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Examining e-learning adoption intention among academic staff in higher education institutions: A developing country context

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E-learning presents a significant opportunity for developing countries to rapidly increase the availability of higher education to their population. However, e-learning is not widely adopted in many developing countries such as Nigeria. This study aims to advance our understanding of the determinants of e-learning adoption by examining the factors influencing e-learning adoption intentions among academic staff in higher education institutions in Nigeria. Applying the decomposed theory of planned behavior and using sample data collected from 188 respondents, the findings of the study demonstrate that e-learning beliefs are significant factors that indirectly influence e-learning adoption. This study extends our understanding of the determinants of e-learning adoption and provides valuable cues to managers of higher education institutions that will aid their e-learning adoption efforts.

Key words: E-learning, e-learning adoption intention, decomposed theory of planned behaviour, higher education institutions, universities.

INTRODUCTION

The adoption and use of e-learning by higher education institutions in developing countries face several challenges, including inadequate infrastructure, knowledge gaps, behavioral barriers and poor planning (Folorunso et al., 2006; Kisanga and Ireson, 2015; King and Boyatt, 2015; Mtebe and Raisamo, 2014; Omeje et al., 2019; Rakhyoot, 2017; Renda dos Santos and Okazaki, 2016; Tandon et al., 2022). While these challenges are well-documented in the literature, our understanding of the factors influencing e-learning adoption among academic staff at higher education institutions is less developed. Despite e-learning being recognized as a viable and cost-effective tool to expand access to higher education (Algahtani, 2011; Arkorful and Abaidoo, 2015), it is not widely adopted as a means to bridge the demand-supply gap in higher education in developing countries, such as Nigeria (Nwagwu, 2020).

This study aims to address this gap and enhance our understanding of the determinants of e-learning adoption by examining the e-learning beliefs and e-learning adoption intention of academic staff in Nigerian universities. This study contributes to our understanding of

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the determinants of e-learning adoption in two significant ways. First, the study applies the decomposed theory of planned behavior (Taylor and Todd, 1995) to examine attitudes, subjective norms, and perceived behavioral controls, and how these factors influence e-learning adoption intention. Understanding how these intention antecedents influence e-learning adoption intention can assist higher education institution managers in developing effective strategies to promote e-learning adoption. Second, the study decomposes the antecedents of intentions into their belief structures. Several studies suggest that teachers' beliefs influence their teaching practices (Bice and Tang, 2022; Fang, 1996). As Richardson et al. (1991, p.560) point out, "ignoring teachers' beliefs in implementing change could lead to disappointing results." Therefore, to understand and influence e-learning adoption among academic staff in higher education institutions, it is essential to examine their e-learning beliefs (Stipek et al., 2001).

The remainder of this paper proceeds as follows: It provides the background and theoretical framework for the study, followed by the development of hypotheses. The next section outlines the research methodology and presents the findings from hypothesis testing. Finally, the implications of the study findings, limitations of the study and suggestions for future research are discussed.

Context of the study

In Nigeria, every year, a significant number of candidates who are seeking admission to universities face rejection because there is not enough space to accommodate all the qualified applicants. In response to the growing demand for university education in the country, the Government of Nigeria has taken steps to address this issue. This includes the establishment of several new universities and the deregulation of the higher education sector, allowing for private participation in the creation of higher educational institutions. Between 1999 and 2019, 138 new universities were licenced by the National Universities Commission (NUC). However, these efforts have not significantly addressed the demand-supply gap in the higher education system in Nigeria. Thus, there is the need to proffer a solution that is both quick to implement and of relatively low cost. The adoption of e-learning by universities meets these two criteria. Moreover, the on-going digital transformation of the global economy and discourse about the future of higher education (Rabin et al., 2020) necessitate e-learning adoption especially among academic staff.

Several studies have proposed the use of e-learning as a viable and cost-effective alternative to rapidly expand access to higher education (Algahtani, 2011; Arkorful and Abaidoo, 2015; Obi et al., 2020). Moreover, the availability of the internet across Nigeria enables institutions to overcome one of the major infrastructural challenges hindering e-learning adoption. Using e-learning to bridge the demand-supply gap will ease the admission crisis in Nigeria (Kanyip, 2013) by increasing the number of students admitted to universities. However, for e-learning to be a viable tool for expanding access to universities, e-learning needs to be widely adopted by academic staff. Several universities in Nigeria have gradually introduced e-learning either by setting up their own e-learning portals or using freely available e-learning tools such as Google Classroom and Moodle. Oluwalola and Omotayo (2019) found that e-learning facilities were moderately available in universities in Nigeria. However, e-learning is still not widely adopted by academic staff.

THEORETICAL FRAMEWORK

E-learning and e-learning adoption intention

E-learning is a new, innovative and evolving method of teaching and learning driven by the advancement in technology, especially the internet. E-learning is not just replicating traditional educational system online, it is distinct pedagogically. E-learning is an educational system that employs communication technologies to mediate the delivery of instructional content in the teaching-learning process (Alhomod and Shafi, 2013; Lee, 2006; Santos and Okazaki, 2016). E-learning integrates technology with pedagogy (Engelbrecht, 2003) to provide a more comprehensive, asynchronous, customizable and learners'-oriented education that is better suited to the knowledge-based, digital and globally interconnected economy (Williams and Goldberg, 2005). In this study, e-learning is defined as the use of the internet and multimedia technology to deliver teaching and learning over the internet to geographically dispersed persons.

Behavioral intention

Behavioral intention has been used as a significant predictor of actual behavior (Gatzioufa and Saprikis, 2022). According to Ajzen (1991), behavioral intentions capture the motivational factors that influence the performance of a behavior. As indicated by Warshaw and Davis (1985), behavioral intention matters when an individual, to a certain degree formulates conscious plans to perform or not perform future behaviors. It is therefore assumed that the individual has volitional control over his or her behavior (Sheppard et al., 1988; Taylor and Todd, 1995). This study aligns with Warshaw and Davis (1985)'s definition of behavioral intention for two reasons. First, the scope and definition espouse clarity and dearth of the construct as most articles reviewed do not provide explicit definitions of the construct. Second, the definition captures the conceptualization of the construct as being the likelihood of an individual to perform or not perform a specific behavior. In this study, behavioral intention towards the use of e-learning is referred to as e-learning adoption intention. Thus, following Warshaw and Davis (1985), e-learning adoption intention was define as the degree to which an academic staff has formulated conscious plans to adopt e-learning methods.

Antecedents of behavioral intention

In the literature, attitude, subjective norm and perceived behavioral control are recognized as key factors influencing behavioral intention (Ajzen, 1991; Taylor and Todd, 1995). Attitude refers to an individual's emotional response toward a particular behavior (Ajjan and Hartshorne, 2008; Ajzen, 1991; Cheon et al., 2012). Numerous studies suggest that attitude is a strong predictor of intention (Baker et al., 2007; Sadaf et al., 2012). This study further breaks down attitude into three components: Perceived usefulness, perceived ease of use and perceived compatibility. Drawing from technology acceptance model (TAM), perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance", while perceived ease of use is "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989. p. 320). Also, drawing from innovation diffusion literature, perceived compatibility is viewed as a significant predictor of attitude. Perceived compatibility is “the degree to which an innovation is perceived as consistent with the existing values, past experiences and needs of potential adopters” (Rogers, 1983, p.223).

Ajzen & Fishbein (1975) defined subjective norms as a “person’s perception that most people who are important to him think he should or should not perform a behavior”. Subjective norm can be described as the social pressure an individual gets from other people that motivate him/her to either perform or not perform a behavior (Ajzen, 1991; Theodorou et al., 2023). Social pressure is the willingness of an individual to be influenced by the perceived opinion of referent others. A referent other is a person or group whose opinion can influence an individual’s decision (Mathieson, 1991). Referent others may be peers, superiors or subordinates (Baker et al., 2007; Taylor and Todd, 1995b). Hence, subjective norm was decomposed into perceived administrators’ influence, perceived peers’ influence, and perceived students’ influence. Administrators are individuals holding leadership positions in their institutions. Administrators are usually responsible for defining the policies as well as for policy implementation. They are also responsible for the allocation of their institutions’ resources and the management of performance. Administrators influence the behaviors of academic staff due to their leadership positions in institutions. Peers usually exert a considerable influence on one another's behavior and reinforce desirable behaviors (Smith and Fowler, 1984). Thus, an individual frequently looks to his or her peers for cues on acceptable or unacceptable behaviors. Students as key participants in the teaching-learning process also exert influence on academic staff. Students are the primary beneficiaries and participants of e-learning adoption. Therefore, the disposition of students towards e-learning will influence the e-learning attitude of academic staff.

Perceived behavioral control reflects beliefs regarding the access to resources and opportunities needed to perform a behavior (Ajzen, 1991; Ong et al., 2023; Taylor and Todd, 1995). Ajzen (1991) describes perceived behavioral control as controlling factors that influences an individual’s intention to perform a behavior as well as the actual performance of the behavior. This implies that irrespective of the individual’s motivation and attitude towards a behavior, the presence or absence of controlling factors may facilitate or inhibit the performance of the specified behavior. Controlling factors may be time, money, opportunity and other resources required to perform a behavior (Ajzen, 1991; Nwagwu, 2020). Taylor and Todd (1995) identified self-efficacy and facilitating conditions as determinants of perceived behavioral controls. Self-efficacy is an individual’s perception of his or her ability to perform a behavior necessary to achieve a specific performance (Bandura, 1977, 1982); while facilitating conditions are environmental factors that influence an individual’s intention to perform a specific behavior (Teo, 2009, 2010; Teo et al., 2008). This study decomposes perceived behavioral control into self-efficacy and facilitating conditions.

Behavioral intention and technology adoption theories

A review of the literature shows that behavioral intention is central to several theories used to predict technology adoption. For example, behavioral intention is central to the theory of reasoned action (TRA) (Ajzen and Fishbein, 1975), technology acceptance model (TAM) (Davis et al., 1989), theory of planned behavior (TPB) (Ajzen, 1991), decomposed theory of planned behavior (DTPB) (Taylor and Todd, 1995) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). These theories are based on the association between behavioral intention and actual behaviour. While these theories have been used extensively in the literature to predict technology adoption, they are not without criticism (Bagozzi, 2007). In his commentary, Bagozzi (2007) critiqued the limitations of the technology acceptance model (TAM), which includes the theory of reasoned action (TRA) and the theory of planned behavior (TPB). He highlighted five shortcomings with TAM. Additionally, Bagozzi criticized the complexity of the unified theory of acceptance and use of technology (UTAUT), noting that it involves "41 independent variables for predicting intentions and at least eight independent variables for predicting behavior." Consequently, there is no consensus in the literature regarding an ideal theory for predicting technology use. However, this study considers the Decomposed Theory of Planned Behavior as an appropriate theory for predicting e-learning adoption. The rationale for applying the Decomposed Theory of Planned Behavior is described following.

Decomposed theory of planned behavior

The decomposed theory of planned behavior (DTPB) is an extension of the theory of planned behavior. DTPB decomposes the antecedents of intention (attitude, subjective norms and perceived behavior control) into their beliefs structure. Taylor and Todd (1995) suggest that the decomposition of the antecedents of intention into their beliefs structure will provide better understanding of the relationship between the beliefs and the antecedents of intention. Several studies have reaffirmed Taylor and Todd (1995) suggestion that the decomposition of the antecedents of intention into their beliefs structure provides better explanatory power and a more precise understanding of the intention to perform a behavior (Ndubisi, 2004; Sadaf et al., 2012; Shih and Fang, 2004).

This study adopted DTPB for the following reasons. First, DTPB encompasses TRA and TPB, however with better explanation for intention as a result of decomposing the antecedents of intentions into their beliefs structure. Second, as argued by Chu and Chen (2016), TAM puts greater emphasis on technology features (such as, perceived usefulness and perceived ease of use) and excludes social influences (subjective norms) which examine how an individual is influenced by other people when making technology adoption decisions. According to Chu and Chen (2016), extending TAM to include social influences will create a more complex model. Third, TPB excludes technology features (such as perceived usefulness and perceived ease of use), which are emphasised by TAM. Technology features such as perceived usefulness and perceived ease of use are important for the formation of intention to adopt a technology. Finally, UTAUT presents a model which is too complex “with 41 independent variables for predicting intentions and at least eight independent variables for predicting behavior” (Bagozzi, 2007). This study employs the decomposed theory of planned behavior because it enables the decomposition of attitude into perceived usefulness and perceived ease of use, thereby integrating key elements of TAM into the model. Additionally, the model includes perceived compatibility, which is drawn from diffusion of innovation (Rogers, 1983). The theory also enables the decomposition of subjective norm (such as administrators’, peers and students’ influence) to measure the social influences that exert social pressures on academic staff with regards to e-learning adoption intention. Finally, the theory decomposes perceived behavioral control into self-efficacy and facilitating conditions and measures its impact on e-learning adoption intention. This makes the decomposed theory of planned behavior appropriate for this study.

E-learning and e-learning beliefs

Beliefs are subjective, conscious or unconscious psychologically held understandings, a type of mental representation, personal judgment formulated from experiences and major determinants of behavior (Brown and Cooney, 1982; Hutner and Markman, 2016; Raymond, 1997; Richardson, 1996; Rokeach, 1972; Pehkonen and Pietilä, 2003). E-learning beliefs was defined as conscious or unconscious subjective held understanding about e-learning that determines the behavior of academic staff towards the use of e-learning. E-learning beliefs are operationalized in the study by decomposing the antecedents of e-learning adoption intentions into their belief’s structures. Thus, eight e-learning beliefs were identified. These include three attitudinal beliefs, three normative and two controlling beliefs.

Hypotheses development

Attitude towards e-learning and e-learning adoption intention

Attitude towards e-learning adoption was defined as the desire of academic staff to use e-learning methods in teaching their courses. According to Ajzen (1991), the more favourable an individual’s attitude towards a specific behavior, the stronger would be the intention of the individual to perform the behavior. Therefore, favourable attitude towards e-learning will significantly influence e-learning adoption intention of academic staff. Several studies have also found that attitude towards e-learning significantly influences e-learning adoption intentions (Cheon et al., 2012; Chu and Chen, 2016; Johnson et al., 2021; Ndubisi, 2004). Thus, the following hypothesis were proposed:

Hypothesis 1a: Attitude towards e-learning will positively influence e-learning adoption intention.

Attitudinal beliefs and attitude towards e-learning

Attitude towards a behavior is determined by the underlying belief structure about the behavior. Pajares (1992) described attitude as a cluster of beliefs that influences an individual’s action in a given situation. Taylor and Todd (1995) referred to the belief structure that influences attitude as attitudinal beliefs. Attitudinal beliefs were decomposed into perceived usefulness, perceived ease of use (Davis, 1989; Davis et al., 1989; Venkatesh and Davis, 1996) and perceived compatibility (Roger, 1983). Perceived usefulness of e-learning refers to the extent to which academic staff believe that using e-learning methods will enhance the teaching-learning experience. Perceived ease of use is the belief that using e-learning will require minimal effort. Perceived compatibility relates to the degree to which e-learning aligns with the existing teaching-learning practices in an institution. Previous studies have consistently demonstrated significant positive effects of perceived usefulness, perceived ease of use, and perceived compatibility on e-learning attitudes (Ajjan and Hartshorne, 2008; Ndubisi, 2004; Renda dos Santos and Okazaki, 2016; Sadaf et al., 2012). Therefore, academic staff are more likely to hold a positive attitude toward e-learning if they perceive that e-learning methods will be user-friendly, integrate well with the existing practices in their institutions, and contribute to the improvement of the teaching-learning experience. Thus, the following hypotheses were proposed:

Hypothesis 1b: Perceived usefulness of e-learning will positively influence attitude towards e-learning.
Hypothesis 1c: Perceived ease of use of e-learning will positively influence attitude toward e-learning
Hypothesis 1d: Perceived compatibility of e-learning will positively influence attitude toward e-learning

Subjective norm and e-learning adoption intention

Subjective norm suggests that social pressure from referent others (Mathieson, 1991) influences behavioral intention. Prior studies have identified positive association between subjective norm and behavioral intention (Baker et al., 2007; Chu and Chen, 2016; Renda dos Santos and Okazaki, 2016). For example, in a study conducted on university students' intention to use e-learning at a university in Taiwan, Chu and Chen (2016) found that subjective norm has significant influence on intention to use e-learning. However, in a similar study conducted by Ndubisi (2006) on Malaysian university students, subjective norm had no significant effect on intention to use e-learning. Other studies (Lee, 2006; Yuen and Ma, 2008) also found that subjective norm had no significant effect on e-learning adoption intention. Thus, the literature is inconclusive with respect to the effects of subjective norm on behavioral intention. However, this study is of the opinion that academic staff intention to use e-learning will be influenced by the social pressure from referent others (such as administrators, peers and students) within their institutions. Hence, subjective norms was decomposed into three normative beliefs - perceived influence of administrators, perceived influence of peers and perceived influence of students.

Administrators are responsible for policy formulation, implementation and performance management. Administrators may also determine the e-learning policy, budget for acquiring the appropriate information technology infrastructure as well as providing the budget for the training and development of employees with regard to the use of e-learning. Considering the role of administrators as policy makers and resource allocators, they can exert significant influence on academic staff.

Peers usually exert a considerable influence on one another's behavior and reinforce desirable behaviors (Smith and Fowler, 1984). Thus, an individual frequently looks up to his or her peers for cues on acceptable or unacceptable behaviors. Academic staff as a peer group exerts influence on each other's behavior. An institution whose academic staff are favourably disposed towards the use of e-learning is more likely to have positive e-learning influence over individual academic staff.

The adoption of e-learning will be problematic if students do not have a favourable disposition towards the use of e-learning. In other words, students' perception of e-learning will either aid or inhibit e-learning adoption. Therefore, students as a referent group can influence the use of e-learning in an institution.

Previous studies (Ajjan and Hartshorne, 2008; Sadaf et al., 2012) found that superiors (that is administrators), peers and students influence the subjective norm. Therefore, the following hypotheses were proposed:

Hypothesis 2a: Subjective norm will positively influence e-learning adoption intention.
Hypothesis 2b: Perceived administrators' influence will positively influence subjective norm.
Hypothesis 2c: Perceived peer influence will positively influence subjective norms.
Hypothesis 2d: Perceived students' influence will positively influence subjective norms

Perceived behavioral control and e-learning adoption intention

The perception of an individual about the availability or lack of availability of resources and opportunities required to perform a behavior influences his/her intention to perform the behavior (Ajzen, 1991). When applied to the current study, the perception of the presence of favourable controlling factors will facilitate e-learning adoption intention, while unfavourable perception of controlling factors will inhibit e-learning adoption intention. Prior studies also suggest that perceived behavioral control significantly influences behavioral intention (Baker et al., 2007; Chu and Chen, 2016; Ndubisi, 2004; Sadaf, Newby and Ertmer, 2012). Thus, the following hypotheses was proposed:

Hypothesis 3a: Perceived behavioral control regarding the use of e-learning will positively influence e-learning adoption intention.

Controlling beliefs are shaped by two controlling factors (Taylor and Todd, 1995). First, the belief in one's ability to perform an intended behavior (Bandura, 1977, 1982; Bandura et al., 1977; Bandura et al., 1980). Second, controlling factors that directly and indirectly influence the performance of the intended behavior. Ajzen (1991) refers to an individual's belief in his or her ability to perform an intended behavior as self-efficacy. While controlling factors that facilitate the performance of an intended behavior are referred to as facilitating conditions. Thus, this study decomposes perceived behavioral control into these two beliefs structure (self-efficacy and facilitating conditions).

Perceived self-efficacy and perceived behavioral control

In this study, self-efficacy was defined as the perceived self-confidence among academic staff with regard to the use of e-learning. Consequently, high levels of self-efficacy among academic staff will aid perceived behavioral control regarding e-learning adoption. While low levels of self-efficacy will impede perceived behavioral control regarding e-learning adoption. Therefore, the following hypothesis was proposed:

Hypothesis 3b: Perceived self-efficacy with regards to e-learning will positively influence perceived behavioral control.

Facilitating conditions and perceived behavioral control

Taylor and Todd (1995) described facilitation conditions as external resource constraints such as time, money and resources that influence an individual's intention to perform a specific behavior. Favourable environmental factors provide incentives to perform a behavior (Lu et al., 2005). In this study, facilitating conditions was defined as environmental factors that are capable of impacting e-learning adoption. Facilitating conditions relate to technological factors such as computer infrastructure, software and multimedia facilities required to effectively use e-learning. Considering the central role played by technological factors in the development and use of e-learning, the availability of an effective technology infrastructure will provide favourable facilitating conditions that aid the use of e-learning. Facilitating conditions also include other factors such as time, finance, training, e-learning knowledge and technical support that influence the use of e-learning (Groves and Zemel, 2000; Ndubisi, 2004; Nwagwu, 2020; Taylor and Todd, 1995). Therefore, favourable facilitating conditions will aid the use of e-learning. Consequently, the following hypothesis was proposed:

Hypothesis 3c: Facilitating conditions with regards to e-learning will positively influence perceived behavioral control.

METHOD

Sampling method

Guided by the literature, a testable conceptual model was developed as depicted in Figure 1. The conceptual model includes patterns of interaction between e-learning beliefs and e-learning adoption intentions. The target population for the study were academic staff at universities in Nigeria. According to the National University Commission, there were 61,000 academic staff in Nigerian universities (Punch, 2019). The study focused attention only on academic staff because they are most likely to be the primary users (together with their students) of e-learning systems in their institutions.

In determining the sample size for the study, the suggestion of Hair et al. (2014) was followed. According to Hair et al. (2014), the minimum observations for each independent variable should be a ratio is 5:1. However, the desired level should be between 15 to 20 observations for each independent variable to enable generalization of the results. Since the current study has eleven independent variables, the desired sample size should be between 165 and 220. Hence, the sample size of 188 is considered appropriate for the current study.

Data collection method

According to the National Universities Commission (NUC), there were 165 universities in Nigeria at the time the survey for the study was administered. This consists of 43 universities established by the federal government, 47 state universities and 75 privately owned universities. To administer the survey, 29 out of the 165 universities in the country were selected. The 29 universities were selected based on the following two criteria. First, the selected universities should be widely spread across the six geopolitical regions in the country. This is to ensure that the sample is representative of the entire country rather than a section of the country. The geographical spread of the selected universities included eleven institutions from South-West, six from South-East, five from South-South, four from North-Central, two from North-West and one from North-East Nigeria. Second, the selected universities should have a good mix of federal, state and private institutions. Thus, the selected institutions included ten federal universities (three each from south-West and South-East, two from North-West, and one each from South-South and North-Central), eight state universities (three each from South-South and South-West, while one each from South-East and North Central) and eleven private universities (five from South-West, two each from South-East and North Central, and one each from South-South and North-East).

The survey for the study was administered via email using 'Google Forms' - a survey administration application. To administer the survey, names and emails of potential respondents were obtained from the websites of the selected universities. The goal of the study was to obtain details (names and emails) of a hundred potential respondents per institution. Some of the largest universities in Nigeria employ less than 2,000 academic staff. For example, the University of Ibadan has 1,217 academic staff (Nwagwu, 2020), Ahmadu Bello University has 1,400 academic staff (Ahmadu Bello University, 2019), and while the University of Lagos has 813

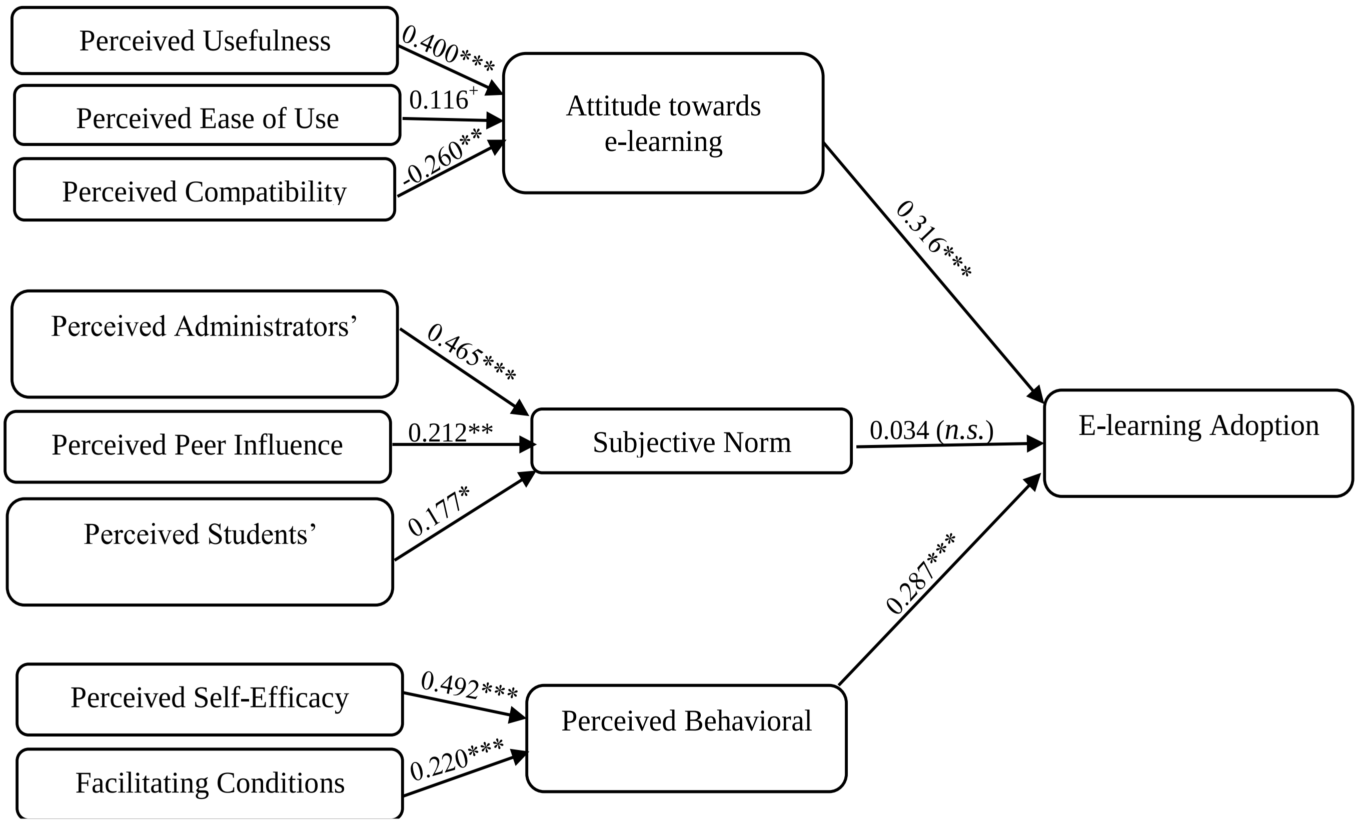

Figure 1. Path analysis of factors influencing e-learning adoption intention. **+**p<0.1, *p<0.05, **p<0.01, ***p<0.001, *n.s.*= not significant.

academic staff (University of Lagos, n.d.). It was rationalized that if these large universities have less than 2,000 academic staff, other smaller universities will have few numbers of academic staff. Based on this rationale, stratified size of one hundred academic staff per the selected institution appropriate for the study was considered. However, this goal was only achieveed for only 11 institutions. In other words, names and emails of 1,100 potential respondents from the websites of eleven large universities (100 potential respondents per university were obtained. Additional 612 names and emails of potential respondents were obtained from the websites of the remaining eighteen universities. In total, 1,712 names and emails of potential respondents from the selected 29 universities were obtained.

Between May 15, 2019 and June 16, 2019, emails were sent to the 1,712 potential respondents inviting them to complete the survey for the study. However, only 1,165 of the emails were delivered (547 emails returned as failure delivery). Out of the 1,165 delivered emails, only 188 persons completed the survey. All responses were usable. Potential response bias was checked for by adopting the technique used in previous studies (Mani et al., 2010). The respondents were grouped into early and late respondents. Then the demographic information of both groups was compared. There were no significant differences in the demographics of the two groups of respondents. Then an independent sample t-test was used to determine if any significant difference exists between early and late respondents to the survey. There was no significant difference. Hence, it was concluded that non-response is not a concern. potential common method was also checked for using the Harman's single factor test. The only component extracted explained a variance of 32.96%. Since the single factor explained a variance of less than 50%, this is an indication that the instrument is not biased.

Measurement development and scales

The measurements were drawn from previous studies and based on a five-point Likert scales using statements anchored "Strongly disagree" (1) to "Strongly agree" (5). E-learning adoption intention (ELAI) was measured using four items sourced from Ajjan and Hartshorne (2008) and Chu and Chen (2016). Attitude towards e-learning (ATT) was measured with five items sourced from Cheon et al. (2012) and Chu and Chen (2016). While the three attitudinal beliefs - perceived usefulness (PU), perceived ease of use (PEU) and perceived compatibility (PC) were measured with items in which thirteen were sourced from Ajjan and Hartshorne (2008), Cheon et al. (2012), Sadaf et al. (2012) and Taylor and Todd (1995).

Subjective norm (SN) was measured using four items sourced from Ajjan and Hartshorne (2008), Cheon et al. (2012), Chu and Chen (2016) and Taylor and Todd (1995). Subjective norm was decomposed into three normative beliefs - perceived administrators' influence (PAI), perceived peer influence (PPI) and perceived students' influence (PSI). All three normative beliefs were measured with ten items sourced from Ajjan and Hartshorne (2008), Cheon et al. (2012) and Chu and Chen (2016).

Perceived behavioral control (PBC) was measured with four items sourced from Chu and Chen (2016) and Shih and Fang (2004). Perceived behavioral control was decomposed into two beliefs - perceived self-efficacy (PSE) and facilitating conditions (FC). Perceived self-efficacy was measured with three items sourced from Cheon et al. (2012) and Sadaf et al (2012), while the six items used

Table 1. Demographic information.

Variable	Sub-group	Frequency	Percentage
Gender	Male	144	0.77
	Female	44	0.23
Age of respondents (years)	<30	4	0.02
	31 to 40	64	0.34
	41 to 50	70	0.37
	51 to 60	38	0.20
	>60	12	0.06
Computer experience (year)	<1	1	0.53
	1-3	2	1.06
	4- 6	10	5.32
	>6	175	93.09
Internet experience (year)	<1	1	0.53
	1-3	2	1.06
	4- 6	12	6.38
	>6	173	92.02

in measuring facilitating conditions were sourced from Renda dos Santos and Okazaki (2016), Shih and Fang (2004) and Taylor and Todd (1995).

RESULTS

Demographic profile of the respondents

The demographic profile of the respondents (Table 1) indicates that 77% are males and 23% female. Majority of the respondents are between the ages of 31 and 60 years. Respondents who are older than sixty years make up 6% of the sample. While only 2% are less than thirty years old. Most of the respondents have over six years of experience using computers (93.09%) and the internet (92.02%). Only 0.53% have less than one year of computer and internet experience. Others have between 1 and 6 years of experience using computers and the internet.

Analysis

The partial least square approach to structural equation modelling (PLS-SEM) on SmartPLS Version 3 was used in analysing the data. This approach allows the testing of causal relationships between the latent variables in the proposed conceptual framework. As suggested by Hair et al. (2014), there are two approaches to SEM: The covariance-based SEM which considers data that show multivariate normality as a pre-condition for further analysis and the variance-based approach PLS-SEM which does not require multivariate normality. Initial data screening and analysis of the data showed that the data exhibited non-normal attributes (Table 6); hence the choice for using PLS-SEM was justified. As suggested by Chin (1998), the two-step approach to evaluating structural equation models was followed. First, the reliability and validity of the measurement model as well as the significance of the structural path between the latent construct in the hypothesized model were tested.

Measurement model assessment

Reliability, convergent validity and discriminant validity were used to assess the model. Reliability, specifically with Cronbach's alpha (α) was assessed. Additionally, reliability was determined holistically with composite reliability (CR). Cronbach's alpha and composite reliability value should be ≥ 0.70 (Henseler et al., 2016; Urbach and Ahlemann, 2010). The Cronbach's alpha and composite reliability values for all constructs are compellingly higher than the recommended threshold 0.7 (Table 2).

Average variance extracted (AVE) was used to measure convergent validity. According to Hair et al. (2014), the AVE must be greater than 0.5 for convergent validity to be assured. All values for the constructs as indicated in Table 2 fall above the minimum threshold of 0.5, indicating a good convergent validity. Forty-nine items were initially loaded, but eight items did not meet the minimum threshold and were deleted.

Discriminant validity is assured when the following three conditions are met: (a) The loadings of each construct is greater than the cross loadings with other constructs (Chin, 1998; Urbach and Ahlemann, 2010); (b) the square

Table 2. Factor loadings and reliability statistics.

Variable	ATT	ELA	FC	PAI	PBC	PC	PEU	PPI	PSE	PSI	PU	SN	*α*	*CR*	*AVE*
ATT1	**0.881**	0.329	0.130	0.281	0.236	-0.418	0.371	0.287	0.303	0.359	0.475	0.368			
ATT2	**0.874**	0.334	0.167	0.298	0.301	-0.468	0.384	0.259	0.330	0.355	0.400	0.329	0.88	0.92	0.73
ATT3	**0.891**	0.367	0.102	0.268	0.258	-0.459	0.400	0.250	0.346	0.367	0.510	0.354			
ATT4	**0.776**	0.398	0.193	0.264	0.300	-0.413	0.493	0.356	0.422	0.383	0.622	0.293			
ELAI1	0.437	**0.907**	0.356	0.295	0.377	-0.459	0.541	0.342	0.481	0.516	0.488	0.279			
ELAI2	0.399	**0.920**	0.379	0.271	0.379	-0.389	0.514	0.290	0.433	0.420	0.488	0.271	0.89	0.93	0.76
ELAI3	0.271	**0.740**	0.173	0.123	0.238	-0.364	0.368	0.124	0.366	0.285	0.457	0.111			
ELAI4	0.333	**0.900**	0.306	0.268	0.373	-0.355	0.502	0.185	0.438	0.395	0.497	0.189			
FC1	0.162	0.424	**0.825**	0.293	0.397	-0.254	0.318	0.286	0.353	0.295	0.281	0.250			
FC2	0.214	0.316	**0.829**	0.389	0.309	-0.238	0.309	0.301	0.351	0.321	0.290	0.304			
FC3	0.114	0.222	**0.807**	0.360	0.242	-0.093	0.273	0.248	0.200	0.254	0.145	0.327	0.89	0.92	0.69
FC5	0.201	0.313	**0.868**	0.455	0.373	-0.233	0.422	0.365	0.326	0.424	0.249	0.362			
FC6	0.000	0.159	**0.835**	0.371	0.274	-0.103	0.276	0.256	0.201	0.220	0.116	0.305			
PAI3	0.254	0.225	0.447	**0.888**	0.212	-0.275	0.307	0.364	0.306	0.427	0.291	0.562	0.74	0.89	0.80
PAI2	0.324	0.283	0.352	**0.896**	0.259	-0.397	0.346	0.341	0.406	0.486	0.288	0.579			
PBC1	0.264	0.394	0.339	0.201	**0.860**	-0.433	0.419	0.277	0.554	0.334	0.305	0.259			
PBC2	0.216	0.267	0.372	0.243	**0.802**	-0.331	0.403	0.196	0.421	0.351	0.221	0.345	0.79	0.88	0.70
PBC3	0.330	0.329	0.283	0.227	**0.848**	-0.384	0.451	0.210	0.441	0.381	0.361	0.257			
PC2	-0.495	-0.412	-0.195	-0.410	-0.472	**0.927**	-0.487	-0.349	-0.382	-0.466	-0.479	-0.452	0.82	0.92	0.85
PC3	-0.449	-0.418	-0.237	-0.278	-0.370	**0.911**	-0.449	-0.243	-0.394	-0.401	-0.413	-0.337			
PEU1	0.394	0.380	0.292	0.289	0.426	-0.391	**0.833**	0.356	0.445	0.425	0.390	0.370			
PEU2	0.448	0.510	0.309	0.218	0.332	-0.438	**0.821**	0.302	0.436	0.397	0.486	0.327			
PEU3	0.308	0.364	0.282	0.281	0.425	-0.421	**0.791**	0.328	0.473	0.367	0.381	0.325	0.82	0.90	0.65
PEU4	0.446	0.519	0.314	0.369	0.465	-0.423	**0.815**	0.377	0.510	0.504	0.589	0.450			
PEU5	0.329	0.454	0.388	0.324	0.398	-0.375	**0.760**	0.348	0.411	0.501	0.535	0.424			
PPI1	0.347	0.311	0.346	0.370	0.196	-0.302	0.417	**0.887**	0.388	0.596	0.439	0.429			
PPI2	0.294	0.274	0.325	0.367	0.278	-0.304	0.429	**0.877**	0.348	0.506	0.392	0.451	0.86	0.91	0.78
PPI3	0.262	0.167	0.269	0.308	0.253	-0.253	0.279	**0.876**	0.344	0.547	0.232	0.457			

Table 2. Cont'd.

PSE1	0.433	0.461	0.244	0.307	0.494	-0.401	0.503	0.350	**0.833**	0.370	0.537	0.319			
PSE2	0.164	0.287	0.303	0.227	0.418	-0.241	0.415	0.306	**0.741**	0.309	0.231	0.177	0.72	0.84	0.65
PSE3	0.382	0.434	0.316	0.423	0.458	-0.362	0.440	0.325	**0.831**	0.375	0.425	0.364			
PSI1	0.329	0.372	0.349	0.239	0.304	-0.238	0.494	0.606	0.346	**0.727**	0.443	0.385			
PSI2	0.241	0.199	0.325	0.473	0.267	-0.275	0.357	0.393	0.200	**0.683**	0.262	0.375	0.78	0.86	0.60
PSI3	0.386	0.449	0.239	0.440	0.352	-0.468	0.461	0.501	0.417	**0.846**	0.395	0.472			
PSI4	0.366	0.428	0.266	0.432	0.376	-0.454	0.387	0.445	0.378	**0.833**	0.328	0.458			
PU1	0.526	0.528	0.276	0.297	0.355	-0.447	0.586	0.371	0.457	0.436	**0.914**	0.339	0.82	0.92	0.85
PU3	0.570	0.489	0.225	0.301	0.299	-0.450	0.516	0.367	0.472	0.413	**0.927**	0.311			
SN1	0.406	0.253	0.232	0.438	0.347	-0.490	0.422	0.294	0.349	0.440	0.392	**0.699**			
SN2	0.390	0.248	0.228	0.444	0.300	-0.405	0.449	0.389	0.351	0.457	0.331	**0.769**	0.74	0.84	0.56
SN3	0.250	0.127	0.287	0.496	0.165	-0.256	0.275	0.419	0.208	0.364	0.186	**0.799**			
SN4	0.133	0.135	0.354	0.532	0.204	-0.148	0.264	0.409	0.176	0.376	0.150	**0.723**			

ATT =Attitude towards e-learning, ELAI = E-learning Adoption Intention, FC = Facilitating Conditions, PAI = Perceived Administrators' Influence, PBC = Perceived Behavioural Control, PC = Perceived Compatibility, PEU = Perceived Ease of Use, PPI = Perceived Peer Influence, PSE = Perceived Self-Efficacy, PSI = Perceived Students' Influence, PU = Perceived Usefulness, SN = Subjective Norm.

root of the AVE for each construct is greater than the correlation between that construct and any other construct (Fornell and Larcker, 1981); (c) the heterotrait-monotrait ratio of correlations (HTMT) values are less than 0.90 (Henseler et al., 2015). From Table 2, it can be seen that the leadings of each construct are greater than the cross-loadings. The results in Table 3 shows that the square root of the AVE for each construct is greater than the cross correlation with other constructs. Finally, results of the $HTMT_{0.90}$ criterion presented in Table 3 also prove discriminant validity. In all, the results showed that the psychometric properties of the measures used in the study were adequate.

Structural model assessment

After a successful verification procedure of the measurement model, the study proceeded to assess the structural model. This was done to verify whether the structural relationships among the constructs were meaningful. To determine the significance of the path coefficients in the structural model, a bootstrap resampling procedure (with an iteration of 5000 sub-samples drawn with replacements from the initial sample of 40) was used. To explain the explanatory power of the structural model, the coefficient of determination R^2 was used to ascertain the predictability of the endogenous constructs (Table 5). According to Cohen (1988), the effect size impact indicator f^2 values can be large ($f^2 > 0.35$), medium ($0.15 \leq f^2 < 0.35$) and small ($0.002 \leq f^2 < 0.15$). Similarly, the predictive relevance Q^2 values are considered as weak effect $0.02 \leq Q^2 < 0.15$, moderate effect $0.15 \leq Q^2 < 0.35$ and strong effect $Q^2 > 0.35$ (Henseler et al., 2009).

The result of the analysis suggests attitude towards e-learning has a positive influence on e-learning adoption intentions (β=0.316, p<.001), supporting H1a. Perceived usefulness (β=0.400, p<0.001) and perceived compatibility (β=-0.260, p<0.01) have positive influence on attitude, supporting H1b and H1d. H1c shows that the effect of perceived ease of use on attitude is significant at 10% (β= 0.116, p<0.1). Contrary to this expectation, subjective norm has no significant influence on e-learning adoption intentions (β= 0.034, p>0.5). Thus, H2a is not supported. Perceived administrators' influence (β= 0.465, p<0.001), perceived peers' influence (β=0.212, p<0.01) and perceived students' influence (β= 0.177, p<0.05). significantly influence subjective norm. Hence, H2b, H2c and H2d are supported.

Table 3. Testing discriminant validity using the HTMT ratio.

Variable	Mean	Std. deviation	ATT	ELAI	FC	PAI	PBC	PC	PEU	PPI	PSE	PSI	PU	SN
ATT	4.415	0.586												
ELAI	4.043	0.687	0.462											
FC	2.816	0.891	0.193	0.373										
PAI	3.673	0.623	0.400	0.337	0.551									
PBC	3.684	0.692	0.384	0.461	0.457	0.348								
PC	3.610	0.744	0.605	0.528	0.260	0.479	0.565							
PEU	3.943	0.699	0.541	0.622	0.439	0.458	0.617	0.604						
PPI	3.823	0.675	0.389	0.312	0.401	0.497	0.330	0.386	0.496					
PSE	3.934	0.764	0.503	0.609	0.431	0.541	0.744	0.543	0.713	0.520				
PSI	3.803	0.643	0.514	0.550	0.447	0.673	0.540	0.580	0.670	0.773	0.577			
PU	3.723	0.434	0.689	0.650	0.304	0.416	0.441	0.593	0.704	0.481	0.643	0.580		
SN	3.606	0.637	0.490	0.302	0.457	0.864	0.450	0.556	0.591	0.636	0.491	0.723	0.456	

ATT = Attitude towards e-learning, ELAI = E-learning Adoption Intention, FC = Facilitating Conditions, PAI = Perceived Administrators' Influence, PBC = Perceived Behavioral Control, PC = Perceived Compatibility, PEU = Perceived Ease of Use, PPI = Perceived Peer Influence, PSE = Perceived Self-Efficacy, PSI = Perceived Students' Influence, PU = Perceived Usefulness, SN = Subjective Norm.

Table 4. Hypotheses testing of direct effects.

Variable	Path coefficient	T statistics	P values	Result
ATT → ELAI (H1a)	0.316	4.049	0.000	Supported
PU → ATT (H1b)	0.400	5.741	0.000	Supported
PEU → ATT (H1c)	0.116	1.580	0.057	Partially supported
PC → ATT (H1d)	-0.260	3.050	0.001	Supported
SN → ELAI (H2a)	0.034	0.342	0.366	Not supported
PAI → SN (H2b)	0.465	7.587	0.000	Supported
PPI → SN (H2c)	0.212	2.414	0.008	Supported
PSI → SN (H2d)	0.177	2.054	0.020	Supported
PBC → ELAI (H3a)	0.287	4.938	0.000	Supported
PSE → PBC (H3b)	0.492	7.525	0.000	Supported
FC → PBC (H3c)	0.220	3.739	0.000	Supported

SRMR 0.075.

Perceived behavioral control has a positive influence on e-learning adoption intentions (β=0.287, p<0.001), supporting H3a. Facilitating conditions (β= 0.220, p<0.001) and perceived self-efficacy (β=0.492, p<0.001) significantly influence perceived behavioral control, thereby supporting H3b and H3c. A summary of the results is presented in Table 4. In all, 25.6% of the variance in e-learning adoption intention was explained by the model. The overall fitness of the model was assessed using the SRMR composite factor model. The composite model SRMR value for the model was 0.075, below the 0.08 threshold recommended by Hu and Bentler (1999).

DISCUSSION

Attitude and attitudinal beliefs regarding e-learning

The findings of the study show that attitude towards e-learning is positively related to e-learning adoption intention (t=4.049, p<0.001). This is consistent with the findings of previous studies on the relationship between attitude and intention (Ajjan and Hartshorne, 2008; Baker et al., 2007; Cheon et al., 2012; Chu and Chen, 2016; Ndubisi, 2004; Park, 2009; Sadaf et al., 2012). Therefore, the more favourable the attitude of academic staff towards e-learning is, the stronger their intentions to adopt e-learning. The findings show that perceived usefulness (t=5.741, p<0.001) and perceived compatibility (t=3.050, p<0.001) have a positive influence on attitude towards e-learning. These findings are also consistent with previous studies; for example, perceived usefulness (Lee, 2006; Ndubisi, 2004; Renda dos Santosa and Okazaki, 2015) and perception of compatibility (Liao and Lu, 2008). Although perception of ease of use has a positive influence on attitude towards e-learning, the influence was not significant as expected (t=1.580, p<0.1).

Table 5. Predictive relevance (Q^2).

Predictor	Endogenous	$Q^2_{Included}$	$Q^2_{Excluded}$	q^2	$R^2_{Included}$	$R^2_{Excluded}$	f^2
Perceived usefulness	Attitude towards e-learning	0.343	0.264	0.120	0.516	0.419	0.200
Perceived ease of use	Attitude towards e-learning	0.343	0.338	0.008	0.516	0.502	0.029
Perceived compatibility	Attitude towards e-learning	0.343	0.339	0.006	0.516	0.502	0.029
Perceived administrators influence	Subjective Norm	0.256	0.180	0.102	0.491	0.346	0.285
Perceived peer influence	Subjective Norm	0.256	0.247	0.012	0.491	0.470	0.041
Perceived student's influence	Subjective Norm	0.256	0.252	0.005	0.491	0.475	0.031
Perceived self-efficacy	Perceived Behavioral Control	0.250	0.192	0.077	0.490	0.406	0.165
Facilitating conditions	Perceived Behavioral Control	0.250	0.176	0.099	0.490	0.337	0.300
Attitude towards e-learning	E-learning Adoption Intention	0.196	0.126	0.087	0.272	0.179	0.128
Subjective norm	E-learning Adoption Intention	0.196	0.198	-0.002	0.272	0.274	-0.003
Perceived behavioral control	E-learning Adoption Intention	0.196	0.150	0.057	0.272	0.214	0.080

Table 6. Normality test.

Variable	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Attitude towards e-learning	0.171	188	0.000	0.837	188	0.000
Perceived ease of use	0.134	188	0.000	0.938	188	0.000
Perceived usefulness	0.158	188	0.000	0.875	188	0.000
Perceived compatibility	0.301	188	0.000	0.819	188	0.000
Subjective norm	0.115	188	0.000	0.973	188	0.001
Perceived administrators influence	0.344	188	0.000	0.812	188	0.000
Perceived peer influence	0.194	188	0.000	0.933	188	0.000
Perceived student's influence	0.152	188	0.000	0.951	188	0.000
Perceived behavioral control	0.108	188	0.000	0.964	188	0.000
Perceived self-efficacy	0.151	188	0.000	0.931	188	0.000
Facilitating conditions	0.104	188	0.000	0.971	188	0.001
E-learning adoption intention	0.209	188	0.000	0.886	188	0.000

Examining e-learning adoption intention among academic staff in higher education institutions: a developing country context.

Reflecting on the attitudinal beliefs, it makes logical sense that they should influence the attitude of academic staff with regard to e-learning adoption intentions. Perceived usefulness indicates that e-learning will be beneficial. Consequently, the perceived belief that e-learning will improve the teaching-learning experience will motivate academic staff to have a positive attitude and influence their intention to adopt e-learning. Although perceived usefulness of e-learning motivates the attitude of the academic staff and positively influence their intention to use e-learning, the lack of compatibility (Rogers, 1983) of e-learning with the existing practices may create a problematic situation. Thus, compatibility of e-learning to the existing system is an important motivator that aids the e-learning adoption intention. Therefore, the combination of these two attitudinal beliefs (perceived usefulness and perceived compatibility) provides significant motivation for academic staff to have positive e-learning adoption intention.

Subjective norm and normative beliefs

The finding of the study indicates that perceived administrators' influence (t=7.587 p<0.001) has a significant positive influence on subjection norm. Administrators as policymakers and resource allocators can exert considerable social pressure on academic staff. For example, a policy that makes the use of e-learning mandatory exerts pressure on academic staff to use e-learning. Hence, administrators use policies to influence the behavior of academic staff by exerting pressures that compel them to align their e-learning behaviors with the e-learning policies of their institution.

According to Smith and Fowler (1984), peers usually exert a considerable influence on one another's behavior and reinforce desirable behaviors. For an academic staff to exert influence on his/her peers, he/she must provide incentives that exert social pressure on his/her peers (Kandel and Lazear, 1992). However, peer influence can be a mixed blessing (Barron and Gjerde, 1997). It can either positively influence the intention of others to adopt e-learning or negatively influence others and inhibit e-learning adoption intentions. The finding of the study indicates that perceived peer influence (*t*=2.414, *p*<0.01) to use e-learning will exert social pressure on academic staff to use e-learning. Perceived peer influence to use e-learning will be effective if it provides incentives for academic staff to use e-learning. This is important as it can be used as a tool to encourage the adoption of e-learning. This can be done by deliberately creating incentives especially for early adopters of e-learning in such a manner that such incentives will exert social pressure on others to use e-learning.

The findings also indicate that perceived students' influence (*t*=2.054 *p*<0.05) to use e-learning will exert social pressure on academic staff, thereby indirectly influencing the intentions of academic staff to use e-learning. Ajjan and Hartshorne (2008) and Sadaf et al. (2012) also found that students exert considerable influence on subjective norm. Students in higher education institutions, especially undergraduates tend to be younger adults usually below the age of 30 years. Younger adults tend to be more technology oriented and more likely to use the internet for their activities including academic related activities. Therefore, students are likely to be more oriented toward e-learning. On the other hand, academic staff, in trying to improve their teaching and the performance of their students, may likely be influenced by their students' technology orientation. Hence, an academic staff who is not positively oriented towards the use of technology may be perceived as out of date with technological development and "obsolete". Thus, academic staff may be compelled to maintain a level of technology awareness to avoid being perceived as "obsolete" by their students. Students' influence on academic staff can also be used to deliberately motivate academic staff to adopt e-learning. This can be done by creating an environment that drives the use of technology among the student population. This use of technology will exert pressure on academic staff to also adopt technology such as the use of e-learning.

Contrary to the study prediction, the results of the study indicate that subjective norm has no significant influence on e-learning adoption intention (*t*=0.342, *p*>0.05). In a similar study examining the factors affecting e-learning adoption among higher education students in Nigeria, Yakubu and Dasuki (2019) also did not find a significant relationship between social influence and behavioural intentions. However, in another study at Covenant university in Nigeria, Odegbesan et al. (2019) found that social influence has a positive effect of the behavioral intention. Thus, subjective norm as a predictor of behavioral intention has inconclusive findings in the literature. Taylor and Todd (1995) described subjective norm as somewhat unclear as a predictor of behavioral intention. Moreover, subjective norm has been found to be more important prior to or at the early stage of technology implementation when users have only limited direct experience of the technology (Taylor and Todd, 1995).

Perceived behavioral controls and controlling beliefs

The result also shows that perceived behavioral control (*t*=4.938, *p*<0.001) positively influences e-learning adoption intentions. Previous studies also reported similar findings (Ajjan and Hartshorne, 2008; Baker et al., 2007; Cheon et al., 2012; Chu and Chen, 2016; Ndubisi, 2004; Sadaf et al., 2012). Perceived behavioral control aids e-learning adoption intention in circumstances where the resources required to effectively use e-learning are available. E-learning resources include adequate e-learning infrastructure, competences in terms of e-learning knowledge and skills required to use e-learning as well as effective institutional e-learning policies that guide the use of e-learning.

Perceived self-efficacy (*t*=7.525, *p*<0.001) positively influences perceived behavioral control. Ajjan and Hartshorne (2008), Cheon et al. (2012) and Sadaf et al. (2012) also had similar findings. Perceived self-efficacy is the individual's perception of his or her ability to perform a behavior necessary to achieve a specific performance (Bandura, 1977, 1982). Perceived self-efficacy does not reflect an individual's skill, rather it is the individual's perception of his/her confidence to perform a specific behavior (de Vries et al., 1988). Perceived self-efficacy of academic staff with regard to e-learning implies that academic staff are confident in their abilities to effectively use e-learning methods. Moreover, perceived self-efficacy can be improved` through the provision of e-learning training. E-learning training will provide academic staff with the skill they need to effectively use e-learning, thereby increasing their confidence to use e-learning.

Facilitating conditions (*t*=3.739, *p*<0.001) also have positive effect on perceived behavioral control. Previous studies (Al-Azawei et al., 2016; Al-Kuwaiti, 2014; Groves and Zemel, 2000) found that favourable facilitating conditions positively influence perceived behavioral control. Favourable facilitating conditions such as the availability of adequate e-learning infrastructure creates a sense of control with regard to the use of e-learning, thereby positively influencing e-learning adoption intentions of academic staff.

Theoretical implications

The study contributes to the determinants of e-learning adoption in higher education institutions in several ways. Prior studies frequently approached the determinants of e-learning adoption in developing countries from the perspectives of inadequate infrastructure, knowledge gap and behavioral barriers (Chu and Chen, 2016; Folorunso et al., 2006; Kisanga and Ireson, 2015; Mtebe and Raisamo, 2014; Omeje et al., 2019; Renda dos Santos and Okazaki, 2016; Sanga et al., 2013; Sife et al., 2007; Unwin et al., 2010). These studies focused only on controlling factors (such as inadequate infrastructure, knowledge gap and behavioral barriers). The argument in these studies assumes that if these factors are available, e-learning will be widely adopted. However, little attention has been paid to the e-learning adoption intention especially of academic staff. Intention is a significant predictor of actual behavior (Ajzen, 1991; Warshaw and Davis, 1985). Hence, understanding the e-learning adoption intention of academic staff provides significant insight into the possible e-learning adoption behavior of academic staff. Additionally, how e-learning beliefs indirectly influence e-learning adoption intention was examined. Beliefs play important roles when implementing change in an institution (Richardson et al., 1991). Thus, in trying to understand the determinants of e-learning adoption in higher education institutions, it is important to understand the e-learning beliefs and e-learning adoption intentions of academic staff who are the primary users (together with their students) of e-learning systems.

Managerial implications

In this era of digital connectivity and rapid growth in the demand for higher education (Marginson, 2016), the challenge before managers of higher education institutions is to find ways of embracing the opportunities offered by the digital economy by adopting innovations such as e-learning. The findings of the study will enable managers of higher education institutions to have a better understanding of how e-learning beliefs and e-learning adoption intentions influences e-learning adoption in their institutions. This study broadens the perception of managers with regard to determinants of e-learning adoption. Rather than focusing only on providing favourable controlling factors, this study enables managers to craft strategies that will motivate favourable beliefs, attitude and social influences that aid e-learning adoption.

Furthermore, the findings of the study provide managers with tools that can be used to positively influence academic staff in their institution towards the use of e-learning. For example, managers can positively influence the attitude of academic staff towards the use of e-learning by creating programmes that emphasize the usefulness of e-learning. Managers as policymakers can also develop policies that enable the compatibility of e-learning with the existing systems and policies of the institution. Therefore, to stimulate the use of e-learning in higher education institutions, managers should not only focus on the provision of adequate e-learning infrastructure, but they (managers) should also focus on the e-learning beliefs of academic staff.

Limitations of the study

As is typical in research endeavours, this study encountered several limitations that may affect the generalizability of the findings. The study relied on self-reported surveys, which are susceptible to potential biases. Like all self-reported surveys, the responses may be influenced by the respondents' biases rather than accurately representing the actual situation in their institutions. Furthermore, the sample only included academic staff. However, non-academic staff and students also play crucial roles in the adoption of e-learning in higher education institutions. Future studies could broaden their scope to encompass both non-academic staff and students to create a more representative sample of the university community concerning e-learning adoption intention.

A longitudinal approach could provide a more in-depth understanding of the adoption intentions of academic staff at higher education institutions. The study also encountered limitations in data collection. While the intention was to collect data from a potential sample of one hundred respondents per institution, this was achieved in only eleven institutions. Finally, even though response bias was not a concern in the study, the response rate of 10.12% is relatively low. A higher response rate would enhance the confidence in the sample's representativeness.

Conclusion

E-learning offers a substantial opportunity for developing countries to rapidly expand the availability of higher education to their populations. It is a cost-effective and easily deployable solution that can be used to enhance the participation rate in higher education. However, for e-learning to have a significant impact and effectively increase higher education participation, it needs to be widely adopted by academic staff.

Prior research on the determinants of e-learning adoption in developing countries primarily focused on controlling factors like inadequate infrastructure, knowledge gaps, and behavioral barriers. While these control factors are undeniably crucial for e-learning adoption, they do not provide a comprehensive understanding of the determinants in developing countries. Based on data collected from a sample of 188 respondents, this study demonstrates that, in addition to addressing these control factors, e-learning beliefs play a significant role in indirectly influencing the e-learning adoption intentions of academic staff.

As a result, this study contributes to our understanding of the determinants of e-learning adoption intentions and offers valuable insights to higher education institution managers, aiding their efforts to promote e-learning adoption.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Ajjan H, Hartshorne R (2008). Investigating faculty decisions to adopt Web 2.0 technologies: Theory and empirical tests. The Internet and Higher Education 11(2):71-80.

Ajzen I (1991). The theory of planned behaviour. Organizational Behaviour and Human Decision Processes 50(2):179-211.

Al-Azawei A, Parslow P, Lundqvist K (2016). Barriers and opportunities of e-learning implementation in Iraq: A case of public universities. The International Review of Research in Open and Distributed Learning 17(5).

Algahtani AF (2011). Evaluating the effectiveness of the e-learning experience in some universities in Saudi Arabia from male students' perceptions. PhD thesis, Durham University, UK.

Alhomod S, Shafi MM (2013). Success Factors of E-Learning Projects: A Technical Perspective. Turkish Online Journal of Educational Technology 12(2):247-253.

Al-Kuwaiti A (2014). The perception of academic staff towards e-learning dental colleges in Saudi Arabia. International Journal of Medicine 504:510.

Ahmadu Bello University (2019). History of Ahmadu Bello University. Available at: https://abu.edu.ng/history/ (accessed 03 September 2020).

Arkorful V, Abaidoo N (2015). The role of e-learning, advantages and disadvantages of its adoption in higher education. International Journal of Instructional Technology and Distance Learning 12(1):29-42.

Ajzen I, Fishbein M (1975). A Bayesian analysis of attribution processes. Psychological bulletin 82(2):261.

Bagozzi RP (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. Journal of the Association for Information Systems 8(4):244-254.

Baker WE, Al-Gahtani SS, Hubona GS (2007). The effects of gender and age on new technology implementation in a developing country: Testing the theory of planned behaviour (TPB). Information Technology and People 20(4):352-375.

Bandura A (1977). Self-efficacy: toward a unifying theory of behavioural change. Psychological Review 84(2):191.

Bandura A (1982). Self-efficacy mechanism in human agency. American Psychologist 37(2):122-147.

Bandura A, Adams NE, Beyer J (1977). Cognitive processes mediating behavioral change. Journal of Personality and Social Psychology 35(3):125-139.

Bandura A, Adams NE, Hardy AB (1980). Tests of the generality of self-efficacy theory. Cognitive Therapy and Research 4(1):39-66.

Barron JM, Gjerde KP (1997). Peer pressure in an agency relationship. Journal of Labor Economics 15(2):234-254.

Bice H, Tang H (2022). Teachers' beliefs and practices of technology integration at a school for students with dyslexia: A mixed methods study. Education and Information Technologies 27(7):10179-10205.

Brown CA, Cooney TJ (1982). Research on Teacher Education: A Philosophical Orientation in Some Contemporary Problems in Mathematics Education. Journal of Research and Development in Education, Athens Ga 15(4):13-18.

Cheon J, Lee S, Crooks SM, Song J (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. Computers & Education 59(3):1054-1064.

Chin WW (1998). The partial least squares approach to structural equation modeling. Modern Methods for Business Research 295(2):295-336.

Chu TH, Chen YY (2016). With good we become good: Understanding e-learning adoption by theory of planned behaviour and group influences. Computers and Education 92:37-52.

Cohen J (1988). Statistical power analysis for the behavioral sciences. 2nd ed. Hillsdale, NJ: Erlbaum.

Davis FD (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly pp. 319-340.

Davis FD, Bagozzi RP, Warshaw PR (1989). User acceptance of computer technology: a comparison of two theoretical models. Management Science 35(8):982-1003.

de Vries H, Dijkstra M, Kuhlman P (1988). Self-efficacy: the third factor besides attitude and subjective norm as a predictor of behavioural intentions. Health Education Research 3(3):273-282.

Engelbrecht E (2003). A look at e-learning models: investigating their value for developing an e-learning strategy. Progressio 25(2):38-47.

Fang Z (1996). A review of research on teacher beliefs and practices. Educational Research 38(1):47-65.

Fishbein M, Ajzen I (1975). Belief, attitude, intention and behavior: An introduction to theory and research. Reading, MA: Addison-Wesley.

Fornell C, Larcker DF (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research 18(1):39-50.

Folorunso O, Ogunseye OS, Sharma SK (2006). An exploratory study of the critical factors affecting the acceptability of e-learning in Nigerian universities. Information Management and Computer Security Journal 14(5):496-505.

Gatzioufa P, Saprikis V (2022). "A literature review on users' behavioral intention toward chatbots' adoption", Applied Computing and Informatics, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/ACI-01-2022-0021

Groves MM, Zemel PC (2000). Instructional technology adoption in higher education: An action research case study. International Journal of Instructional Media 27(1):57.

Hair JF, Black WC, Babin BJ, Anderson RE (2014). Multivariate data analysis. 7th Edition. Edinburg: Pearson.

Henseler J, Ringle CM, Sarstedt M (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the academy of marketing science 43:115-135.

Henseler J, Hubona G, Ray PA (2016). Using PLS path modeling in new technology research: updated guidelines. Industrial Management and Data Systems 116(1):2-20.

Henseler J, Ringle CM, Sinkovics RR (2009). The use of partial least squares path modeling in international marketing. In New Challenges to International Marketing. Emerald Group Publishing Limited.

Hu LT, Bentler PM (1999). Cut off criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal 6(1):1-55.

Johnson JB, Reddy P, Chand R, Naiker M (2021). Attitudes and awareness of regional Pacific Island students towards e-learning. International Journal of Educational Technology in Higher Education 18(1):1-20.

Kandel E, Lazear EP (1992). Peer pressure and partnerships. Journal of Political Economy 100(4):801-817.

Kanyip BP (2013). Admission Crisis in Nigerian Universities: The challenges youth and parents face in seeking admission. PhD Thesis, Seton Hall University, NJ.

King E, Boyatt R (2015). Exploring factors that influence adoption of e-learning within higher education. British Journal of Educational Technology 46(6):1272-1280.

Kisanga D, Ireson G (2015). Barriers and strategies on the adoption of e-learning in Tanzanian higher learning institutions: Lessons for adopters. International Journal of Education and Development using Information and Communication Technology 11(2):126-137.

Lee YC (2006). An empirical investigation into factors influencing the adoption of an e-learning system. Online Information Review 30(5):517-541.

Liao HL, Lu HP (2008). The role of experience and innovation characteristics in the adoption and continued use of e-learning websites. Computers and Education 51(4):1405-1416.

Lu J, Yu CS, Liu C (2005). Facilitating conditions, wireless trust and adoption intention. Journal of Computer Information Systems 46(1):17-24.

Mani D, Barua A, Whinston A (2010). An empirical analysis of the impact of information capabilities design on business process outsourcing performance. MIS Quarterly 34(1):39-62.

Marginson S (2016). The worldwide trend to high participation higher education: dynamics of social stratification in inclusive systems. Higher Education 72:413-434.

Mathieson K (1991). Predicting user intentions: Comparing the

technology acceptance model with the theory of planned behaviour. Information Systems Research 2(3):173-191.
Mtebe JS, Raisamo R (2014). Investigating perceived barriers to the use of open educational resources in higher education in Tanzania. The International Review of Research in Open and Distributed Learning 15(2).
Ndubisi N (2006). Factors of online learning adoption: A comparative juxtaposition of the theory of planned behaviour and the technology acceptance model. International Journal on E-learning 5(4):571-591.
Ndubisi NO (2004). Factors influencing e-learning adoption intention: Examining the determinant structure of the decomposed theory of planned behaviour constructs. In Proceedings of the 27th Annual Conference of HERDSA pp. 252-262.
Nwagwu WN (2020). E-learning readiness of universities in Nigeria - what are the opinions of the academic staff of Nigeria's premier university? Education and Information Technologies 25:1343-1370.
Obi OA, Eze SE, Ogochukwu NW (2020). E-learning: A Trend for Effective TVET Sustainability in Nigeria. Vocational and Technical Education Journal 2(1):195-201.
Odegbesan OA, Charles A, Aderonke AO, Adeoba TF (2019). The prospects of adopting e-learning in the Nigerian education system: a case study of Covenant University. In Journal of Physics: Conference Series 1299(1):012058.
Oluwalola FK, Omotayo AA (2019). Availability and utilization of e-learning facilities for management and business courses in universities in Kwara State, Nigeria. Nigerian Journal of Business Education 6(2):346-357.
Omeje HO, Orji CT, Okereke GK (2019). Assessing the extent of e-learning utilization by industrial technical education lecturers for effective teaching and learning in universities. Journal of Engineering and Applied Sciences 14(11):3790-3796.
Ong AKS, Prasetyo YT, Borja AKFP, Hosillos FA, Perez YFN, Robas KP, Persada SF, Nadlifatin R (2023). Factors affecting revisiting behavior to Taal Volcano during the post recovery 2020 eruption: An extended theory of planned behavior approach. International Journal of Disaster Risk Reduction. P 103552.
Pajares MF (1992). Teachers' beliefs and educational research: Cleaning up a messy construct. Review of Educational Research 62(3):307-332.
Park SY (2009). An Analysis of the Technology Acceptance Model in Understanding University Students' Behavioral Intention to Use e-Learning. Educational Technology and Society 12(3):150-162.
Pehkonen E, Pietilä A (2003, February). On relationships between beliefs and knowledge in mathematics education. In Proceedings of the CERME-3 (Bellaria) meeting (pp. 1-8).
Rabin E, Kalman YM, Kalz M (2020). The cathedral's ivory tower and the open education bazaar–catalyzing innovation in the higher education sector. Open Learning: The Journal of Open, Distance and e-Learning 35(1):82-99.
Rakhyoot WAA (2017). Institutional and individual barriers of e-learning adoption in higher education in Oman: academics' perspectives. PhD Thesis, University of Strathclyde, UK.
Renda dos Santos LM, Okazaki S (2016). Planned e-learning adoption and occupational socialisation in Brazilian higher education. Studies in Higher Education 41(11):1974-1994.
Richardson V, Anders P, Tidwell D, Lloyd C (1991). The relationship between teachers' beliefs and practices in reading comprehension instruction. American Educational Research Journal 28(3):559-586.
Rogers EM (1983). Diffusion of innovations. The Free Press.
Rokeach M (1972). Beliefs, attitudes and values: A theory of organization and change. Jossey-Bass.
Sadaf A, Newby TJ, Ertmer PA (2012). Exploring factors that predict pre-service teachers' intentions to use Web 2.0 technologies using decomposed theory of planned behaviour. Journal of Research on Technology in Education 45(2):171-196.
Sanga C, Magesa MM, Chingonikaya E, Kayunze KA (2013). Can e-learning promote participation of female students in STEM disciplines in higher learning institutions of Tanzania? International Journal of Education and Development using ICT 9(3).
Sheppard BH, Hartwick J, Warshaw PR (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. Journal of Consumer Research 15(3):325-343.
Shih YY, Fang K (2004). The use of a decomposed theory of planned behaviour to study Internet banking in Taiwan. Internet Research 14(3):213-223.
Sife A, Lwoga E, Sanga C (2007). New technologies for teaching and learning: Challenges for higher learning institutions in developing countries. International Journal of Education and Development using ICT 3(2):57-67.
Smith LKC, Fowler SA (1984). Positive peer pressure: The effects of peer monitoring on children's disruptive behaviour. Journal of Applied Behaviour Analysis 17(2):213-227.
Stipek DJ, Givvin KB, Salmon JM (2001). Teachers' beliefs and practices related to mathematics instruction. Teaching and Teacher Education 17(2):213-226.
Tandon U, Mittal A, Bhandari H, Bansal K (2022). E-learning adoption by undergraduate architecture students: Facilitators and inhibitors. Engineering, Construction and Architectural Management 29(10):4287-4312.
Taylor S, Todd P (1995a). Decomposition and crossover effects in the theory of planned behaviour: A study of consumer adoption intentions. International Journal of Research in Marketing 12(2):137-155.
Taylor S, Todd P (1995b). Understanding information technology usage: A test of competing models. Information Systems Research 6(2):144-176.
Teo T (2009). The impact of subjective norm and facilitating conditions on pre-service teachers' attitude toward computer use: A structural equation modeling of an extended technology acceptance model. Journal of Educational Computing Research 40(1):89-109.
Teo T (2010). Examining the influence of subjective norm and facilitating conditions on the intention to use technology among pre-service teachers: A structural equation modeling of an extended technology acceptance model. Asia Pacific Education Review 11(2):253-262.
Teo T, Lee CB, Chai CS (2008). Understanding pre-service teachers' computer attitudes: Applying and extending the Technology Acceptance Model. Journal of Computer Assisted Learning 24(2):128-143.
Theodorou A, Hatzithomas L, Fotiadis T, Diamantidis A, Gasteratos A (2023). The impact of the COVID-19 pandemic on online consumer behavior: Applying the theory of planned behavior. Sustainability 15(3):2545.
University of Lagos (n.d.). About us. Available at: https://unilag.edu.ng/?page_id=7 (Accessed 03 September 2020).
Unwin T, Kleessen B, Hollow D (2010). Digital learning management systems in Africa: myths and realities. Open Learning: The Journal of Open, Distance and E-Learning 25(1):5-23.
Urbach N, Ahlemann F (2010). Structural equation modelling in information systems research using partial least squares. Journal of Information Technology Theory and Application 11(2):5-40.
Venkatesh V, Davis FD (1996). A model of the antecedents of perceived ease of use: Development and test. Decision Sciences 27(3):451-481.
Venkatesh V, Morris MG, Davis GB, Davis FD (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly pp. 425-478.
Warshaw PR, Davis FD (1985). Disentangling behavioural intention and behavioural expectation. Journal of Experimental Social Psychology 21(3):213-228.
Williams JB, Goldberg M (2005). The evolution of e-learning, balance, fidelity, mobility: Maintaining the momentum? 725-728. Proceedings of the 22nd ASCILITE Conference Brisbane, 4-7 December 2005. Queensland University of Technology, Department of Teaching and Learning Support Services.
Yakubu MN, Dasuki SI (2019). Factors affecting the adoption of e-learning technologies among higher education students in Nigeria: A structural equation modelling approach. Information Development 35(3):1-11.
Yuen AH, Ma WW (2008). Exploring teachers' acceptance of e-learning technology. Asia-Pacific Journal of Teacher Education 36(3):229-243.