAS	0.843	0.713	*0.887*				
PC	0.353	0.352	0.262	*0.889*			
PEU	0.842	0.728	0.851	0.262	*0.909*		
POSQ	0.799	0.700	0.824	0.270	0.799	*0.934*	
PU	0.841	0.690	0.854	0.288	0.840	0.868	*0.900*

Table 5. HTMT criterion

	CO	IE	OLAS	PC	PEU	POSQ	PU
CO							
IE	0.844						
OLAS	0.782	0.854					
PC	0.403	0.422	0.302				
PEU	0.689	0.712	0.826	0.316			
POSQ	0.719	0.843	0.759	0.314	0.773		
PU	0.651	0.819	0.856	0.329	0.804	0.573	

4.3 Assessment of Structural Model

According to Hair et al. (2019), the following stage in reviewing the output of PLS-SEM is to examine the structural model after analyzing the measurement model requirement. This might be accomplished using the normal assessment criteria of the path coefficients' significance level, as determined by the measurement of R2. In this study, the generated R2 was 0.813, suggesting that 81.3% of the variance of online learning acceptance and satisfaction (OLAS) could be explained by perceived usefulness (PU), perceived ease of use (PEU), perceived cost (PC), compatibility (CO), perceived online service quality (POSQ), and infrastructure enablers (IE). Prior to the assessment of the structural relationships, collinearity should be examined to ensure that the regression results are not distorted (Hair et al., 2019). This could be done through the determination of VIF values. The rule of thumb of the VIF test is that, if the VIF value is above the value of 5, then there might be an indication of probable collinearity issues among the predictor constructs (Becker et al., 2015).

As depicted in Table 3, the VIF values of the study's items ranged between 1.749 to 2.743, indicating that all items of this study possess acceptable values with regards to collinearity. In addition, the statistical significance and relevance of the path coefficients should be performed through the bootstrap analysis with 5000 cases, as suggested by Hair et al. (2011). According to the output shown in Table 6, perceived usefulness (PU -> OLAS, $\beta = 0.242$, $t = 3.342$, $p < 0.05$), perceived ease of use (PEU -> OLAS, $\beta = 0.276$, $t = 3.831$, $p < 0.00$), compatibility (CO -> OLAS, $\beta = 0.239$, $t = 3.497$, $p < 0.00$), and perceived online service quality (POSQ -> OLAS, $\beta = 0.170$, $t = 2.304$, $p < 0.05$) were found to have a positive and significant relationship with the online learning acceptance and satisfaction of students in selected African nations. However, two variables were found to have an insignificant relationship with the online learning acceptance and satisfaction, which were perceived cost (PC -> OLAS, $\beta = -0.031$, $t = 1.191$, $p > 0.05$), and infrastructure enablers (IE -> OLAS, $\beta = 0.059$, $t = 1.209$, $p > 0.05$). Therefore, H1, H2, H4 and H5 are supported. The validated model is shown in Figure 1 below.

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Table 6. Results of structural model

Hypothesis	Relationship	Std. Beta	Std. error	*t*-value	*p*-value	Decision
H1	PU -> OLAS	0.242	0.072	3.342**	0.001	Supported
H2	PEU -> OLAS	0.276	0.072	3.831***	0.000	Supported
H3	PC -> OLAS	-0.031	0.026	1.191	0.234	Not supported
H4	CO -> OLAS	0.239	0.068	3.497***	0.000	Supported
H5	POSQ -> OLAS	0.170	0.074	2.304*	0.021	Supported
H6	IE -> OLAS	0.059	0.048	1.209	0.227	Not supported

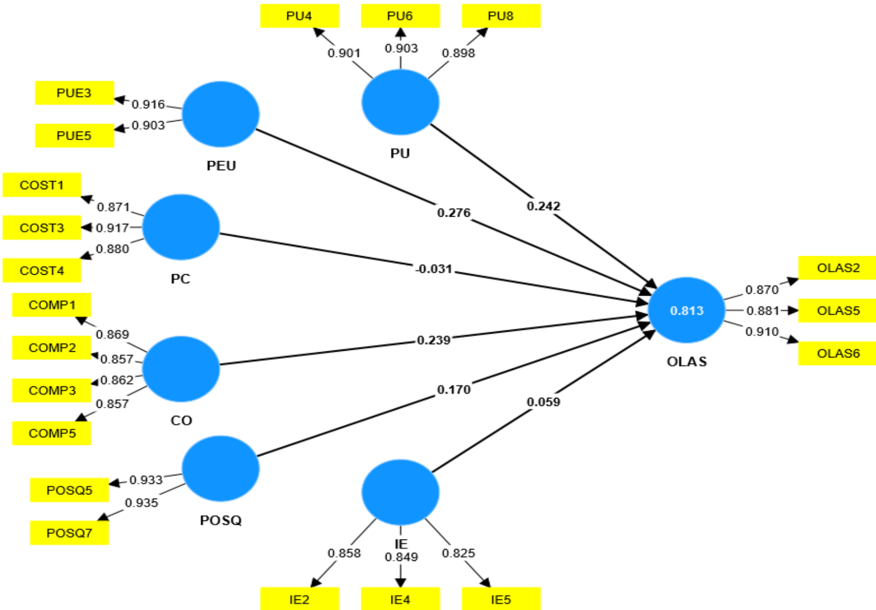

Figure 2. Validated model

5. DISCUSSION

The main objective of this study was to investigate factors that influence student utilization of online learning platforms in selected countries across Africa. African countries considered in this study are Nigeria, The Gambia, Zimbabwe, Mozambique, Rwanda, Ivory coast and Uganda. This study is based on the theoretical argument of Technology Acceptance Model (TAM). TAM has been shown to be a theoretical paradigm for explaining students' acceptance of online learning. Overall, the empirical results showed that some factors have been contributing positively towards the acceptance and utilization of online learning platforms among African students, while others have not. The findings revealed that perceived usefulness (PU), perceived ease of use (PEU), compatibility (COMP), and perceived online service quality

(POSQ) had a positive and significant relationship with online learning acceptance and satisfaction (OLAS), while perceived cost (PC) and infrastructure enablers (IE) were found to have no significant role.

The results showed that students' online learning acceptance and satisfaction were directly influenced by perceived usefulness (PU) and perceived ease of use (PEU) of learning platforms. The results suggest that students in selected African countries perceive online learning as useful, beneficial, and easy to use. These results are in line with past literature (Amadu et al., 2018; Ayodele et al., 2018; Eze et al., 2020; Farahat, 2012; Guzman et al., 2021; Lazim et al., 2021; Lee, 2010; Nguyen et al., 2020).

Compatibility (CO) was found to be an important factor in this study and had a significant relationship with online learning acceptance and satisfaction (OLAS), and this is also in line with the past literature (Chang & Tung, 2008; Changchit & Klaus, 2010; Ifinedo, 2018; Kotoua et al., 2015). This result is also proven, particularly when students are obliged to work or fulfil other duties while studying, as is the case in most African countries. This result also validates proposed extended DMISM model by Aldholay et al. (2018). The result is also in line with Guzman et al. (2021), who found that students with a preference for online learning are likely to be older, work more, be married, and have children.

In addition, perceived online service quality (POSQ) had a significant effect on online learning acceptance and satisfaction (OLAS) among students in Africa. This study perceives online learning and distance education as a solution to the problem of school dropouts in Africa and as an effective means of spreading knowledge and virtue as well. The finding of this study is also supported by Ghazal et al. (2017) in the case of Yemen, who found system quality to be the most significant positive factor affecting students' acceptance and satisfaction. It is also consistent with the findings of Buabeng-Andoh (2022) in the context of Ghana and Lee (2010) in a comparative study between South Korea and the USA, who revealed that students from both countries perceived the quality of online support services as a significant predictor of online learning acceptance and satisfaction.

On the other hand, perceived cost (PC) was not significantly associated with online learning acceptance and satisfaction (OLAS) among students in Africa, posing cost as a major impediment to the spread of online learning in the continent. In spite of the huge efforts provided by online learning platforms in Africa, low-income levels strongly affect students' acceptance levels, as is the case with this study, which showed that 82.7 % of respondents receive an income of below 250 dollars. These findings are in support of Changchit and Klaus (2010) who claimed that online courses can be costly to develop and to implement, and incorrectly categorizing courses for online participation might result in lesser student retention rates. Unlike the situation in Indonesia, where the cost of internet connectivity and online learning subscriptions seems affordable (Sarosa, 2022), the cost of online learning seems not to be affordable for many African students.

In the same vein, infrastructure enablers (IE) did not support online learning acceptance and satisfaction (OLAS) among students in Africa. In other words, all infrastructure-related means, such as ICT infrastructure, internet access, speed, and other facilitating conditions, are perceived as obstacles to the spread of online learning. These results confirm the challenges confronting online learning in Africa provided by Adarkwah (2021) and other researchers (Asampana et al., 2017; Maphalala et al., 2021; Palvia et al., 2018). This result is also compatible with the findings of Maheshwari (2021) in the context of Vietnam. Similarly, it also validates the acceptance model of online learning proposed by Azhar et al. (2021) for urban poor students in Malaysia.

6. COMPARISON OF THE COST EDUCATION IN DIFFERENT UNIVERSITIES IN AFRICA

It is important to mention here that due to extreme poverty and lack of basic facilities in many African countries, acquisition of education whether through on the ground universities or by online mode is a big challenge. This was also reflected during the survey carried out for this study. However, when researchers compared the tuition fees of seven on-the-ground universities in the sample countries with the tuition fee charged by the IOU, they saw a big difference (table 7). For instance, as compared to McPherson University Nigeria, the cost of acquisition of a bachelor degree in IOU is only its 7.5 percent. A similar situation can also be seen in the case of Catholic University of Mozambique and University of Zimbabwe where the respective figures are 11.8 and 22.9 percent. Even in the case of Uganda Martyrs University, acquisition of undergraduate education at IOU is much cheaper. For postgraduate programs, the scenario is almost the same which means the tuition fees at the IOU is the lowest. In addition, IOU charges customized tuition fees based on different slabs formulated on the basis of per capita GDP of those countries, which means the students from poorest countries pay the least. As reflected from the survey results that it is not only the less cost, when considering the online learning acceptance and satisfaction, its perceived usefulness, perceived ease of use, compatibility, perceived online service quality and infrastructure enablers, students are advantageous. On a different note, it is also worth mentioning here that a large number of IOU's needy students are on scholarship. By covering their full fees, IOU's One Million African Scholarships (1MAS) program covers the full fees of disadvantaged students who have no opportunity to acquire higher education elsewhere.

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Table 7. A comparative overview of various universities' fees in relation to IOU

Country	University	Cost of Bachelor Degree (US$)	IOU's Cost of Bachelor Degree (US$)	Difference (US$ & %)
Nigieria	McPherson University	12,320	920	11,400 (7.5%)
The Gambia	University of the Gambia	2,252	920	1,332 (40.8%)
Zimbabwe	University of Zimbabwe	4,024	920	3,104 (22.9%)
Mozambique	Catholic University of Mozambique	7,820	920	6,900 (11.8%)
Rwanda	University of Rwanda	3,024	920	2,104 (30.4%)
Ivory coast	Ecole Normale Supérieure d'Abidjan	4,007	1,240	2,767 (30.9%)
Uganda	Uganda Martyrs University	1,836	1,240	596 (67.6%)

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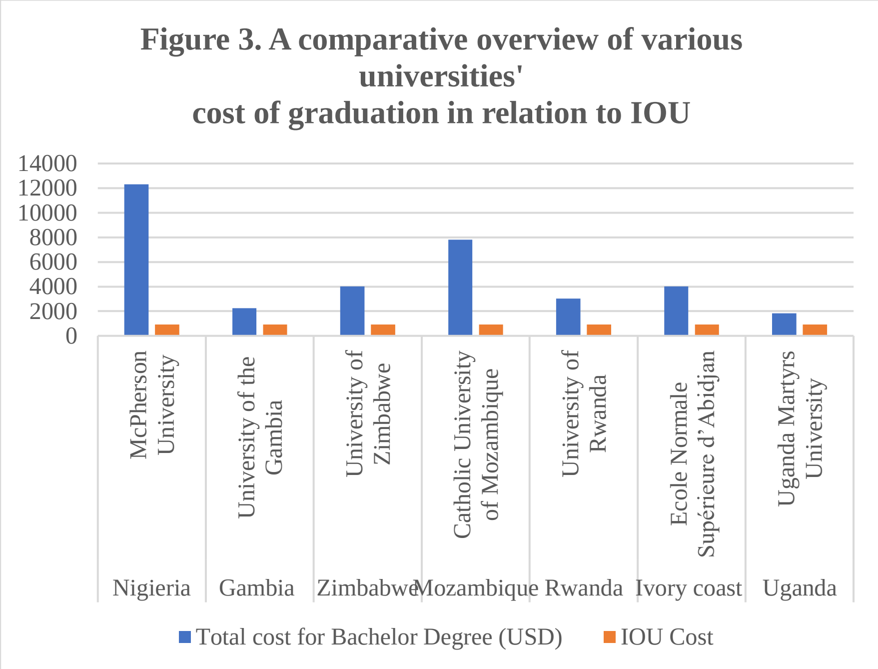

7. CONCLUSION, IMPLICATIONS AND LIMITATIONS

Online learning has huge potential in Africa. Many African students perceive online learning as useful, beneficial, and easy to use. Others also perceive it as compatible with the way they like to learn as it fits well with their lifestyle. The study also shows that IOU offers better quality education with the lowest and most customized education costs among African universities. However, there are many students who cannot join online learning due to economic conditions and lack of infrastructure support such as internet connectivity and IT support. Therefore, based on the results of this study which reflects the potential of online learning in Africa, it is recommended that decision-makers and governments in Africa must work to improve the economic conditions of people in Africa by rationalizing and optimizing the use of resources, as well as fighting corruption, especially as it is the richest continent in the world in terms of natural resources. In view of the great development challenges facing governments in Africa, it is advisable to take advantage of online learning to raise the educational level of individuals and qualify them for various tasks, and this can only be done by providing supportive infrastructure, such as providing Internet networks in remote cities and villages. The limitation of this study was that not all factors which might affect students' acceptance and preference towards online learning were considered. Future studies might investigate other factors such as social influence, perceived enjoyment, effort expectancy, and so on. Also, the sample of this study did not cover a large number of African countries, which are perceived to be rich and well-grounded in terms of infrastructure. Therefore, for the sake of generalizing the results, a larger sample size would be recommended for future studies.

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