Article

JACE

Journal of Adult and Continuing Education
2023, Vol. 29(1) 124–146

DOI: 10.1177/14779714221135655
journals.sagepub.com/home/adu
SAGE

Determinants of the Behavioural Intention of Open Distance Learning Students to Use Digital Tools and Resources for Learning in Nigeria

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Abstract

This study investigated determinants of the behavioural intention of Open Distance Learning (ODL) students to use digital tools and resources for learning in Nigeria. The study utilized an online questionnaire to gather data from 522 ODL students from an ODL institution in Nigeria. The Unified Theory of Acceptance and Use of Technology (UTAUT) was the main framework used for the analysis in which attitude was included as an additional variable to seek out a much better model capable of improving the understanding of ODL students' behavioural intention to use digital tools and resources for learning. Thus, an extended UTAUT model was developed and tested in this study. The model consisted of six constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, attitude and behavioural intention. A Partial Least Square-Structural Equation Modelling (PLS-SEM) was used for data analysis. Results revealed that the proposed model successfully explained critical factors that determine ODL students' behavioural intention to use digital tools and resources for learning. The study suggested that attitude, performance expectancy and facilitating conditions are the major determinants of behavioural intention to use digital tools and resources but attitude is the most prominent factor. Thus, implications and suggestions for further studies were highlighted.

Keywords

digital tools and resources, Behavioural intention, ODL students, UTUAT, Nigeria

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Introduction

The 21st century ushered in a digital landscape that provides unprecedented access to information in the fastest way possible within the frame of individual needs. Specifically, the emergence and growth of the internet in the last couple of decades increased networking capacities and made the world a global village in which relationships and identities are formed in new ways and in which people independently exchange information irrespective of where they live (Säljö, 2010). Virtual communities continue to grow exponentially with applications and sites that promote such activities. Many people easily access information through websites such as Google, YouTube and Wikipedia and send and receive messages via e-mails. Banking and shopping are made online and people connect through social networks such as Facebook, and Twitter. Also, databases, libraries and other learning platforms are accessible in the comfort of people's homes (Ozdamar-Keskin et al., 2015). Digitization has therefore simplified our daily lives as every daily life aspect continues to be built around digital technologies, thereby raising our living standards effectively (Patel, 2018). According to the United Nations (2020), digital technologies amongst many other innovations in the world's history have advanced faster, reaching about 50% of the population in developing countries in only 2 decades and transforming societies. Connectivity, financial inclusion, and access to trade and public services have been greatly impacted and this serves as a great equalizer (United Nations, 2020).

The proliferation of digital tools and resources has transformed the way learning occurs. Digital tools and resources have made learning more accessible, flexible, and personalized, and have increased access to resources, especially for learners in hard-to-reach rural areas or those who don't have access to the traditional school library. Digital tools and resources in this context refer to particular platforms and tools using computer chips, digital applications and networking in any existing forms that encourage active learning, knowledge construction, inquiry, and exploration on the part of the learners and which allow people to communicate and share data remotely (Genova, 2019). The impact of digital tools and resources in transforming the teaching and learning process cannot be overemphasized. It helps to facilitate learning and provide social interaction. Notably, digital tools and resources have a wide reach, a strong user base and an abundance of evidence of impact (UNESCO, 2020). Specifically, the use of digital tools and resources for learning has been observed to significantly turn learners into participative and active individuals who gather, process, and produce information (Ozdamar-Keskin et al., 2015). These tools and resources have been the basis of distance education and have continued to widen the frontiers of distance education (Arthur-Nyarko et al., 2020).

Distance education refers to the technology-mediated teaching and learning process in which learners are physically separated from their instructors (Itasanmi & Oni, 2021). Any learning activity whether formal, informal or non-formal that is facilitated through a multiplicity of both print and digital media in a way that increases the interactivity and communication among learners, learning sources and facilitators with fewer physical contacts is called open and distance learning (ODL) (Itasanmi et al., 2020). ODL has become an accepted part of the mainstream educational system all over the world. Access to simple, flexible and cheaper education is made easy through open and distance learning. ODL has been recognized as a tool that provides opportunities for educational access especially higher education to the unreached and allows a massification of education to combat the limitation of spaces in the conventional higher education system (Arthur-Nyarko et al., 2020). According to Kotzé (2021), conventional education failed to lead to sustainable education for all, and ODL appears to be the most cost-effective, and cost-efficient method of solving many of the endemic challenges in education and training, especially in developing countries.

Nigeria like other developing nations has embraced ODL as a means of providing educational opportunities at reduced costs to those who are constrained by work, family responsibility, geographical location and disability to attend regular educational establishments. ODL has also played a major role in helping universities meet the demands of teeming youth desirous of university education but could not due to admission gridlock in Nigerian universities that has become so stifling and overwhelming. Providing quality education for a population estimated at over 200 million through conventional education is somewhat unachievable (Itasanmi et al., 2020). With the emergence of COVID-19 and the need to curtail its spread, distance education provision in the country has increased. Several institutions of learning have taken to using technologies to mediate the teaching and learning process (Itasanmi, Oni, et al., 2022b; Itasanmi, Ekpenyong, et al., 2022a). While online interaction has been the major means of lecture delivery and course materials provided in multiple formats to ODL learners in the country, no emphasis is placed on augmenting the course materials with a wide array of educational resources available through ubiquitous digital platforms. Thus, learners have been limited to the learning materials made available to them. Also, given the steady growth of digital tools and resources, the future is bright for ODL in Nigeria. However, the use of digital tools and resources for learning has been observed not to be well promoted by ODL institutions in the country. There exists no particular structure or strategies put in place to encourage ODL students to use digital tools and resources for learning and this constitutes a serious impediment to its actual by students. Also, to the best of the researcher's knowledge, there is a dearth of empirical evidence on antecedents of students' behavioural intention to use digital tools and resources for learning and factors that could promote actual use of it among the ODL students for qualitative ODL delivery and capability enhancement of the students in Nigeria.

Several scholars have asserted that behavioural intention is the most important predictor of actual use behaviour. Ajzen (1991), opined that the motivational factor that influences behaviour is considered to be the intention. Behavioural intention is the likelihood of a person performing or executing a particular behaviour. It is also described as a person's behaviour that can be explained by the individual's intention regarding his/her personal decision to perform certain future behaviour (Tey & Moses, 2018). According to Ajzen (1991), behavioural intention is how hard people are willing to try out something, and how much effort they are planning to commit to performing the behaviour. In other words, the stronger the intention to engage in a particular behaviour, the higher the likelihood of its performance (Liebenberg et al., 2018). Within the context of this study, behavioural intention indicates ODL students' intention or plan to utilize digital tools and resources for learning whether or not they are currently using them for learning.

Many factors have been found as antecedents of the behavioural intention of learners to use digital technologies generally. These antecedents of behavioural intention include perceived usefulness, perceived ease of use, attitude, normative norms etc. Also, a multitude of theories and models has been espoused to explain the behavioural intention and use of digital tools. The Unified Theory of Acceptance and Use of Technology (UTUAT) is the most outstanding model in explaining behavioural intention and use thus far (Tey & Moses, 2018; Naranjo-Zolotov et al., 2018; Lim et al., 2019). Based on this, many technology acceptance studies have applied the UTUAT theory and some have extended it through the integration of other theories to study technology adoption in various contexts (Venkatesh et al., 2016). Among studies that extended the UTUAT theory are Jere (2020), Tey and Moses (2018), and Mailizar et al. (2021). This current study, therefore, extends the UTUAT theory by adding attitude as a construct to the UTUAT constructs. This is done to propose a better model capable of explaining behavioural intention to use digital tools and resources in the Nigerian context. Considering the documented evidence in support of attitude as a great factor in predicting behavioural intention in the context of developing countries (Thomas et al., 2013), this study seeks to understand the explanatory power of attitude in ODL behavioural intention in Nigeria (a developing country).

The objective of the current study is therefore to explore ODL students' behavioural intention to use digital tools and resources for learning. The study measured the ODL students' behavioural intention to use digital tools and resources for learning instead of their use behaviour. Also, the study focused to explore the factors such as performance expectancy, effort expectancy, social influence, facilitating conditions and attitudes that influence the behavioural intention of ODL students to use digital tools and resources for learning. This is done to understand factors that could promote the actual use of digital tools and resources for learning among ODL students. Also, this study prompts a better understanding of critical factors that influence the behavioural intention of ODL students to use digital tools and resources for better policymaking by ODL stakeholders to promote digital tools and resources for learning among ODL students. Furthermore, the study contributes to the discourse on the application of the UTUAT model in technology acceptance, especially in developing nations like Nigeria.

Theoretical Framework

This study is hinged on the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003). UTAUT was developed based on the review, identification and comparison of eight prominent technology acceptance theories/models (Theory of reasoned action (TRA), Technology acceptance model (TAM), Motivation model (MM), Theory of planned behaviour (TPB), Combined TAM and TPB, Model of PC utilization (MPCU), Innovation diffusion theory (IDT) and Social cognitive theory (SCT)). UTAUT outlined the key theoretical construct of each of the theories/models to produce a single and synthesized framework suitable to understand technology acceptance and use. Specifically, Vankatesh et al. (2003) upon the synthesis of the construct of the existing theories and models, concluded that seven of them appeared to significantly determine intention or usage in one or more of the individual theories. The seven constructs were further broken down into four constructs, namely; performance expectancy, effort expectancy, social influence and facilitating conditions.

Performance expectancy on one hand refers to the degree to which a person believes that the use of a system will help achieve appreciable gains in work performance. According to the theorists, this is the most important factor when it comes to predicting an individual's behavioural intention to use a given technology or system. Though, Venkatesh et al. (2003) opined that certain external factors such as age and gender relating to the user may moderate the effect of performance expectancy on intention to use a given technology. On the other hand, effort expectancy is the "degree of ease" related to the use of the technology or system. The measure of the required effort and knowledge an individual perceived as necessary to comfortably use the technology is what is referred to as effort expectancy (Isaias et al., 2017). Age, gender and experience were considered as external factors that will moderate the impact of the effort expectancy. While social influence refers to the degree to which a person believes that powerful others may influence his decision to use the new technology. It is believed that in human society, social influence is ubiquitous (Izuma, 2017). People are subjected to the pressure of social interactions and will, especially in social environments. This makes social influence significant when considering the use of technology in a particular context. Venkatesh et al. (2003) therefore proposed that external factors like age, gender, experience and voluntariness will influence the impact of the social influence on an individual's use of the technology. Facilitating conditions are however defined as the extent to which people believe that there is the availability of necessary infrastructure and technical support that will aid the use of the technology. Though, Venkatesh et al. (2003), believed that facilitating conditions do not influence the intention of use, but do influence the actual use of the technology.

To better illustrate these constructs and their interrelationships as well as the moderation role of external factors, a diagrammatic shape was provided to understand the workings of the theory. Below is the diagram showcasing the key constructs of the theory and their external moderating factors. (Figure 1)

Generally, the UTUAT theory provides a better understanding of behavioural intention and use of technologies compared to other theories in the technology acceptance and use domains. The theory has been found to account for about 70% of the variance in behavioural intention and only about 50% in the actual use of technology (Venkatesh et al., 2012). Though it has been argued that the UTUAT theory failed to incorporate some possibly significant relationships, made some hypotheses about some relationships that may probably not be appropriate in all circumstances, and omitted some constructs that may be critical in explaining technology acceptance and use (Dwivedi et al., 2017). UTUAT theory has been tested and verified to be better than other individual technology acceptance theories/models, thus making it very useful for scholars to predict intention and acceptance of technology. The theory appears to be less general and its constructs provide valuable insights into e-survey participation (Naranjo-Zolotov et al., 2018).

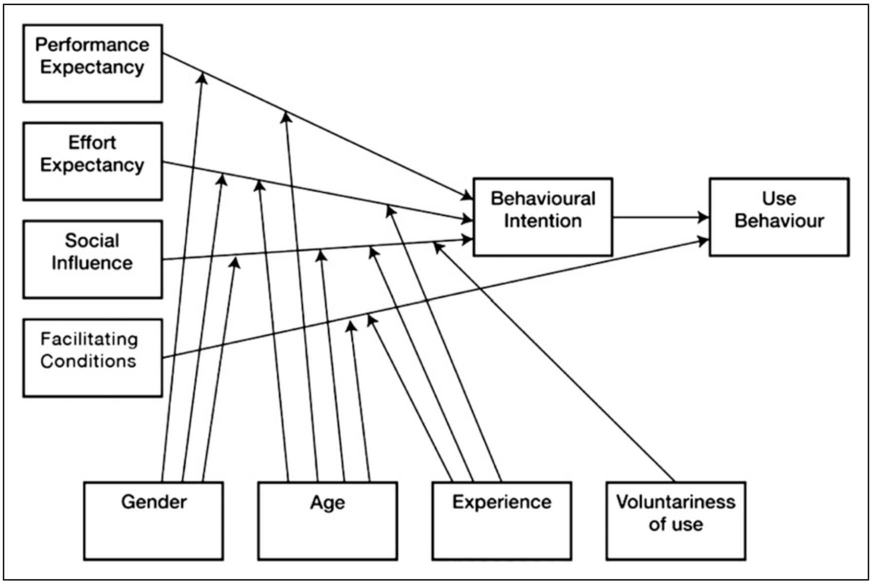

Figure 1. Synopsis of UTAUT theory showcasing the key constructs and their moderating factors (Venkatesh et al., 2003).

Specifically, since the theory has been postulated, it has become a benchmark used for various technology adoption-related studies in different contexts across the globe (Lim et al., 2019).

UTUAT theory has been empirically tested in several studies to explain the behavioural intention and actual use of technologies as well as provide insights into the moderating role of external factors such as age, gender, experience etc. in diverse contexts across the world (Mtebe & Raisamo, 2014; Attuquayefio & Addo, 2014; Zuiderwijk et al., 2015; Magsamen-Conrad, 2015; Ibrahim et al., 2016; Berry, 2017; Krismadinata et al., 2019; Chang, 2020; Ramllah & Nurkhin, 2020; Abbad, 2021; Humida et al., 2021; Madzamba & Govender, 2021; Lutfi, 2022). For instance, Mtebe and Raisamo (2014), investigated students' behavioural intention to adopt and use mobile learning in higher education in East Africa by applying the UTUAT theory. Results of their study indicated that performance expectancy, effort expectancy, social influence and facilitating conditions positively and significantly predict students' mobile learning acceptance with performance expectancy being the greatest predictor. Similarly, Zuiderwijk et al. (2015), examined the acceptance and use of open data technologies drawing upon the UTUAT model. Their results showed that performance expectancy, effort expectancy, social influence, facilitating conditions and voluntariness of use accounted for 45% of the variability of the respondents' behavioural intention to use open data technologies. Furthermore, Abbad (2021), used the UTUAT theory to understand students' usage of e-learning systems in developing countries. He found out that performance expectancy and effort expectancy affected behavioural intentions to use Moodle whereas, social influence did not. He equally found out that behavioural intention and facilitating conditions greatly impacted students' use of Moodle.

The rationale for the adoption of the UTUAT theory for this study was based on having a clearer construct to predict behavioural intention compared to other technology acceptance theories. Also, the theory makes it easy for researchers to extend its constructs by adding new constructs or reducing the existing constructs to suit a particular context of the study. Specifically, UTUAT clearly outlined the relationship between performance expectancy, effort expectancy, social factors and facilitating conditions as well as the interaction effect of age, gender and experience on behavioural intentions. However, the attitude was omitted in the model. Venkatesh et al. (2003) believed that the effect of attitude on behavioural intention is spurious and it can only be considered when performance expectancy and effort expectancy are not included in the theory. Attitude refers to an individual's feelings which could either be positive or negative towards the use of the technology. Attitude is an important element of the TRA and TAM. This study's researcher believed that attitude is a strong predictor of the behavioural intention of students to use digital tools and resources for learning. Hence, the study incorporates attitude into the study. This will help the researcher to understand the relationship between attitude and UTUAT constructs. Equally, the study substituted experience with programme level as this is considered to showcase their study experiences which might influence some of the constructs.

Research Hypotheses

This study did not measure the actual use of digital tools and resources for learning among ODL students since it is the researcher's considered opinion that there exists no tangible initiative implemented as regards encouraging ODL students to use digital tools and resources for learning in Nigeria. All four UTUAT constructs (performance expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC)) are hypothesized to significantly influence Attitude (A) towards the use of digital tools and resources for learning. Equally, PE, EE, SI, and FC are hypothesized to significantly influence BI. Also, A is hypothesized to significantly influence Behavioural Intention to use digital tools and resources for learning. Furthermore, the effect of gender, age and programme level were hypothesized to moderate the relationship among the construct of the study. The study's hypotheses are stated as follows:

H1: Performance Expectancy (PE) has a significant influence on Attitude (A).
H2: Effort Expectancy (EE) has a significant influence on Attitude (A).
H3: Social Influence (SI) has a significant influence on Attitude (A).
H4: Facilitating Conditions (FC) have a significant influence on Attitude (A).
H5: Performance Expectancy (PE) has a significant influence on Behavioural Intention (BI).
H6: Effort Expectancy (EE) has a significant influence on Behavioural Intention (BI).
H7: Social Influence (SI) has a significant influence on Behavioural Intention (BI).

H8: Facilitating Conditions (FC) have a significant influence on Behavioural Intention (BI).
H9: Attitude (A) has a significant influence on behavioural intention (BI).
H10: Gender significantly moderates the relationship between Performance Expectancy (PE) and Behavioural Intention (BI).
H11: Gender significantly moderates the relationship between Effort Expectancy (EE) and Behavioural Intention (BI).
H12: Gender significantly moderates the relationship between Social Influence (SI) and Behavioural Intention (BI).
H13: Age significantly moderates the relationship between Performance Expectancy (PE) and Behavioural Intention (BI).
H14: Age significantly moderates the relationship between Effort Expectancy (EE) and Behavioural Intention (BI).
H15: Age significantly moderates the relationship between Social Influence (SI) and Behavioural Intention (BI).
H16: Age significantly moderates the relationship between Social Influence (SI) and Behavioural Intention (BI).
H17: Programme level (PL) significantly moderates the relationship between Effort Expectancy (EE) and Behavioural Intention (BI).
H18: Programme level (PL) significantly moderates the relationship between Social Influence (SI) and Behavioural Intention (BI).
H19: Programme level (PL) significantly moderates the relationship between Facilitating Conditions (FC) and Behavioural Intention (BI).

Conceptual Model

Below is the proposed conceptual model for the study. (Figure 2).

Methods

Design

The study adopted a quantitative survey approach based on structural equation modelling (SEM) analysis in which the predictive influences of Performance Expectancy (PE), Effort Expectancy (EE), Social Factors (SF), Facilitating Conditions (FC) on Attitude (A) and predictive influences of PE, EE, SF, FC and A on Behavioural Intention (BI) were investigated. Also, the moderation role of gender, age and programme level on the relationship among the variables were examined.

Participants

The study participants consisted of 522 ODL students from Nigeria's premier university, the University of Ibadan. The university was selected as the case study for data collection due to easy access by the researcher and for being one of the leading ODL institutions in

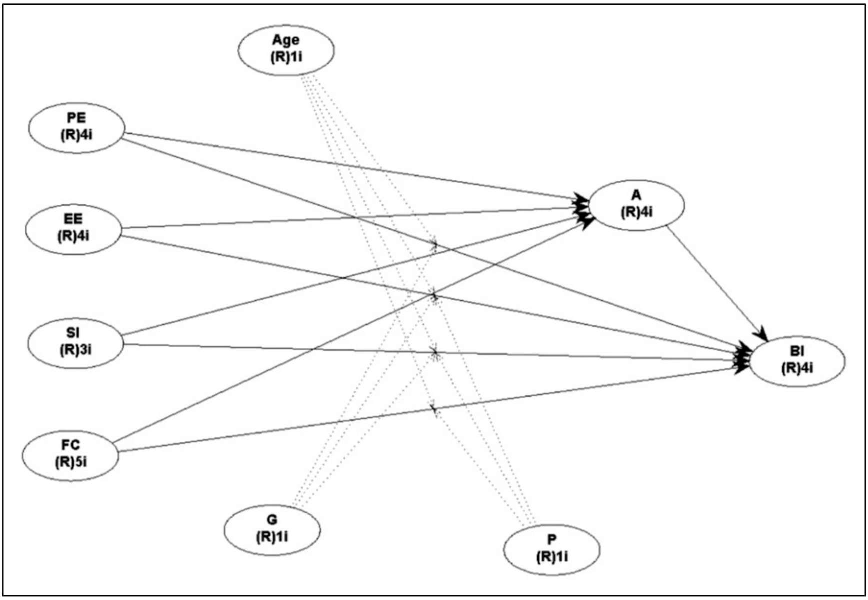

Figure 2. Conceptual Model for the study.

the country. The participants participated through an online survey link sent to the email addresses of all registered ODL students for the 2020/2021 academic session between September and November 2021. The invitations sent to the ODL students sought their participation in the study after the general objective of the study was outlined to them for better understanding. They were asked to participate voluntarily and were assured of the confidentiality of the information provided. Out of the 522 ODL students, 273 (52.30%) were males and they constituted the majority of the participants in the study. 148 ODL students (28.35%) fall within the age range of 26-30 and 115 (22.3%) are within the 21-25 age bracket. Others are within age range of 31-35, 36-40, 41-45, 16-20, 46-50, 51-55 and 56-60 with 15.33%, 12.07%, 9.58%, 6.32%, 4.6%, 1.15% and .57% respectively. While the majority of the respondents (57.5) are single, 41.2% married and only 4 and 3 students are divorced and widowed respectively. Also, 242 (46.36%) of the respondents are employed, 187 (35.82) are self-employed and 93 (17.82%) of them are unemployed. While 154 ODL students (29.5%) are in the second level of their academic programme, 132 (25.3) are in their fifth level. Others are in their third, first and fourth levels with 18.4%, 14.9% and 11.9% respectively.

Instrument

The instrument for data collection for the study was a questionnaire. The questionnaire consisted of a section on demographic characteristics and a section on the UTAUT with attitude measurements. Items on UTAUT and attitude were drawn from various studies

(Jairak et al., 2009; Nassuora, 2013; Teo, 2011; Thomas et al., 2013; Venkatesh et al., 2003; Wang & Shih, 2009) that has implemented UTAUT model and many mobile learning studies. Items drawn from previous studies were modified to suit the context of the current study (digital tools and resources) and anchored on a 5-point Likert scale of strongly disagree-1, disagree-2, Neutral-3, agree-4 and strongly agree-5. The questionnaire was pilot-tested among regular undergraduate students of the university and a 0.82 alpha coefficient was obtained. Table 1 shows the variable construct for UTAUT along with attitude

Statistical Analysis

A Partial Least Square- Structural Equation Modelling (PLS-SEM) technique with latent variables in WarpPLS 7.0 software was used to analyze the study data in two important phases, namely, model fit measurements and Structural model's path coefficients. The first phase involved assessing the validity and reliability of the measurement model while the second phase entails analyzing the structural model to test the research hypotheses.

Results

Table 2 presents the Composite Reliability (CR), Cronbach alpha test (CA) and Average Extracted Variance (AVE) for the variables (Performance Expectancy (PE), Behavioural Intention (BI), Effort Expectancy (EE), Social Factors (SF), Facilitating Conditions (FC) and Attitude (A)**.** Table 2 indicated that all the CA values are greater than the recommended threshold value of 0.7, indicating that the variables are internally consistent. (Hair et al., 2014) suggested a CR value of greater than 0.7 and an AVE value of greater than 0.5. The CR and AVE values, therefore, meet the suggested thresholds. The findings suggest that the measurement constructs are accurate. According to Hair et al. (2009), VIFs values below 5 indicate a lack of multicollinearity. Based on the values in Table 2, it is evident that all the VIFs values are less than 5, suggesting the absence of multicollinearity.

The cross-loadings for the variables were calculated to see if convergent validity existed, and the results are shown in Table 3. It was revealed in Table 3 that all of the cross-loadings are more than 0.6. This indicates that the measurement constructs have convergent validity, allowing for model fitting. Variables with low factor loadings of less than 0.6 were eliminated from the model.

Correlations of latent variables and the square root of AVEs were assessed to confirm the discriminant validity of the measuring items. Table 4 summarizes the findings. Discriminant validity was validated on all of the latent variables, as shown in Table 4 because the square root of the AVE values (diagonal values) for the latent variables exceeded the corresponding correlation coefficient values.

Model fit

Various measures were examined to check if the data meet the approved cut-off points using model diagnostics. Table 5 displays the model fit indices that were calculated. The

Table 1. Variable Construct for the study.

Construct	Items
Performance expectancy (PE)	Digital tools and resources are useful in education generally Using digital tools and resources will enable me to accomplish my academic tasks more quickly and easier Digital tools and resources would enhance my academic performance Digital tools and resources would increase my motivation and engagement with academic activities
Effort expectancy	Digital tools and resources for learning are easy to access Digital tools and resources are easy to use Using the digital tools and resources for learning requires little effort to use Learning to use digital tools and resources for learning will be easy for me Using digital tools and resource platforms is clear and understandable to me
Social influence	People who influence my behaviour think that I should use digital tools and resources to aid my learning My peers will recommend I use digital tools and resources for learning The use of digital tools and resources will elevate my class Facilitators and lecturers are supportive of the use of digital tools and resources for learning
Facilitating conditions	Generally, the ODL institution provides the infrastructural and policy support for the use of digital tools and resources for learning I have the personal resources necessary for the use of digital tools and resources for learning I have the requisite knowledge to use digital tools and resources for learning There is good internet connectivity to use digital tools and resources for learning There are adequate support services when problems are encountered using digital tools and resources for learning
Attitude	Using digital tools and resources for learning is a good idea I Would love to use digital tools and resources for learning I Believe that using digital tools and resources for learning would be fun Using digital tools and resources provide an opportunity to learn at one's pace and in place
Behavioural intention	I Intend to use digital tools and resources to enhance my learning going forward I Predict I will use digital tools and resources for learning in my courses I have a plan to use digital tools and resources for learning soon I Think digital tools and resources will be a basis for future learning

table revealed that the provided values for APC (0.134), ARS (0.784), and AARS (0.781) of the model are all statistically significant at a 0.001 level. The AVIF (4.921) and AFVIF (3.098) estimates are lower than the ideal AVIF and AFBIF values. The TenehausGoF value of 0.851 shows a large explanatory power for the model. This, therefore, indicates good and satisfactory compliance to the criterion of model quality and goodness of fit

Table 2. Reliability statistics.

	PE	EE	SI	FC	A	BI
CR	0.947	0.913	0.88	0.903	0.94	0.929
CA	0.925	0.873	0.794	0.866	0.872	0.848
AVE	0.817	0.724	0.709	0.653	0.887	0.869
VIF	4.338	4.810	3.816	2.668		

Table 3. Cross loadings.

	PE	EE	SI	FC	A	BI
PE1	**0.874**	0.612	0.562	0.458	0.63	0.587
PE2	**0.928**	0.684	0.633	0.509	0.7	0.649
PE3	**0.935**	0.67	0.64	0.508	0.684	0.634
PE4	**0.877**	0.654	0.639	0.511	0.656	0.615
EE1	0.574	**0.835**	0.59	0.607	0.492	0.49
EE3	0.517	**0.818**	0.595	0.574	0.448	0.435
EE4	0.715	**0.871**	0.684	0.618	0.618	0.614
EE5	0.655	**0.878**	0.696	0.673	0.615	0.594
SF1	0.483	0.594	**0.824**	0.506	0.441	0.463
SF3	0.694	0.711	**0.886**	0.593	0.64	0.636
SF4	0.546	0.599	**0.814**	0.63	0.517	0.513
FC1	0.458	0.511	0.582	**0.734**	0.433	0.441
FC2	0.477	0.624	0.553	**0.827**	0.526	0.517
FC3	0.534	0.685	0.575	**0.813**	0.573	0.584
FC4	0.396	0.566	0.54	**0.842**	0.497	0.444
FC5	0.36	0.547	0.52	**0.818**	0.443	0.432
A1	0.715	0.602	0.59	0.582	**0.942**	0.769
A3	0.677	0.605	0.605	0.572	**0.942**	0.742
BI3	0.623	0.612	0.603	0.578	0.735	**0.932**
BI4	0.658	0.56	0.59	0.538	0.761	**0.932**

Table 4. Correlations among latent variables with the square root of AVEs.

	PE	EE	SI	FC	A	BI
PE	**0.904**	0.725	0.685	0.549	0.739	0.688
EE	0.725	**0.851**	0.755	0.727	0.641	0.629
SI	0.685	0.755	**0.842**	0.684	0.635	0.64
FC	0.549	0.727	0.684	**0.808**	0.613	0.599
A	0.739	0.641	0.635	0.613	**0.942**	0.803
BI	0.688	0.629	0.64	0.599	0.803	**0.932**

Note. The bolded diagonal values are the square roots of the AVE values.

Table 5. Model fit test.

Indices	Decision criteria	Comment
Average path coefficient (APC) = 0.134	$P < 0.001$	Significant
Average R-squared (ARS) = 0.784	$P < 0.001$	Significant
Average adjusted R-squared (AARS) = 0.781	$P < 0.001$	Significant
Average block VIF (AVIF) = 4.921	Acceptable if <= 5 and ideally if <= 3.3	Ideally
Average full collinearity VIF (AFVIF) = 3.098	Acceptable if <= 5 and ideally if <= 3.3	Ideally
Tenenhaus GoF (GoF) = 0.851	Small if >= 0.1, medium if >= 0.25 and large if >= 0.36	Large
Sympson's paradox ratio (SPR) = 0.842	Acceptable if >= 0.7 and ideally if = 1	Acceptable
R-squared contribution ratio (RSCR) = 0.954	Acceptable if >= 0.9 and ideally if = 1	Ideally
Statistical suppression ratio (SSR) = 1.000	Acceptable if >= 0.7	Acceptable
Nonlinear bivariate causality direction ratio (NLBCDR) = 1.000	Acceptable if >= 0.7	Acceptable
Standardized root mean squared residual (SRMR) = 0.057	Acceptable if <= 0.1	Acceptable
Standardized mean absolute residual (SMAR) = 0.044	Acceptable if <= 0.1	Acceptable

Hypotheses testing

The results in Table 6 suggest PE had a statistically significant positive effect on A (β = 0.567, $p < 0.001$), SI had a statistically significant positive effect on A (β = 0.025, p = 0.020), FC had a statistically significant positive effect on A (β = 0.260, $p < 0.001$), PE had a statistically significant positive effect on BI (β = 0.125, p = 0.002), FC had a statistically significant positive effect on BI (β = 0.109, p = 0.006) and A had a statistically significant positive effect on BI (β = 0.739, $p < 0.001$). Gender significantly and positively moderates the relationship between EE and BI (β = 0.057, p = 0.094), Gender significantly and positively moderates the relationship between SI and BI (β = 0.110, p = 0.005), Program level significantly and positively moderates the relationship between SI and BI (β = 0.125, p = 0.002) and Program level significantly and negatively moderates the relationship between FC and BI (β = −0.104, p =0.008). However, the other hypotheses are insignificant. These research results imply that the hypotheses H_1, H_3, H_4, H_5, H_8, H_9, H_{11}, H_{12}, H_{18} and H_{19} are supported and statistically significant at 10% while the hypotheses H_2, H_6, H_7, H_{10}, H_{13}, H_{14}, H_{15}, H_{16} and H_{17} were found to be statistically insignificant.

Figure 3 displays the SEM with model parameters. The figure shows that the independent variables (PE, EE, SF and FC) explain 68 per cent (R^2 = 0.68) of the entire variance in A in the model, whereas the independent variables (A, PE, EE, SI and FC) explain 89 per cent (R^2 = 0.89) of the whole variation in BI

Table 6. Structural model path coefficients.

Hypothesis	Relationship	Coefficient	*p*-values	Decision
H_1	PE-->A	0.567	<0.001	Supported
H_2	EE-->A	0.025	0.284	Not Supported
H_3	SI-->A	0.090	0.020	Supported
H_4	FC-->A	0.260	<0.001	Supported
H_5	PE-->BI	0.125	0.002	Supported
H_6	EE-->BI	0.007	0.438	Not Supported
H_7	SI-->BI	0.046	0.145	Not Supported
H_8	FC-->BI	0.109	0.006	Supported
H_9	A-->BI	0.739	<0.001	Supported
H_{10}	PE-->G-->BI	−0.046	0.145	Not Supported
H_{11}	EE-->G-->BI	0.057	0.094	Supported
H_{12}	SI-->G-->BI	0.110	0.005	Supported
H_{13}	PE-->AGE-->BI	0.020	0.327	Not Supported
H_{14}	EE-->AGE-->BI	−0.017	0.350	Not Supported
H_{15}	SI-->AGE-->BI	−0.035	0.214	Not Supported
H_{16}	FC-->AGE-->BI	−0.038	0.192	Not Supported
H_{17}	EE-->P-->BI	0.020	0.321	Not Supported
H_{18}	SI-->P-->BI	0.125	0.002	Supported
H_{19}	FC-->P-->BI	−0.104	0.008	Supported

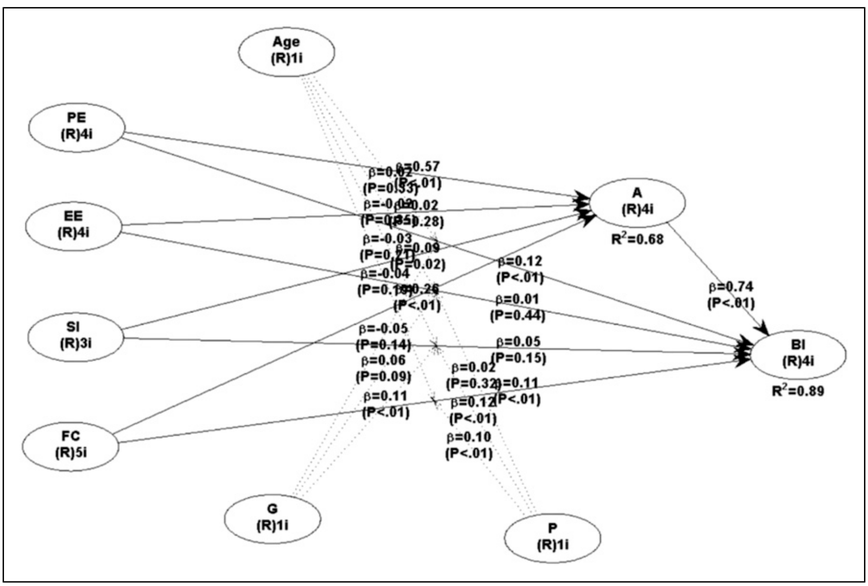

Figure 3. The Structural Equation Model (SEM) with parameters.

Discussion and Implications

The primary focus of the study was to identify the factors in the UTUAT model along with the attitude that determines ODL students' behavioural intention to use digital tools and resources for learning in Nigeria. The results showed that out of the four UTUAT model constructs namely, performance expectancy, effort expectancy, social influence and facilitating conditions, only effort expectancy does not significantly influence ODL students' attitude towards using digital tools and resources for learning. This result is inconsistent with previous studies (Ghalandari, 2012; Thomas et al., 2013; Pangaribuan & Wulandar, 2019; Ryu & Fortenberry, 2021) that founds UTUAT constructs, especially effort expectancy to positively significantly influence attitudes towards the use of technologies. These results implied that ODL students who positively perceive digital tools and resources to enhance learning believe that friends and colleagues are in support of its use and there appears to be a positive view of the availability of required infrastructural facilities to use digital tools and resources for learning, tend to have a positive attitude towards the use of digital tools and resources for learning. The ease of use associated with digital tools and resources for learning becomes secondary. Also, it was indicated that out of the four UTUAL constructs, performance expectancy is the greatest determinant of attitude toward using digital tools and resources for learning among ODL students. Thus, the perceived benefits of the use of digital tools and resources are the most important factor that determines ODL students' attitudes towards the use of digital tools and resources for learning.

Results further show that the behavioural intention of ODL students to use digital tools and resources for learning is significantly determined by performance expectancy and facilitating conditions. Effort expectancy and social influence do not predict ODL students' behavioural intention to use digital tools and resources for learning. This result implied that usefulness and enabling environment serve as the major determinants of behavioural intention to use digital tools and resources among the ODL students in Nigeria. This result is inconsistent with the research finding of Venkatesh et al. (2003) who found facilitating conditions to be nonsignificant to behavioural intention. Generally, this result adds to the conflicting findings from previous research (Im et al., 2011; Lakhal et al., 2013; Attuquayefio & Addo, 2014; Mtebe & Raisamo, 2014; Suki & Suki, 2017; Chua et al., 2018; Purwanto & Loisa, 2020; Abbad, 2021) that have used UTUAT constructs to predict behavioural intention to use technologies. For instance, Purwanto and Loisa (2020), found out that effort expectancy and facilitating conditions significantly predict behavioural intention while performance expectancy and social influence did not. Abbad (2021), found out that performance expectancy and effort expectancy predicted behavioural intention whereas social influence did not. However, Suki and Suki (2017) found out that students' behavioural intention to use technologies was determined by performance expectancy, facilitating conditions and effort expectancy in order of influence respectively. The conflicting results emanating from the use of the UTUAT model to predict behavioural intention have been hinged on differences in the context in which the model has been applied (Thomas et al., 2013). Considering the context in which this study is carried out – Nigeria (a developing country), this result is not surprising.

Developing countries lack enabling digital infrastructure whereas the ubiquity of digital tools and resources is common knowledge. Thus, the sense that digital tools and resources could enhance learning and the availability of resources to use them may serve as a motivating factor to desire to use them for learning. While the proponents of the UTUAT model neglected the impact of facilitating conditions on behavioural intentions probably on the assumption that there are basic resources that could not affect behavioural intention but actual use (in the western context), in the developing context, this may not be the case due to lack or insufficient technological infrastructure. This study provided an opportunity to recognize the importance of facilitating conditions in predicting behavioural intention as omitting it could have led to a spurious effect of effort expectancy on behavioural intention.

Attitude has proven to significantly predict ODL students' behavioural intention to use digital tools and resources for learning. Though attitude is not included in the original UTUAT model, the results of this study show that attitude has the largest influence on students' behavioural intention to use digital tools and resources for learning in the Nigerian context. This implies that a positive predisposition to digital tools and resources by ODL students greatly influences their behavioural intention to use them for learning. This result is consistent with previous studies (Ajzen & Fishbein, 1972; Sample & Warland, 1973; Hussein, 2017; Zhang et al., 2020; Jere, 2020; Mailizar et al., 2021). However, this result is inconsistence with Venkatesh et al. (2003) who opined that attitude is nonsignificant to behavioural intention. This result resonates with the assertions made by Bruess (2003) and Wangpipatwong (2008) that attitude is a significant factor when considering students' behavioural intention to use digital technologies.

On the moderating role of gender, age and programme level on the relationship between the four UTUAT constructs and behavioural intention of ODL students to use digital tools and resources for learning. Results revealed that only the relationship between Performance expectancy and behavioural intention and the relationship between social influence and behavioural intention is moderated by gender. Programme level moderate relationship between social influence and behavioural intention and the relationship between facilitating conditions and behavioural intentions. This is in congruence with the findings of Venkatesh et al. (2003). This result implies that ODL students' behavioural intention to use digital tools and resources for learning through the lens of perceived ease of use associated with it and the level of influence from friends and colleagues is gender sensitive. Equally, it appears that while the relationship between social influence and behavioural intention is positively moderated by the programme level of the ODL student, the programme level negatively moderates the relationship between facilitating conditions and behavioural intention.

Finally, the results of this study reveal that the UTUAT model constructs can explain 68 per cent of the entire variance in attitude towards using digital tools and resources for learning among the ODL students while the UTUAT constructs along with attitude explain 89 per cent of the whole variation in behavioural intention to use digital tools and resources for learning. This indicates that the inclusion of attitude in the study's model increases the explained variance in behavioural intention beyond the 70% suggested by Venkatesh et al. (2003). Unlike studies that have majorly used the four UTUAT constructs to predict behavioural intention reporting a lower explanatory power. For instance, Kaba and Touré (2014) reported the explanatory power of UTUAT to be about 42% while Bawack and Kala Kamdjoug (2018) reported 12%. Thus, these results suggest that UTUAT along with attitude provide a model that gives higher explanatory variance in behavioural intention. While attitude is the most important predictor of behavioural intention to use digital tools and resources for learning among the ODL students, performance expectancy, effort expectancy, social influence and facilitating condition remain very relevant as they either have a significant net impact on behavioural intention or they significantly predict attitude towards the use of digital tools and resources for learning.

Conclusion

This study presents a model for a better understanding of ODL students' behavioural intention to use digital tools and resources for learning. The unified theory of acceptance and use of technology (UTAUT) was employed for analysis in which attitude was added as another construct. The proposed conceptual model effectively explains the behavioural intention of ODL students to use digital tools and resources for learning. The findings suggested that attitude is the greatest predictor of behavioural intention followed by performance expectancy and facilitating conditions. On the other hand, effort expectancy and social influence did not significantly influence ODL students' behavioural intention to use digital tools and resources for learning. Furthermore, the relationship between behavioural intention and effort expectancy and the relationship between social influence and behavioural intention is moderated by gender. While the Programme level moderate relationship between social influence and behavioural intention and the relationship between facilitating conditions and behavioural intentions.

This study suggests that for ODL students to desire to use digital tools and resources to complement learning materials given to them and for ODL institutions to improve potential and actual use of digital tools and resources, students' attitude towards it is vital. Thus, ODL institutions in the country need to orientate and inculcate positive attitudes in the ODL students, especially regarding the inherent opportunities in using digital tools and resources to expand their knowledge base in their various disciplines. Also, maintenance of positive student attitude by the ODL institutions towards the use of digital tools and resources must be made a key element as it is the greatest predictor of behavioural intention among ODL students. Furthermore, this study showed that performance expectancy, social influence and facilitating conditions significantly influenced ODL students' attitudes towards the use of digital tools and resources for learning. Based on these, sustainable use of digital tools and resources by the ODL student is based on perceived usefulness, influential role of facilitators and colleagues as well as enabling environment in terms of adequate infrastructural facilities that support its use. Hence, ODL institutions and stakeholders must strive to emphasize the need for students to augment their learning through the use of digital tools and resources, encourage learners to use them and provides adequate technological infrastructure that can support and promote its actual use among the students. However, consideration must be given to gender differences when dealing with ease of use and influential roles of peers and colleagues as regards ODL students' intention to use digital tools and resources. Also, the programme level attained by ODL students must be considered in policy formulation when dealing with peer influence and infrastructural facilities provisions by ODL institutions and stakeholders to promote intention and actual use of digital tools and resources for learning.

This study's results provide clear evidence that the UTUAT theory does not sufficiently address the weaknesses or perhaps failed to rightly synthesized the eight well-known technology acceptance models. Specifically, the attitude strongly emphasized by TAM was omitted in the UTUAT theory and it was found in this study to hold a strong influence on behavioural intention. This study, therefore, suggests that researchers should endeavour to go beyond the UTUAT constructs by adding some other constructs for a better explanation of behavioural intention and to address issues relating to continued use. There is a need to particularly reawaken discussion on the role of attitude in influencing behavioural intention, especially within the framework of the UTUAT construct to avoid likely non-detection of important factors and the possibility of detecting spurious relationships. Though UTUAT was developed in the western context and this study's results have highlighted the similarities and differences in cultural contexts. While performance expectancy resisted cultural differences in behavioural intention, the impact of facilitating conditions on behavioural intention proved to be culture-specific. It is therefore recommended that consideration should be given to culture and context when applying the UTUAT theory to predict technology acceptance.

Limitations and suggestions for future research

This study's result cannot be easily generalized to all ODL students in Nigeria as the study was carried out in only one ODL institution among many ODL institutions in the country. Also, the application of the UTUAT model is basically for digital tools and resources, hence, future studies should endeavour to test it on other domains such as e-learning, mobile learning, LMS etc. to assess the external validity of the research model. Furthermore, the proposed model in this study is not the same as the original UTUAT model, thus, the explained variance may be affected. While this study is cross-sectional in nature in terms of data collection, the original UTUAT model was based on longitudinal research. Hence, future studies are advised to conduct a longitudinal study to observe possible changes that may occur over a while in the relationships among the examined constructs. Also, there is a need to cross-culturally evaluate this study's model, especially between western and non-western countries and cross-nationally in either of the two for extension of the current knowledge base.

Acknowledgements

This study's researcher appreciates Mrs Elizabeth M. Ogunmoye for her assistance during the data collection for this study and her immense encouragement during the writing of this article.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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