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Influencing Factors Determine Students Behavioural Intentions to Adopt an E-Learning System in Tertiary Institution

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Abstract:** This study aims to investigate into the factor influencing tertiary institution adoption of e-learning systems. As a case study, the study included 3,77 undergraduate students from seven faculties at Abubakar Tafawa Balewa University in Bauchi, Nigeria, which made up the study's target population of 17,654 individuals. Consequently, the unified theory of acceptance and use of technology (UTAUT) model was developed using the multistage random sampling approach. The gathered data were examined utilising SmartPLSv3 SEM based on SPSSv23 for analysis. The study's results also showed that PE, EE, and FC significantly influenced students' BI to embrace e-learning systems. However, the effects of SI alone on students' behavioural intentions were not significant.

***Keywords:** E-Learning System Adoption, Tertiary Institution, SEM, Internal Consistency Reliability, Discriminant Validity, and Convergent Validity*

1. INTRODUCTION

The conventional technique of conducting teaching and learning has evolved, and IT has also helped turn the old approach gradually into the new and developing trend known as e-learning. Nowadays, many institutions, particularly in developing nations, have started observing the development in the way teaching, learning, and evaluating the students' performance is done (Lu, Lin, Raphael, & Wen, 2022; Yakubu & Dasuki, 2018). E-learning is a new trend that many colleges throughout the world have foreseen and embraced. While some integrated the two (partial adoption) together, there are still some colleges that solely use the old method of teaching and learning. Numerous research on the acceptance and usage of e-learning have been undertaken in recent years (Ansong et al., 2016; Ming et al., 2021;

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Ming et al., 2021; Tan, 2019; Wang et al., 2019; Zhang & Huang, 2021; Zhang & Cao, 2020).

Yakubu and Dasuki (2018) examine whether new factors of the prior research model (modified UTAUT) have a positive influence on students' behavioural intention to adopt and use an e-learning system. It was discovered that, in contrast to all other parameters, FC had no direct influence on the inclination to utilise e- learning technology. In contrast, all other components had a greater impact on student's intention to embrace and use e-Learning. The construct facilitating condition (FC) was evaluated on students' intentions to use an e-learning system in tertiary institution instead of system actual usage (AU).The drivers and determinants of e-learning acceptance and use in the context of poor nations are mostly unknown (Yakubu & Dasuki, 2018). Research has shown that tertiary institutions in poor nations have lagged behind their Western counterparts in adopting e- learning. The ones that were already accessible were insufficient to solve the problem. Students' intention to adopt and utilise an e-learning system has been examined in a study by Uur and Turan (2018) and Abdekhoda et al. (2016) at the University of Nottingham.

The suggested study model was tasked with determining if the following factors had a favourable impact on students' behavioural intention to adopt an e-learning system:

- Whether performance expectation, effort expectancy, social influence, and facilitating conditions have positive effects on students' behavioural intention to adopt e-learning system?

The objectives of this study are:

- To examine the impact of performance expectations, effort expectations, social influence, and enabling conditions on students' behavioural intention to adopt an e-learning system is unified study's goals.

The UTAUT model served as the research model for the study, as previously noted. At order to investigate the factors that affect the acceptance and usage of e-learning in tertiary institutions from the perspective of the students, the study makes use of the constructs and hypotheses listed below:

H_1**:** PE has positive influence the student’s BI to adopt e-learning system.
H_2: EE has positive influence the student’s BI to adopt e-learning system.
H_3: SI has positive influence the student’s BI to adopt e-learning system.
H_4: FC has positive influence the students’ BI to adopt e-learning system.

This study has added to the body of knowledge since the literature that was previously accessible was insufficient to address the issue of technology adoption. From the perspective of the students, this study will be useful since it emphasised aspects that affect students' behavioural intentions regarding the adoption and utilisation of e-learning in tertiary institutions. The study provides other academics who desire to do research in the field as well as IT specialists who would benefit from its design and development. This study used a modified version of the UTAUT model where the dependent variable was behaviour intention. Cross-sectional rather than a longitudinal study was the format employed for the research design. Given that tertiary schools contain several faculties, departments, or branches, as well as a wide range of students, this study also used the multi-stage random sample approach. Students are the primary audience for any academic activity, including teaching and learning activities, this should be applied to their viewpoints instead (Yakubu & Dasuki, 2018, Zawaideh, 2017). This study would instead analyse the factors influencing

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students' behavioural intention toward adoption of the e-learning system in tertiary institutions.

1.1 Literature Review and Related Studies

The concepts, theories/models of the previous studies were consulted with the aim of adding to the body of knowledge and empirically, to provide evidence of the subject matter of the study by examining the proposed and previous study, in terms of applications, methodologies and findings.

1.2 The Current Status of E-learning Adoption in Nigerian Tertiary Institutions

The emergence of telecommunications in 1886 marked the beginning of e-learning in Nigeria. In 1893, all government offices in Lagos were connected by telephone for simple communication. Nigeria had 18,724 phone lines at the time of independence in 1960, translating to a tele-density of around 0.5 telephones per 1,000 persons (Olatunbosun, Olusoga & Samuel, 2015). Nigeria's telecommunications liberalisation led to the introduction of four private Global System for Mobile Communication (GSM) businesses in 1999. The Teledensity of Nigerian telecommunication services, which includes data and voice, is 103.2% as a result of the liberalisation of telecommunications in Nigeria. 3G enabled smart phones to download common web pages, movies, and audios for a comparatively low price (Al-Adwan, Al-Adwan, & Smedley, 2013; and Elkaseh, Wong, & Fung, 2016).

Higher education institutions in Nigeria have progressively made investments in course management software throughout time to offer a virtual learning environment for students. The advent of the Internet has significantly altered how many processes, such as e-government, e-banking and e-education, are carried out. This generation is distinct from earlier generations thanks to Internet technology (Olatubsoun, Fasoranbaku, & Oluwadare, 2015). In Nigeria's higher institutions, e-learning started with the storage of prepared lecture materials on CD-ROMs that could be played back at a later time as needed. Although this offers the benefit of making lecture materials always accessible, it also has the disadvantage of having fewer computers per student. Low bandwidths provide another difficulty, making it impossible for the students to broadcast interactive lectures in real time (Adu, Eze, Salako & Nyangechi, 2013).

ATBU was unable to adopt and execute an e-learning system because of lack of ICT infrastructure. The majority of Nigeria's higher education institutions just build up ICT centres and offer Internet access, without additional e- learning infrastructures. Some higher educational institutions, such Obafemi Awolowo University in Ile-Ife and the Federal School of Surveying in Oyo, have already established e-Learning facilities (Hamilton-Ekeke, and Mbachu, 2015).

1.3 Conceptual Review

To investigate the elements impacting the students' behavioural intention and usage of the e-learning system, the study applied the unified theory of acceptance and use of technology (UTAUT). Four independent variables (PE, EE, SI, and FC) and one dependent variable are drawn from the conceptual model that is provided (BI). Additionally, this study explains how the aforementioned variables affect the e-learning system, e-learning adoption, motivations

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for selecting UTAUT, tertiary institution e-learning preparedness, obstacles and advantages of tertiary institution e-learning adoption in Nigeria.

Table 1. Conceptual review

Construct	Description
Performance expectancy (PE)	The concept of PE is "the extent to which a person thinks that utilising the system has assisted him or her in attaining increases in work performance" (Venkatesh, et al., 2003; Ming et al., 2021).
Effort expectancy (EE)	When utilising the system for the first time, EE is a reliable predictor of behavioural intention. Previous research has demonstrated that EE has a favourable impact on both a system or technology's intended and actual uses (Wang, 2016; El-Masri & Tarhini, 2017; Sarabadani, et al., 2017).
Social influence (SI)	SI is the belief of an individual that individuals who are significant to them think they should utilise the system (Venkatesh, et al., 2003; Ming et al., 2021).
Facilitating condition (FC)	FC is a person's assessment of the level of support provided by the organisational and technological infrastructure to the person in order to promote system utilisation (Venkatesh, et al., 2003).
Behavioural intention (BI)	According to the UTAUT model, PE, EE, and SI have an impact on people's behavioural intents to utilise technology (Venkatesh, et al., 2003). However, much like in the study by Zawaideh (2017), FC has a substantial positive link with Behavioral intention to utilise e-learning. It also has a positive and significant effect on students' BI in this study.

1.4 E-Learning System
The deliberate application of networked information and communications technology for teaching and learning is referred to as e-learning. E-learning is the process of learning via the use of computers and the Internet. When students connect with their teacher and other students as well, their chances of increasing their own knowledge are increased (Asoodar et al., 2016; Lai et al., 2022; Ray et al., 2020; Thepwongsa et al., 2021).

1.5 E-Learning Adoption
The adoption of e-learning in developed nations cannot be based on data from developing countries. In order to evaluate the causes, this work employs a strong theoretical approach together with novel technology advancements. E-learning is a technological advancement that may be used in numerous areas of education (Ansong et al., 2016).

1.6 Reasons for Choosing UTAUT
The UTAUT model was developed under consolidation of eight models such as: social cognitive theory, theory of reasoned action, innovation diffusion theory, and technology acceptance model. This study adopts a strong theoretical approach together with novel

technology advancements. It aims to analyse the variables influencing the adoption of e-learning from the perspective of a developing nation (Boateng et al., 2016; Lin et al., 2020).

1.7 Challenges to E-Learning Adoption in Nigeria's Tertiary Institution

More research is needed to confirm and combine the numerous drivers that were not missed in prior studies. A review of the e-learning literature reveals a dearth of research from poor nations, particularly in Africa. Challenges with social customs, technical infrastructure, and organisational culture may cause this transfer to be delayed (Aulia et al., 2019).

Many obstacles must be overcome for E-learning to be implemented in Nigerian universities. Learning online requires students to put more effort and emphasis into their studies than traditional classroom instruction. According to Adu, Eze, Salako, and Nyangechi (2013), the main issues preventing the full adoption of e-learning are hardware acquisition costs and bandwidth costs.

1.8 Benefits of E-Learning Adoption among Tertiary Institutions

There are several reasons why the proposed research model must be changed and put to the test. It provides opportunity, flexibility, and availability to optimise investments in e-learning systems. If deployed, the approach will guarantee effectiveness and raise student performance. The technologies chosen for online learning should be simple for academics to use and must benefit the students. (Yakubu & Dasuki, 2018; Asoodar et al. 2016).

1.9 Theoretical Review

The use of technology and behavioural intents to use are the foundation of this study. About 30 years ago, a number of hypotheses were put up in an effort to explain how people use technology and their motivations behind it. The two theories most frequently mentioned by scholars in the field of technology acceptance are the unified theory of acceptance and use of technology (UTAUT) (Venkatesh, et al., 2003) and the technology acceptance model (TAM) Davis, (1989). Based on the original UTAUT model, UTAUT2 Venkatesh et al. (2012) is an updated model that takes into account three (3) more constructs: hedonic motivation, price value, and habit. For this study, UTAUT was chosen over TAM because the TAM theory's elements - namely, perceived usefulness and perceived ease of use - were included into UTAUT's performance expectation and effort expectancy constructs, respectively. The UTAUT's social impact construct also included the TAM2 concept of subjective norm.

This study assumes that students would only use the application to access course materials when necessary or as instructed by their teachers. The habit construct in UTAUT2 was evaluated on a technology (Mobile Internet users) where an addictive habit might arise (Venkatesh et al., 2012). This research anticipates that students will only utilise it to obtain course content when necessary (Ain, et al., 2016).

1.10 Empirical Review

Despite a delayed uptake by students, e-learning has several advantages for both people and corporations. According to Abdekhoda et al. (2016), users' acceptability is a key factor in the widespread adoption and implementation of e- learning. It is appropriate to utilise acceptance models like UTAUT to analyse user behaviour in order to determine how well new technologies are being adopted. Yakubu and Dasuki's (2018) study used the UTAUT model

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to examine the factors influencing the adoption of e-learning technologies among students in higher education institutions in Nigeria. The study's findings demonstrated that SI had no influence on students' behavioural intentions to use e- learning systems. Ugur and Turan (2018) extended the UTAUT model to uncover factors impacting academicians' acceptance of e-learning. The results of this study showed that FC had no appreciable impact on the adoption and use of online learning. Lai et al.'s in particular from 2022 used integrated models (Lin et al., 2020) and made use of the theory of planned behaviour (Mehrolia et al,. 2021) Table 2 summarises several earlier studies on the adoption of e-learning and provides information on the authors, year of publication, title, constructs (variables) evaluated, methodology, study environment, and underlying theoretical frameworks.

Table 2: Empirical Review

Author/Title	Model/Methodology	Variables	Findings
Hu et al. (2022) E-learning intention of students with anxiety: Evidence from the first wave of COVID-19 pandemic in China	TAM n = 512 college students	Continuance Intention (DV) Attitude, PEOU, PU (IVs)	PU is reinforced, PEOU are attenuated with Anxiety
Lu et al. (92022) A study investigating user adoptive behavior and the continuance intention to use mobile health applications during the COVID-19 pandemic era : Evidence from the telemedicine applications utilized in Indonesia	Expectation Confirmation Theory (ECT) n = 472 AMOS_SEM	Health Stress, Convenience, Perceived Usefulness, Satisfaction, Continuance Intention	Conv. is sig. on PU., Health Stress is partly sig. on Conv., Conv. had partly support Satisfaction, Health Stress supported Satisfaction, PU doesn't influe. Cont. Intention, but influenced Satis. Satisfaction. Influenced Cont. Intention
Lai et al. (2022) University students ' use of mobile technology in self-directed language learning : Using the integrative model of behavior prediction	INTEGRATED Model - Students - n = 676 - SEM	Behavioral Intention (DV), Attitude (ATT), Subjective-Norm(SN), Self-Efficiency(SE), Self-Regulation Skills (SRS), PE, SI, and Actual Behavior (AB)	ATT, SN Had Significant Relationship With Intention SE Did Not Have Direct Relationship With SRS And Intention Is A Significant Predictor Of Actual Use
Ming et al. (2021)	Grounded Theory,	System (Accessibility,	Users' BI influenced

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Factors Influencing User Behavior Intention to Use Mobile Library Application: A Theoretical and Empirical Research based on Grounded Theory	Mixed (Qualitative & Quantitative) method, SEM Undergraduate Students	correlation, System help) Interface (Screen design, Navigation term) Individual Difference (Performance expectancy, Domain knowledge, Social influence)	by System, Individual Diff. (PE, DK and SI)
Mehrolia et al. (2021) Moderating effects of academic involvement in web-based learning management system success: A multigroup analysis	Dlone & Mclean IS Success Model, n = 512 undergraduate and postgraduate students	Tech. system quality, Edu. System quality, Infor. quality, Service Quality, Intention to use, User satisfaction, Net benefits Higher Academic involvement	System, Infor., Edu., Service Qualities Explained Intention To Use. Support Team, User Satisfaction, Higher Acad. Involvement moderated the impact of Service Quality on User's Satisfaction and intention
Thepwongsa et al. (2021) The effects of a newly established online learning management system : the perspectives of Thai medical students in a public medical school	TAM (modified), Mixed (Qualitative & Quantitative) method, Descriptive Binary Logistic, n = 283	PU, Content Quality (CQ), Test Scores (TSc), Time Spent (TS), User-friendliness (UF), Class-interaction (CI), Platform Infrastructure (PI)	Most of the respondents believed that there is lot of adv. And benefits from using system. PU and CQ were sign., CI, UF and PI were insignificant
Sa et al. (2020) Gamification as a motivation strategy for higher education students in tourism face-to-face learning	Integrated Theories, n = 85 Undergraduate Students	Functional, Hedonic, & Social Benefits, Attitude towads learning, Attitude towards Innovation, Gender, Age, Loss of Privacy, Difficulty in using Tech., Intention to use HEgame App	Hedonic and Social Benefits, are sig. on Students' Intention to Use HEgame App., Loaa of Privacy employed moderating effects on relationship b/w Intention and Functional Benefits
Lin et al. (2020) Behavioral intention towards mobile learning in Taiwan, China, Indonesia, and	Theory of Planned Behavior (TPB), n = 947 Undergraduate Students	Behavioral Intention (DV), Attitude, (A) Subjective Norms (SN), Perceived Behavioral Control (PBC), PEOU,	A, SN, PBC are Sig. on BI in both countries. PBC is Sig. on BI in Taiwan & Viatnam but not

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Vietnam		PU, Instructors & Students Readiness (ISR), Self-efficiency & Learning Authonomy, and Behavioral Control	in China. SN is Sig. on BI in China and Indonesia but not in Viatmnam
(Ray et al., 2020) Behavioral intention towards mobile learning in Taiwan, China, Indonesia, and Vietnam	Quantitative, n = 378 respondents	Customer experience (CE), Brand meaning (BM), Customer satisfaction (CS), Brand quality (BQ), Brand awareness (BA), Brand equity (BE)	CE is a strongest determinant of both BM, and CS, BM impacts BE. BE and CS are positive and Significant impact on Intention
Wang et al. (2019) Usability factors predicting continuance of intention to use cloud e-learning application	TAM, Social Cognitive Theory (SCT) and Motivational Theory, - Qualitative & Quantitative method, - SEM - 170 IT Students	Computer Self-Efficiency (CE), Enjoyment (E), PEOU, Perceived Usefulness, User Perception, and Continuance Intention (DV)	
M. Nasir Yakubu & Salihu Ibrahim Dasuki (2018). Factors affecting the adoption of e-learning technologies among higher education students in Nigeria	- UTAUT model - Target group: Students - SEM was used	- PE, EE, SI, FC, BI, and AU. - very little is known about the factors in e-learning adoption and use in the context of Nigeria	SI has no significant effect on students' BI to use the system
Naciye Guiliz Ugur And Aykut Hamit Turan, (2018). E-Leaning Adoption of Academicians: Proposed for an extended model	- UTAUT model - SEM was used	- PE, EE, SI, FC, BI. Lack clear e-learning strategy is the major barriers that can restrict wider adoption of e-learning by academician staff	- FC and SI were excluded because of their insignificant nature on BI
Mohammadhiwa Abdekhoda, Afsaneh Dehnad Sayd Javad Ghazi Mirsaeed, and Vahindeh Zarea Gaugani (2016). Factors influencing the adoption of e-learning in Tabriz University of Medical	UTAUT model Cross-sectional study Stratified sampling was used Structural Equation Model (SEM)	- PE, EE, SI, FC, BI, and AU. Instructors believed that e-learning does not cover all aspect of teaching nor does it support all features of e-learning	The findings also revealed that PE, EE, SI and BI had direct and significant effects on faculty members' Behaviour towards the use of e-learning. However, FC had no significant effects on

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Science.			the use of e-learning.
(Zawaideh, 2017). Acceptance Model for e-Learning Services: A Case Study at Al-Madinah International University in Malaysia	UTAUT model Zero-order correlation test was used	PE, EE, SI, FC, Culture (C), BI and UB. While it is true that e-learning in education has expanded substantially and its perceived benefits are well acknowledged, the efficiency of such tools have not be maximally used if the users refuse to take in and employ the system.	The factor of PE, SI, FC and C motivates the students to engage on e-learning. All the hypothesis were supported

1.11 Theoretical Framework
The aim and usage of technology among people were eventually discovered and explained by a variety of theories. Additionally, Yakubu and Dasuki (2018) used UTAUT to perform a study on the elements influencing the adoption of e-learning technologies among Nigerian students enrolled in higher education institutions. The previous study updated the UTAUT model, which was created by using 4 independent variables (IVs): PE, EE, SI, and FC with 2 dependent variables (DVs): BI and AU (Venkatesh et al., 2003). Five different hypotheses were examined in all; one was rejected, suggesting that there is insufficient evidence to conclude that SI significantly influences students' intentions to embrace and use e-learning tools.
The study focused on the adoption period rather than the post adoption phase (system usage) because Nigeria's higher institutions as a whole have yet to take off. Venkatesh et al. (2003) created UTAUT, which included eight (8) distinct social theories that were utilised to establish and deduce the seven (7) components. Four of these constructs - performance

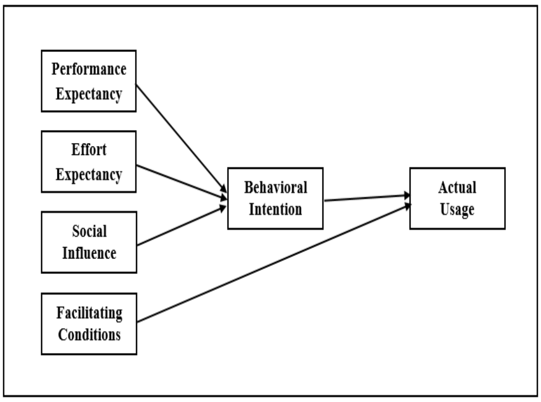

Figure 1: Theoretical model
Source: Yakubu and Dasuki, (2018)

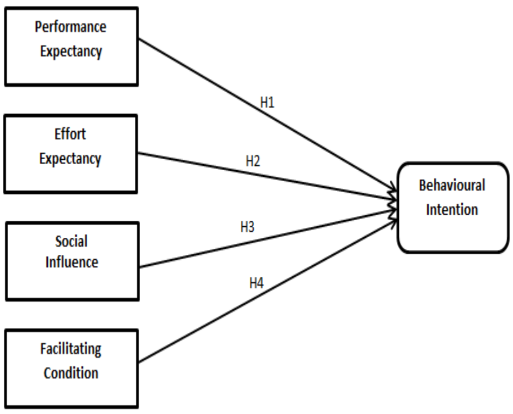

Figure 2: Conceptual Model
Source: Authors

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expectation (PE), effort expectancy (EE), social influence (SI), and enabling condition - were discovered to be independent variables (FC). Despite the UTAUT incorporating the eight diverse social theories listed above, certain crucial concepts have been left out of these theories (Yakubu & Dasuki, 2018). Two of them are dependent variables (DVs): actual usage and behavioural intention (BI) (AU). AU is a study to see if there is a significant relationship between FC and students' behavioural intention to use an e-learning system. Four (4) hypotheses overall were produced from the study model using various components (variables), with behavioural intention serving as a determining variable. These constructions include, among others, performance expectation, effort expectancy, social impact, and enabling circumstance. In essence, each construct has a definition and a reason for being included in the model that has been suggested.

2. METHODOLOGY

The research design used for this study was quantitative. In addition, the survey's questions were created based on the suggested model to satisfy the research goals from the literature review, in order to respond to the study's questions and validate the relationships between the constructs (variables) in the model. The questionnaire was divided into two parts to assist gather information on the respondents' demographics, their experiences participating in academic activities online, and their adoption and usage of e-learning. Each of the five Likert scales used to test the constructs' numerous elements ranged from Strongly Agree (1) to Strongly Disagree (5). (5).

The study concentrated on the variables that affect students' behavioural intentions to utilise e-learning systems. The study's target audience consists of Abubakar Tafawa Balewa University in Bauchi students. The study model is based on a modified version of UTAUT by Venkatesh et al. (2003) and a questionnaire that was developed from the work of Abdekhoda et al. (2016) and Maqueira-marn et al., respectively. Questionnaires were utilised as a method of data collection, and the replies were quantified (2017).

Population and Sample of the study

The Abubakar Tarawa Balewa University (ATBU) in Bauchi undergraduate students that participated in the study were the study's population. Except for 400 level students in the faculties of management science, science, agriculture & agricultural technology, and technology education who are engaged in industrial training (IT) and teaching practise, the target population (N) as a whole is seventeen thousand, six hundred, and fifty-four (17,654). (TP). While the Medical Sciences College at ATBU only has 100 to 300 level students because the staff is new. Based on data from all students in the six (6) faculties, this number (see, table 3, 4 and 5 below).

Table 3: Faculties (clusters) and levels (strata) of students

	Faculty of Manageme nt Science	**Facul ty of Scien ce**	**Faculty of Envr. & Envr. Tech**	**Faculty of Technolo gy Edu.**	**Faculty of Engr & Engr. Tech.**	**Faculty of Agric. & Agric Tech.**	**College of Medical Science**	**T ot al**
1 0	611	981	889	966	876	336	57	4 7

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0								16
200	568	861	798	841	806	251	49	4174
300	573	898	736	764	779	212	36	3998
400	471	894	693	647	734	202	-	3641
500	452	878	782	517	513	197	-	3339
Total	2675	4512	3898	3735	3708	1198	142	19868

Table 4: Net population of the study

Faculty (Cluster)	**No. of Students**	**IT/TP Students**
Faculty of Management Science	2675	471
Faculty of Science	4512	894
Faculty of Environment & Environmental Technology	3898	-
Faculty of Technology Education	3735	647
Faculty Engineering & Engineering Technology	3708	-
Faculty of Agriculture & Agricultural Technology	1198	202
College of Medical Science	142	-
Gross Total	19868	2214
Less Students on IT/TP	2214	
Net Total	17654	

Three hundred and seventy-seven (377) students were chosen as the study sample from among those enrolled in various faculties and colleges. Only undergraduate students were contacted since the questionnaire was administered using a multi-stage sampling approach. The multi-stage sampling methodology combines many sample methods, including basic random sampling, faculty-based clustering, and level-based stratification. Students from six distinct faculties (clusters), students at varied levels (stratifications), and a straightforward random sample approach were all used in the study. The questionnaire was distributed using

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a multi-stage sampling procedure. Multi-stage cluster sampling is another name for the multi-stage sampling. One or more sub-clusters from the main cluster were formed using this procedure. This method included adding one or more sub-clusters from the primary cluster at random. Additionally, there is an equal probability that any student inside the sampling frame will be chosen as a research sample. In order to eliminate repeat replies, a multi-stage sampling method was used to contact the students face-to-face rather than through an online survey. The number of enrolled students is depicted in the table below.

Table 5: Sample size based on each faculty

Faculty (Cluster)	**No. of Students**	**Percentage (%)**	**Sample**
Faculty of Management Science	2204	12.5	47
Faculty of Science	3618	20.5	77
Faculty of Environment & Environmental Technology	3898	22.1	83
Faculty of Technology Education	3088	17.5	66
Faculty Engineering & Engineering Technology	3708	21	80
Faculty of Agriculture & Agricultural Technology	996	5.6	21
College of Medical Science	142	0.8	3
Total	17654	100	377

The study by Abdehkoda et al. (2016), Ramirez-Anormaliza, and Sabaté tested the research hypotheses in order to provide supporting empirical evidence from the prior literature. The UTAUT sought to comprehend the students' behavioural intent to adopt and use an e-learning system. Under the measurement and structural models, the independent variables' effects on behavioural intention were statistically confirmed.

3. DATA ANALYSIS AND DISCUSSIONS

Seven ATBU Bauchi faculties each received a survey questionnaire, for a total of 377. Out of these, 353 (93.6%) were returned within the allotted time frame, and 341 (85.3%) were deemed suitable to be entered into the data file for analysis. The remaining 17 (4.5%) questionnaires were distributed but not returned, and the remaining 19 (5%) were disqualified due to inappropriate respondents or incomplete responses. Table 6 shows the proper distribution..

Table 6: Response rates

Questionnaires	**No. of Questionnaires**	**Response Rate (%)**
Used for analysis	341	90.5
Not Returned	17	4.5
Rejected	19	5.0
Total	377	100

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3.1 Descriptive Analysis

For the analysis, data from 353 (93.6%) survey forms were loaded into the data file (using SPSS). However, 12 instances with outliers were removed during the data cleaning procedure, leaving 341 (90.5%) that were deemed adequate for the final study. This section presents the descriptive statistics for the demographic variables and factors that were utilised in the study.

3.2 Descriptive statistics of demographic factors

According to the table 7 below, there are 92 female students and 249 male students, or 73% and 27%, respectively. By completing the offered surveys, the male students gave the researcher with support for their request. Most of them urged their coworkers to participate in the study since they never knew when it may be their time. In addition, men are more likely to participate than women for reasons related to gender sensitivity. This demonstrated that female students participated less actively than male pupils. This is a result of the researcher's lack of gender awareness. As the majority of them thought they shouldn't participate, several of them made fabricated explanations in their complaints.

According to table 7 below, ATBU students, in particular, make up the majority of students in higher institutions. According to table 7 below, there were 261 and 71 responses overall, or a total response rate of 76.5% and 20.8%, respectively, for students at higher institutions, mainly ATBU, who were most often between the ages of 18 and 25 and 26 to 33. Only 8 out of 353 respondents (with response rates of 2.3% and 0.3%, respectively) were above the age of 34 to 41. Additionally, only one respondent (0.3%) was over the age of 42. The study noted that youth enrolment in higher institutions has significantly improved since the 1980s.

Students from the seven faculties of ATBU were the study's target demographics, as was seen above. With 80, 74, 62, and 57 respondents respectively, the faculties of Environmental Technology, Engineering and Engineering Technology, Science, and Technology Education had the highest response rates at 23.5%, 21.7%, 18.2%, and 16.7%. The faculty of medical science was in the lowest stratum, followed by agriculture, agricultural technology, and management science, with just 3, 24, and 41 respondents, respectively, and response rates of 0.9%, 7%, and 12%. According to the percentage of the sample size and the method of sampling, the respondents received questionnaires.

According to the table above, more students from the 200 level than any other level participated in the research, with 108 responding (31.7%) out of 353 respondents. The 100 level and the 400 level had the lowest response rates, with 51 (15%) and 39 (11.4%), respectively. Out of the seven faculties, five (5) had students in the 400 level who were enrolled in industrial training and teaching practise. These five faculties included the faculties of Management Science, Science, Technology Education, Medical Science, and Agriculture and Agricultural Technology. Because only two (2) of the seven faculties were available to participate in the research, there were very few 400-level students. Additionally, students at the 300 level responded with 70 (20.5%) and those at the 500 level responded with 73 (21.4%). While the 100 level students were accessible, many of the questionnaires that were given to them were destroyed because of their lack of experience in filling them out.

The degree of students' e-learning experience is also depicted in the table above. The fact that 257 students responded "Yes" while 84 said "No" with response rates of 75.4% and 24.6%,

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respectively, showed that the majority of students were either familiar with or knew little about the e-learning system.

3.3 Assessment of Measurement (Outer) Model

The measurement model evaluates how a latent construct and its observable indicators are related (Henseler, Hubona, & Ray, 2016). Indicators for evaluating the reflective measurement model, according to Hair et al. (2014), include indicator outer loadings for assessing the reliability of each individual indicator, Composite Reliability (CR) for assessing internal consistency, Average Variance Extracted (AVE) for assessing convergent validity, and square root of AVE (Fornell-Larcker criterion) for assessing discriminant validity. But because of the Fornell-Larcker criterion's obvious flaws. Heenseler, Ringle, and Sarstedt (2015) suggested the heterotrait-monotrait (HTMT) ratio of correlations across latent constructs as a superior criteria for evaluating discriminant validity. The aforementioned indices were generated using the standard PLS technique and are shown in Tables 9 and 10 correspondingly.

Table 7: Descriptive Statistics of Demographic Factors

Demographic	Characteristic	Frequency	Percent
Gender	Male	249	73
	Female	92	27
Age	18 – 25	261	76.5
	26 – 33	71	20.8
	34 – 41	8	2.3
	42 – above	1	0.3
Faculties	Science	62	18.2
	Engineering and Engineering Technology	74	21.7
	Agriculture and Agricultural Technology	24	7.0
	Management Science	41	12.0
	Technology Education	57	16.7
	Environmental Technology	80	23.5
	Medical Sciences	3	0.9
Students' Level	100 Level	51	15.0
	200 Level	108	31.7
	300 Level	70	20.5
	400 Level	39	11.4
	500 Level	73	21.4
Experience	Yes	257	75.4
	No	84	24.6

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3.4 Indicator reliability

Generally speaking, the value for each item's outside loading should be more than 0.70. (Hair et al., 2014 & Henseler et al., 2015). According to Hair et al. (2014), indicators with loadings between 0.40 and 0.70 should only be removed from the scale if doing so causes the CR or AVE to rise over the specified threshold value. The threshold values for CR and AVE are more than or equal to, respectively, 0.708 and 0.50. (Hair et al., 2014 & Henseler et al., 2016). All of the model's constructs had CRs that were higher than 0.708 when the SmartPLS method was calculated (Table 8). These have the greatest CR and AVE among all structures. BI (CR=0.85, AVE=0.5255), SI (AVE=0.577), PE (AVE=0.582), FC (AVE=0.576), and EE (AVE= 0.538) are the next-highest performers.

3.5 Internal consistency reliability

Cronbach's Alpha is a commonly used metric for gauging internal consistency dependability. However, academics have lately criticised the use of Cronbach's Alpha as a conservative reliability measure (Garson, 2016 & Hair et al., 2014). Since Cronbach's alpha is sensitive to the amount of indications in a scale, it frequently overestimates or underestimates internal consistency dependability (Garson, 2016 & Hair et al., 2014). In PLS-based research, CR is therefore chosen by writers because it yields superior estimations of real dependability. Since CR considers the various outer loadings of the indicator variables, it is typically interpreted similarly to Cronbach's alpha. The CR for all of the latent components in this investigation exceeded the minimal threshold value of 0.708, as shown in Table 8. With regard to composite dependability, BI has the greatest rating (0.847), followed by SI (0.843), PE (0.805), FC (0.802), and EE (0.777), which is the lowest. They all scaled the composite reliability cutoff of 0.70. (CR).

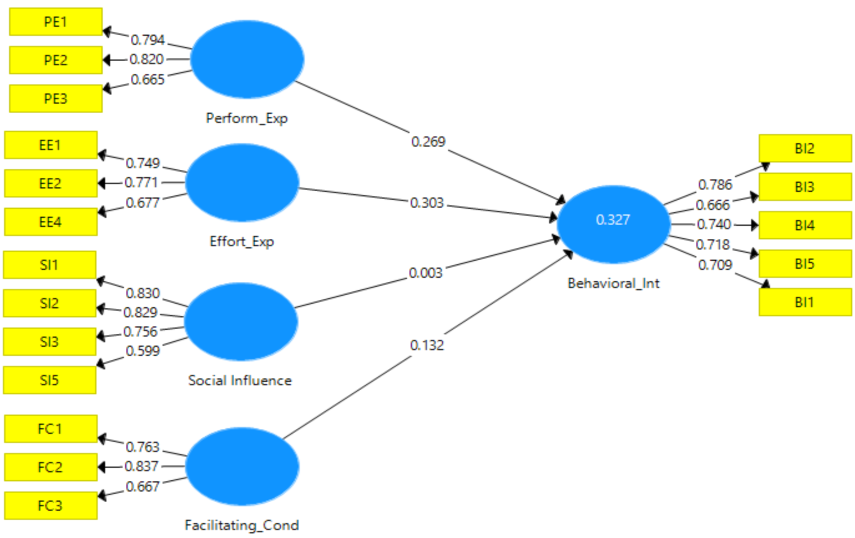

Figure 3: Measurement ModelAssessment of Structural (Inner) Model

3.6 Convergent validity

A concept must be unidimensional in order for there to be convergent validity, which calls for a decent level of agreement among the indicators used to measure the construct (Hair et al.,

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2014). AVE is the primary indicator of convergent validity, and an AVE of 0.5 or more is considered to be acceptable (Hair et al., 2014, Garson, 2016 & Henseler et al., 2016). The PLS algorithm's output, shown in Table 8, demonstrates that the AVE for each construct reached or above the minimal threshold value mentioned above. While the dependent variable (BI) has an AVE value of 0.526, the independent variables (PE, EE, SI, and FC) have AVE values of 0.582, 0.538, 0.577, and 0.576, respectively. According to these results, it can be concluded that each indicator's latent construct in this study showed convergent validity due to its unidimensionality.

Table 8: Internal Consistency Reliability and Convergent Validity

Construct	Indicators	Loadings	Composite Reliability	Average Variance Extracted (AVE)
Behavioural intention	BI2	0.7859	0.8467	0.5255
	BI3	0.6660		
	BI4	0.7402		
	BI5	0.7179		
	BI1	0.7092		
Performance expectancy	PE1	0.7939	0.8054	0.5817
	PE2	0.8205		
	PE3	0.6646		
Effort expectancy	EE1	0.7487	0.7770	0.5380
	EE2	0.7711		
	EE4	0.6774		
Social Influence	SI1	0.8300	0.8430	0.5769
	SI2	0.8294		
	SI3	0.7561		
	SI5	0.5993		
Facilitating condition	FC1	0.7629	0.8015	0.5759
	FC2	0.8369		
	FC3	0.6673		

3.7 Discriminant validity

A construct measure must be empirically distinct and describe phenomena of interest that other constructs in a model do not capture in order to be considered discriminantly valid (Hair et al., 2014). The Fornell-Larcker criteria and cross-loadings are the two most used methods for evaluating discriminant validity in variance-based SEM, such as PLS. Henseler et al. (2015), however, offered studies that support the methodologies' limitations in determining discriminant validity. As a result, they recommended the Heterotrait-Monotrait (HTMT) ratio of correlations as a more effective strategy. Due to these factors, the Fornell-Larcker criterion and HTMT ratio were used in this work to establish discriminant validity (see, Table 9 and 10 respectively). According to the Fornell-Larcker criterion, each construct's square root of AVE value must be higher than the value of its correlations with other constructs. According to the Fornell-Larcker criterion, each construct's square root of

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AVE value must be higher than the correlations between those constructs (Fornell & Larcker, 1981). According to the HTMT ratio, "the ratio of the average correlations of indicators measuring distinct constructs, compared to the geometric mean of the correlations of indicators measuring the same construct, should be less than or equal to 0.85 or 0.90" (Henseler et al., 2015). Additionally, the HTMT ratios' bootstrapped confidence interval should be considerably different from 1. (Hair, Hult, Ringle & Sarstedt, 2017).

From the standpoint of both techniques, the PLS algorithm result showed strong discriminant validity for all constructs, as shown in Table 9. The correlations between the constructs are shown to vary between 0.2602 and 0.5175 on the top of the table, while the greatest value for the square root of AVE is 0.7627 (PE), which indicates extremely excellent discriminant validity according to the Fornell-Larcker criteria. Similar to this, Table 10's link between PE and EE had the highest HTMT ratio (0.8602), which is even higher than the strictest 0.85 threshold number. As neither of the confidence intervals includes the number 1, the bootstrapped confidence intervals further demonstrated that the constructs in this study are empirically distinct from one another.

Table 9: Fornell-Larcker Criterion

Construct	**PE**	**EE**	**SI**	**FC**	**BI**
Performance Expectancy	0.7627				
Effort Expectancy	0.5175	0.7335			
Social Influence	0.3319	0.3827	0.7596		
Facilitating condition	0.3570	0.4450	0.3974	0.7589	
Behavioural Intention	0.4732	0.5014	0.2602	0.3634	0.7249

Table 10: Heterotrait-Monotrait Ratio (HTMT)

Construct	**PE**	**EE**	**SI**	**FC**	**BI**
Performance Expectancy					
Effort Expectancy	0.8602				
Social Influence	0.4744	0.5768			
Facilitating condition	0.5587	0.7528	0.5786		
Behavioural Intention	0.638	0.7401	0.3362	0.5204	

3.8 Model predictive capability or quality

In PLS-SEM, model quality is evaluated using coefficient of determination (R^2), effect size (f^2) of the exogenous variables, predictive relevance (Q^2), and effect size (q^2) of the Q^2 (Hair *et al.*, 2014). This section presents the results for these indices in this study.

3.9 Coefficient of determination (R^2)

The examination of the coefficient of determination constitutes the primary component of structural model evaluation (R2). R2 is a metric for how much of an endogenous variable's variation is explained by one or more exogenous variables that point to it (Pallant, 2011). R2 values vary from 0 to 1, and higher numbers denote more accurate prediction. According to Table 11's SmartPLS algorithm results, this study model's R2 value is 0.327. This demonstrates that the four external factors together account for 32.7% of the variation in work performance (PE, EE, SI, and FC). On the precise meaning of the R2 value level, authors disagree. According to Cohen (1988), the ranges for small, medium, and big R2

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values are 0.10 to 0.29, 0.30 to 0.49, and 0.50 to 1.0, respectively. Although 0.65, 0.33, and 0.19 were indicated as large, moderate, and modest levels, respectively, by Hock and Ringle (2011) and Chin (1998), respectively. Consequently, the R2 of 0.327 found in this study might be regarded as modest.

3.10 Effect sizes (f^2) of the R^2

Aside from determining the R2 value, it is also necessary to determine the impact of a particular exogenous construct if it is removed from the model. This may be done by determining their effect sizes (f2) (Hair et al., 2014). However, SmartPLS 3 immediately offers the values for f2. According to Table 11, EE has the highest f2 (0.09), which is followed by PE (0.08), FC (0.02), and SI (0.00), in that order. Cohen (1988) defined big, medium, and small, respectively, as f2 values exceeding 0.35, 0.15, and 0.02. Therefore, it may be said that EE, PE, and FC have minimal impact sizes in the model. However, because the value is zero and below the minimal threshold, SI did not demonstrate any discernible effect (i.e. 0.02). This shouldn't come as a surprise because the construct initially didn't appear to have much of an effect on BI. Chin and Todd (1995) contend that it's important to consider all impact sizes, no matter how tiny.

3.11 Predictive relevance (Q^2) of the model

Using Stone-predictive Geisser's relevance - Q2 is another criterion for assessing the quality of the structural model in PLS-SEM (Hair et al., 2011 & Hair et al., 2014). To determine how well a reflective measurement model anticipated the data points of endogenous construct indicators, the Q2 must be evaluated (Wang, 2016). By excluding the eighth data point from the indicators of the endogenous construct, the blindfolding technique in SmartPLS 3 was used to calculate the Q2 value for this investigation. According to Hair et al. (2014), cross-validated redundancy technique for PLS-SEM should be used and should be more than 0 for the model to be predictively relevant.

3.12 Effect size (q^2) of the predictive relevance

Just like R^2 effect size (f^2) approach, q^2 effect sizes (see, Table 11) were computed to compare the relative impact of predictive relevance (Q^2) across exogenous constructs. Similar to f^2, q^2 values of 0.02, 0.15, and 0.35 indicate that an exogenous construct has a small, medium, or large predictive relevance for a certain endogenous construct. Depict the results of the q^2 calculations. The result indicates that EE (0.03) and PE (0.02) have small q^2 effect sizes, whereas, FC (0.01) and SI (0.00) have no significant effect. As stated earlier, Chin *et al.* (2003) also argued that even a small effect is important, as long as the resultant beta is significant.

Table 11: Endogenous and Exogenous Constructs

Endogenous Construct	**Exogenous Constructs**	R^2	Q^2	f^2	q^2
BI	PE			0.08 (Small)	0.02 (Small)
	EE	0.3275	0.156	0.09 (Small)	0.03 (Small)
	SI			0.00 (No)	0.00 (No)
	FC			0.02 (Small)	0.01 (No)

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3.13 Structural Model (Hypotheses Testing and Decisions)

After a reliable measurement model has been established, evaluating the structural or inner model comes next. A structural model evaluates the model's quality or prediction powers as well as the connections between the components (Henseler et al., 2016 & Hair et al., 2014). However, Hair et al. (2014) propose the requirement to first evaluate the degree of collinearity among predictor variables in order to guarantee the findings are free of bias. The Variance Inflation Factor was used in this study to evaluate collinearity (VIF). If the VIF of a particular exogenous variable is more than 5, collinearity might be a concern (Garson, 2016 & Hair et al., 2014). According to Table 12's findings, the construct with the greatest VIF is EE (VIF 1.5769), which is followed in order by PE (VIF 1.4286), BI (VIF 1.3701), and SI (VIF 1.2890). The fact that the VIFs for all of the constructs are much below 5 or even the stricter cut-off value of 4 shows that collinearity is not a problem in this study.

The links between the model constructs that are postulated are represented by structural path coefficients (Hair et al., 2014). The SmartPLS standard bootstrapping approach with 5,000 subsamples was used in this work to estimate the route coefficients (Henseler etal., 2016). Using a two-tailed test with a critical value of 1.96 (t 1.96) and a 5% significance threshold (p 0.05), the significance of the path coefficients was determined (Hair et al., 2011 & Garson, 2016). Based on the various hypotheses, Table 12 shows the findings for assessing the importance of the four (4) hypotheses in this study. The typical bootstrapping procedure's graphical output, which shows which route coefficients are important, is shown. In this part, the findings based on each hypothesis are further examined.

With the exception of H3, all of the hypothesised associations were validated by the route co-efficient reported in Table 12. BI was positively and significantly impacted by PE (= 0.2686, t-value = 4.2634, p 0.05), EE (= 0.3026, t-value = 4.2634, p 0.05), and FC (= 0.1316, t-value = 2.3849, p 0.05). The association between SI and BI was non-significant, although SI (= 0.1316, t-value = 2.3849, p > 0.05) suggested that there was no support for the link.

Table 12: Structural Model

H	Path	Path Coefficient	Standard Error	t-value	VIF	p-value	Decision
H1	BI <== PE	0.2686	0.0630	4.2634	1.4286	0.0000	Accepted
H2	BI <== EE	0.3026	0.0612	4.9436	1.5769	0.0000	Accepted
H3	BI <== SI	0.0029	0.0556	0.0531	1.2890	0.9577	Rejected
H4	BI <==FC	0.1316	0.0552	2.3849	1.3701	0.0171	Accepted

3.14 Findings

Structural equation modelling (SEM using SmartPLS3) techniques are very sensitive for internal consistency reliability and convergent validity. The study employed the UTAUT model to examine students' Behavioural intention to adopt e-learning system in tertiary institutions in Nigeria. E-learning adoption in tertiary institutions significantly depend on the users' (students') acceptance. The student's resistance and the issue of technophobia about the

adoption of e-learning system played a negative role. This consistent with the similar studies on learning technologies, m-learning, and ICT.
The internal consistency, reliability, and convergent validity of structural equation modelling (SEM utilising SmartPLS3) approaches are quite sensitive. The UTAUT model was used in this study to analyse students' behavioural intentions to use e-learning systems in Nigerian tertiary institutions. The acceptability of the users (students) is crucial to the uptake of e-learning at higher institutions. The implementation of the e-learning system was negatively impacted by the students' reluctance and the problem of technophobia. This is consistent with research of a similar nature on m-learning, ICT, and learning technology.

The majority of the study's findings demonstrate that students accept e-learning systems as true for all hypotheses, with the exception of one route coefficient that was statistically insignificant. Investigating users' behavioural intentions to use an e-learning system required significant input from PE and EE. Another important aspect influencing students' behavioural intention to embrace an e-learning system is that their FC is modest. However, it was determined that just the SI construct had no influence on students' BI to embrace an e-learning system. The original UTAUT model, which revealed that SI significantly and favourably influenced behavioural intentions, is at odds with these findings (Venkatesh, et al., 2003). According to this study, the EE has the biggest impact on BI. This is consistent with research on the adoption of e-learning systems, educational technology, mobile learning, and ICT. This is consistent with research on the adoption of e-learning systems, educational technology, mobile learning, and ICT (Bamidele, 2015 and Yakubu & Dasuki, 2018).

The results also corroborate earlier research that found that performance expectations and effort expectations, as described in the original UTAUT model (Venkatesh et al., 2003), are good indicators of e-learning adoption in relation to gender, culture, and age. In the case of the voluntary moderator, however, it was not taken into consideration since it was believed that all students must switch from a conventional learning system to an e-learning system when the institution wishes and is prepared to do so. The voluntariness moderator should be eliminated in a configuration that is required (Yakubu & Dasuki, 2018).

The results of this study showed that user (student) acceptability is a key factor in tertiary institutions' adoption of comprehensive e-learning. The introduction of an e-learning system was hampered by the students' opposition and the problem of technophobia, which both had a negative effect.

3.15 Performance expectancy and Behavioural intention

With respect to the first research objective the PE have positively influence the student's BI to adopt e-learning system. The findings also revealed (see, Table 12) that performance expectancy, effort expectancy, social influences and Behaviour indentation had direct and significant effects on faculty members' Behaviour towards the use of e-learning. PE (β = 0.2686, $p < 0.05$) (Hair *et al.*, 2011; Garson, 2016). This also shows that there is consistency between this study and the previous ones especially Abdekhoda et al., (2016); Ming et al., (2021) Yakubu and Dasuki, (2018); and Uğur and Turan, (2018). On the other hand the study conducted by Aggelidis and Chatzoglou (2009) and Pai and Tu (2011) found performance

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expectancy had no significant effect on students, behavioral intention to adopt e-learning system.

3.16 Effort expectancy and Behavioural intention

Based on the findings of this study EE has positive and significant influence on student's BI to adopt e-learning system and the same result was found by many researchers such as (Masa, Tarhini, Mohammed, and Maqableh, 2016; Abdekhoda et al., 2016; and Saleem, Al-saqri, & Ahmad, 2016)**.** Based on the Table 12 above the EE (β = 0.3026, $p < 0.05$). This partially opposed the study conducted by Ibrahim, Adu-gyamfi, and Kassim, (2018) and Uğur & Turan, (2018) where found that EE has least effect on BI to adopt ICT for learning.

3.17 Social influence and Behavioural intention

Table 12 shown that SI had no significant influence the student's BI to adopt e-learning system. SI was the weaker predictor on students' BI among other variables. There is consistence between this research and the previous studies (Yakubu & Dasuki, 2018). Based on the results the SI (β = 0 .0531, $p > 0.9577$). This conversely, opposed the findings of Pratama and Zhou (2019) found that social influence factors were found to be in significant. Likewise, the results of this study contradict the original UTAUT model of Venkatesh et al, (2003) and Ming et al. (2021) which SI positively and significantly influenced students' BI to adopt e-learning system.

3.18 Facilitating condition and Behavioural intention

FC have positively influence the students' BI to adopt e-learning system and this supported the research objective. Based on the Table 12 the EE (β = 0.0029, $p > 0.05$). The findings support the previous literature on facilitating condition that it is useful indicator and strongest predictor of students' Behavioural intention to e-learning (Yakubu & Dasuki, 2018). Even though the constructs FC was found non-significant on BI in the work of (Abdekhoda et al., 2016) but it was found significant in this study.

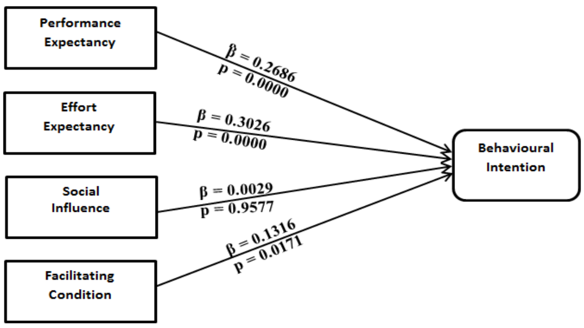

Figure 4: Structural Model

Only one measure, the SI, had no statistically significant impact on the BI of the pupils. This goes against the original UTAUT paradigm, which held that students' BI was significantly impacted by SI. This study validated the conclusions of Yakubu and Dasuki's (2018) earlier research. Using IBM Amos v22.0, the data were also examined in the prior study using a structural equation model (SEM). The SEM was used in this investigation as well, however it

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was based on SmartPLS v3. According to the outcomes of both studies, there was no discernible influence on students' BI to use an e-learning system in a postsecondary setting. This study's multi-stage sample approach includes basic random sampling technique, students at various levels (stratifications), and students from different faculties (clusters). Being a nonprobability sampling indicates that the results of that study cannot be extended to this study, according to Creswell (2012).

4 CONCLUSION

The main aim of this study is to examine whether all the four independent variables have positive and significant effects on students' Behavioural intention to adopt e-learning system. The multistage random sampling technique was employed with the total population of 17654 and sample size of 377. A total of 4 hypotheses were tested based on structural equation model using SmartPLS3.

Students have accept e-learning system adoption in tertiary institutions without referral of any colleagues, relatives or lecturers. Rather, motivated by self-satisfaction of the system. Adoption and implementation remains the most challenging aspect of technology and innovation toward the educational sector in Nigeria. Overall, the study empirically provided comprehensively support the proposed research hypotheses. Adoption and implementation of e-learning considerably depend on the users' acceptance toward the adoption of online learning system. A total of 4 hypotheses were tested based on structural equation model using SmartPLS3, found that the three hypotheses (H1, H2 and H4) were significant to students' intention to adopt e-Learning system. Conversely, one of the hypotheses was found non-significant on students' Behavioural intention.

Recommendations

Consequently, this study provided evidences and the following recommendations of various researchers who chosen to conduct a study on adoption of e-learning system or learning technologies.

(i) This study shows that students believed that using e-learning system have ease the processes of acquiring knowledge and skills and also help them in achieving their goals. The finding also showed that FC has positive and significant influence on students' BI. This signifies that students' perception on the degree of support given by organizational and technical infrastructure to encourage the use of the system.

(ii) The EE is the strongest predictor among all other proposed hypotheses that shows that ease of use associated with system. This new proposed research model will be best applicable in a situation where there is no any existing e-learning system or e-learning technologies on the actual ground.

(iii) The SI in this study has no significant influence on BI because there were no adequate supports and recommendations from someone that motivated the students to accept the e-learning system. This leads to it non-significant influence on students’ BI to adopt e-learning system. The study recommended that for social influence to be significant

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there should be moderator (Voluntariness of use). By then some important people to the student may be motivate them to use. This also added to the existing literatures.

(iv) The finding also showed that FC has positive and significant influence on students' BI. This signifies that students' perception on the degree of support given by the organizational and technical infrastructure to encourage the use of the system was in place.

Limitations and Recommendation for Future Study

The aim of this study was to examine the possible factors influencing students' Behavioural intention to adopt e-learning system with the exclusion of one depending factor which was actual use.

(i) Therefore, this study proposed only one dependent variable (i.e. Behavioural intention) rather than the two (ignored the system actual usage) as it was originally in the initial study. It was modified by removing AU because almost all Nigerian tertiary institutions were not adopted and implement e-learning system.

(ii) This lead to the removal of one of the construct from proposed research model. In the future research, the researcher(s) could focus on introducing actual usage of the system with the other constructs especially when there is adoption and full implementation of the e-learning system on the ground with the same target population.

(iii) The Cross sectional study was employed not longitudinal study. Therefore, the future research could apply longitudinal study instead of cross sectional study to enable the researcher to gather adequate information about the topic.

(iv) The findings of this study cannot be also generalized to the entire population of the Nigerian tertiary institutions. Because, the study targeted undergraduate students of ATBU Bauchi. Hence, the future research have to consider the lager population like based on geo-political zones, public universities or some selected states.

(v) User resistance, technophobia and unfamiliarity with e-learning system appear to be the main obstacles when e-learning implementation is considered. Analyzing the users' behaviour by such acceptance models as UTAUT is a proper method to define the adoption of new technologies like e-learning. Therefore, the future study should focus on the barriers to e-learning adoption.

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