Acceptance of e-Learning and Associated Factors among Postgraduate Medical and Health Science Student's at First Generation Universities, Amhara Region, 2023 Using Modified Technology Acceptance Model

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Abstract

Background

Electronic learning, also known as e-learning, is the process of remotely teaching and learning through the use of electronic media. University students are voracious information seekers who are eager to learn new concepts, ideas, technologies, and methods of knowledge acquisition. Students can access their learning materials at any time and from any location through e-learning, which takes place on the Internet. In a world where having up-to-date information and expertise is critical for benefiting from the current knowledge-based economy, e-learning is critical.

Methods

An institutional-based cross-sectional study was conducted from March 15 to April 20, 2023 in Amhara region first generation universities, Ethiopia. A total of 659 students participated in the study. simple random sampling technique was used. A self-administered questionnaire in Amharic language was used to collect data. data was manually coded and clean then entered into Epi data version 4.6 and SPSS version 25 was used for further analysis. A median score was used to assess the proportion of acceptance. A SEM analysis was employed to test, the proposed model and the relationships among factors using AMOS version 26.

Result

The proportion of postgraduate students' acceptance to use e-learning was 60.7%, 95%CI (56.9–64.4). The SEM analysis had shown that accessibility (β = 0.216, $P < 0.001$), computer self-efficacy(β = 0.156, $P < 0.01$) and facilitating condition (β = 0.381, $P < 0.001$), had a positive direct relationship with perceived ease of use and facilitating condition (β = 0.274, $P < 0.001$), computer self-efficacy(β = 0.426, $P < 0.001$) and Perceived ease of use (β = 0.201, $P < 0.001$) had a positive direct relationship with perceived usefulness and also Perceived ease of use (β = 0.156, $P < 0.001$) and perceived usefulness (β = 0.606, $P < 0.001$) had a positive direct relationship with attitude. Perceived ease of use (β = 0.183, $P < 0.001$), attitude (β = 0.353, $P < 0.001$) and perceived usefulness (β = 0.307, $P < 0.001$) had a positive direct relationship with acceptance of e-learning.

Conclusion and recommendation:

Overall, proportion of postgraduate students' acceptance of e-learning is promising. facilitating condition, self-efficacy, perceived usefulness, perceived ease of use and attitude had a positive direct and indirect effect on acceptance of e-learning, and attitude played a major role in determining students' acceptance of e-learning. Thus, the implementers need to give priority to enhancing, the provision of devices, students' skills, and knowledge of e-learning by giving continuous support to improve students' acceptance to use e-learning.

Introduction

E-learning is defined as "learning that is enabled electronically". Typically, e-learning takes place on the Internet, where students can access their learning materials at any time and from any location. Online courses, online degrees, and online programs are the most common forms of e-learning(1). It also supported the newly developed Action Plan to Integrate E-Learning into Higher Education(2). Globally, higher education sector has demonstrated a proclivity to use technology-based learning to bring innovation to the teaching and learning process(3, 4).

E-learning is a formal learning system that uses electronic resources(5). E-learning is critical in a world where having up-to-date information and expertise is critical for benefiting from the current knowledge-based economy(6). Educational practices and methodologies are shifting toward collaborative, online and offline computer-supported learning as a result of modern digital technologies. Students and adults in higher education rely heavily on massive online educational platforms and self-directed learning via their own smart and mobile devices. In the twenty-first century, the use of eLearning systems in higher education is a must. Students and adults in higher education rely heavily on massive online educational platforms and self-directed learning via their own smart and mobile devices(7).

Previously, the primary goal of e-learning in Universities were supposed to implement fundamental changes in teaching and learning methods(8). E-learning is playing an important role in the current educational setting, as it is changing the entire education system and becoming one of the most popular academic topics(9). Jordan's higher education institutions have formally adopted e-learning on both staff and students were utilizing a variety of technological tools. However, higher education institutions in developing nations continue to adopt e-learning systems at a slower rate than institutions from other countries(10).

Compared to developed countries, it was found that developing countries face many challenges in applying e-learning, including poor internet connection, insufficient knowledge about the use of information and communication technology, and weak content development(11). according to some researchers, developing countries have faced difficulties in adopting e-learning technology due to professional and student resistance, as well as a lack of appropriate facilitating conditions(12).

Many higher education institutions in African countries, including Ethiopia, have made investments in e-learning content development and timely updates, salaries and incentives paid to direct and indirect e-learning staff involved in e-learning system implementations, and e-learning infrastructure such as dedicated e-learning labs and e-studios, relevant e-learning software such as authoring systems, and data centers(13). To address the issues of scarce resources and access to high-quality education, many higher education systems around the world are moving from face-to-face to online learning. Examining emerging technologies and the underlying pedagogy of how learning occurs on a virtual platform is one of the essential prerequisites for the successful implementation of e-learning(14). Modified TAM is the most commonly used theory in existing e-learning technology studies to understand the acceptance of e-learning(15). e-learning saves time, speeds up overall work, saves money, and plays a vital role in increasing accessibility and enhancing the relationships and cooperation of students, teachers, and institutions.

In the world between 2011 and 2021, massive open online courses (MOOCs) increased their reach from 300,000 to 220 million learners(16). In the fall of 2020, approximately 8.6 million college students in the United States were enrolled solely in distance education courses through post-secondary institutions. In that same year, 5.42 million students enrolled in at least one distance education course. The impact of the COVID-19 pandemic has resulted in a high level of enrollment in distance education courses by using e-learning (17). According to E-Learning Statistics 2022 report, European data, 27 percent of E.U. citizens aged 16 to 74 reported taking an online course or using online learning material in 2021, up from 23 percent in 2020. In 2021, Ireland had the highest percentage of citizens aged 16 to 74 enrolled in online courses or using online learning resources (46%). Finland and Sweden came in second with 45 percent each, followed by the Netherlands with 44 percent. On the other end of the spectrum, Croatia (18%), Bulgaria (12%), and Romania (10%) had the lowest percentages of people taking online courses or using online learning resources(16). In Egypt, the e-learning system implemented was with high acceptance level(18). In Developing countries, recent study indicates that the magnitude of intention to use e-learning system in higher education institutions is low(19–21). In Ethiopia, recent study indicate that the magnitude of intention to use e-learning system in higher education institutions is low (19%) in the case of teachers (22).

There is a gap between interest and uptake in e-learning, which is due in part to students' resistance to acceptance and lack of a foundation to assess students' behavioral intention to use an e-learning system (12). In Egypt, the most significant Factors in higher education institutions were insufficient/unstable internet connectivity, inadequate computer labs, lack of computers/laptops and technical problems(18). Developing countries have limited resources, inadequate administrative and technical support, and inadequate staff development, all of which prevent them from implementing e-learning systems(23, 24). In Ethiopia, intention to use e-learning system in higher education institutions were affected by infrastructure problem, lack of awareness and motivation, lack of ICT skills, lack of training, lack of administrative management and technical support, and resistance of individuals to change(23).

Previous studies conducted around the world have several limitations, including secondary data analysis, sampling bias, self-selection bias, non-response bias, non-probability sampling strategies, small sample size, low response rate, and outdated data(25–28). Facilitating condition, computer self-efficacy and accessibility are external variables to affect perceived usefulness and perceived ease of use(27, 29–33). PEOU and PU are the most important TAM constructs for predicting user acceptance or rejection of technologies(34–36). PEOU, PU and attitude towards using e-learning are the main predictors (constructs) affecting acceptance of e-learning. As much as my literature searching capacity in Ethiopia, the magnitude of acceptance of e-learning among postgraduate medical and health science students is under-researched. Therefore, this study is crucial to fill the gaps by: (a)applying a modified technology acceptance model for determining the acceptance of e-learning among postgraduate medical and health science students; and (b)identify factors associated with e-learning acceptance among postgraduate medical and health science in college of medicine and Health sciences students by applying a modified technology acceptance model at first generation universities in Amhara region.

Theoretical background and hypothesis

The Technology Acceptance Model (TAM), which is originally proposed by F. D. Davis in 1986(37) and later revised in 1989(38). TAM 1 has been modified into modified technology acceptance model(TAM 2), particularly by Venkatash and Davis(39). It contends that a user's choice regarding a new technology is influenced by a number of factors. Two crucial factors are: Davis defines perceived usefulness as "the degree to which a person believes that using a particular system would enhance his or her job performance"(38) and perceived ease-of-use "the degree to which a person believes that using a particular system would be free from effort" (38). TAM provides a foundation for tracing how external variables influence perception, attitude, intention to use a specific technology, and actual technology use (figure 1).

Figure 1. The original Technology Acceptance Model (TAM 1)(37, 38)

TAM has been extensively researched and accepted as a valid model for predicting individual acceptance behavior across a wide range of technologies and users(38, 40). Despite the large body of existing TAM research, ongoing research efforts in TAM extension can be seen in the literature(38, 41). TAM currently has two revisions or upgrades (that is, TAM 2 and 3). This study will be conducted by Modified TAM(TAM2). factors such as Perceived usefulness and perceived ease of use in the TAM model are influenced by External factors(42). The external factors for this study are facilitating condition, computer self-efficacy, and accessibility. additional research refined their significance and gave more weight to Facilitating condition(43) (44) (45, 46), self-efficacy(29-32, 47, 48), Accessibility(27, 30, 32) on perceived ease of use and perceived usefulness. The study conducted in Malaysia students' intention to use e-learning is significantly impacted by their perceptions of the usefulness and ease of use of the technology(48). And also based on Chahal et' al perceived ease of use significantly affects intension to use e-learning(42). Previous research has validated the relationships between PEOU and PU, as well as between PEOU and PU and BI(38). The acceptance of new technology is aided by its perceived usefulness and perceived ease of use. TAM and other pertinent studies demonstrate that these factors have a significant impact on behavior intention to use.

TAM3 presents a comprehensive nomological network of the factors that influence people's IT adoption and use(46). TAM3 proposes three relationships that were not tested empirically in Venkatesh(39). There is different mediation Hypothesis for Modified TAM based on (fig 2).

Figure 2. The proposed model

Based on the above actual UTAUT model, the following hypothesis was developed.

Facilitating condition

The degree of accessibility to the means and possessions needed to complete a task is defined as a facilitating condition(43). However, the facilitation conditions are subjective, and thus vary according to individuals' perceptions of working within specific systems(44). A supportive external environment includes adequate infrastructure and organizational resources(45, 46). The E-learning Acceptance Model is a model that validates technical support and online resources as important factors in e-learning. They also identified adequate computer availability, network reliability, and access to online repositories as supportive conditions for e-learning(49). The study conducted at Bangladesh facilitating condition significantly affects perceived ease of use(50). In East Africa's higher education, facilitating conditions had a statistically significant impact on students' acceptance of mobile learning solutions(51). conditions are necessary for perceived ease of use(52, 53).

Two hypotheses can be generated from the aforementioned arguments.

H1a: facilitation conditions will have a significant influence on the perceived ease of use (PEOU).

H1b: facilitation conditions will have a significant influence on the perceived usefulness (PU).

Computer self-efficacy

CSE refers to a person's ability to perform information technology-related activities on a computer system(54). CSE has been validated as a critical determinant of IS acceptance and use. Empirical evidence suggests that higher CSE leads to increased confidence and motivation in an individual's attitude toward adoption and acceptance in the context of e-learning. Furthermore, people with higher CSE are more willing to use e-learning systems and put forth effort to overcome difficult obstacles than people with low CSE(55). There is a need to investigate the acceptance of such technologies in various ways and using different criteria(56). Revythi & Tselios assessed BIU learning management system acceptance via an adapted version of the TAM (57). The findings revealed that self-efficacy influenced both PEOU and BIU(47). Other studies show that Computer self-efficacy has significant positive effects on perceived ease of use and perceived usefulness(48). According to Abdullah(29), 33 of 41 studies reviewed confirmed a positive relationship between self-efficacy and perceived ease of use in the context of e-learning. Similarly, 10 of the 27 studies examined reported a positive relationship between perceived usefulness and self-efficacy.

Two hypotheses can be generated from the aforementioned arguments.

H2a: Computer self-efficacy will have a significant influence on the perceived ease of use (PEOU)

H2b: Computer self-efficacy will have a significant influence on the perceived usefulness (PU).

Accessibility

The term accessibility (ACC) refers to “the degree of ease of how a user can access and use the information and extracted from the system”(58). The degree of ease with which students can access and use the e-learning system is referred to as system accessibility(59). Many researchers have been conducted on how E-learning acceptance is affected by system accessibility. According to (6), the perceived ease of use of an e-learning system is greatly influenced by system accessibility. When a student considers an e-learning system to be accessible, he or she is more likely to have a positive impact on the usefulness and ease of use of that system(60). Two hypotheses can be generated from the aforementioned arguments.

H3a: Accessibility will have a significant influence on the perceived ease of use (PEOU)

H3b: Accessibility will have a significant influence on the perceived usefulness (PU).

Perceived Usefulness

According to the study done in University of Huddersfield (UK) perceived usefulness affects learners' intention to use e-learning systems and also affects attitude(29). And the study done in Haryana (India) perceived usefulness significantly affects intention to use e-learning systems(42). And also the study done in King Abdulaziz University (Saudi Arabia) p values for the correlations between the perceived usefulness and behavioral intension to use e-learning were less than 0.05 so perceived usefulness significantly affects acceptance of e-learning systems(61).

According to study done among university students in United Arab Emirates perceived usefulness significantly affects intention to use e-learning systems(27). Other research shows that acceptance of e-learning was affected by perceived usefulness(30, 32, 48). Perceived usefulness is significantly affects Attitude(31).

According to the study done at Addis Ababa University (Ethiopia) distance learners' behavioral intent to use an e-learning system in low-income countries was significantly influenced by perceived usefulness(62). Two hypotheses can be generated from the aforementioned arguments.

H4a: Perceived usefulness will have a significant influence on the Acceptance of e-learning systems.

H4b: Perceived usefulness will have a significant influence on the attitude towards using e-learning systems.

Perceived ease of use

According to the study done in University of Huddersfield (UK) perceived ease of use significantly affects perceived usefulness and attitude but it does not significantly affects intention to use e-learning system(29). And the study done at Abu Dhabi University (United Arab Emirates) perceived ease of use significantly affects intension to use e-learning system(27). On the other hand the study done at Muhammadiyah University (Yogyakarta) perceived ease of use does not directly affects behavioral intension to use e-learning system(63). Perceived ease of use is significantly affects Attitude(31).

According to a study conducted at Addis Ababa University (Ethiopia), perceived ease of use significantly influenced distance learners' behavioral intent to use an e-learning system in low-income countries(62). PEOU is regarded as one of the most important TAM constructs for predicting user acceptance or rejection of technologies(34-36). In agreement with the findings above, we would like to broaden the hypotheses by testing the following hypotheses:

H5a: Perceived ease of use will have a significant influence on perceived usefulness (PU).

H5b: Perceived ease of use will have a significant influence on the acceptance of e-learning systems.

H5c: Perceived ease of use will have a significant influence on user's attitude towards e-learning.

Attitude Towards e-learning

Attitude is a predisposed state of mind regarding the benefits of a system in improving work performance, time management to conduct their work, and its effect on improving the quality of their work(64). The study conducted in University of Huddersfield (UK), Attitude Toward Using significantly affects learners' intention to use e-learning systems(29). Studies conducted in kuwait university(47), Pakistan(31), Colombia(65) attitude towards using significantly affects intension to use e-learning systems. In light of the preceding findings, the following hypotheses are tested in this study:

H6a: Attitude towards e-learning will have a significant influence Acceptance of e-learning systems.

Methods and Materials

Study Design

This study uses a quantitative research method with an institution-based cross-sectional study to determine the acceptance level of e-learning and its associated factors among postgraduate Medical and health science students at first-generation universities (Bahir Dar University and University of Gondar) in Amhara region by applying a modified technology acceptance model.

Study area and period

The study was carried out in first generation universities in Northwest Ethiopia in 2023. The two first generation universities in Amhara region, Northwest Ethiopia are the University of Gondar and Bahir Dar University. In this region there are ten universities: University of Gondar, Bahir Dar University, Wollo University, Debre Markose University, Debre Birhan University, Woldiya University, Mekidela Amba University, Debre Tabor University, Debark University, and Injibara University.

Generally, universities are classified into three categories: first-generation universities (University of Gondar and Bahir Dar University); second-generation universities (Dessie University, Debre Markose University, and Debre Birhan University); and third-generation universities (Woldiya University, Mekidela Amba University, Debre Tabor University, Debark University, and Injibara University). Gondar universities offer their services through five campuses and two institutions and also Bahir Dar university offer their services through five campuses. The two Universities serves a total of 7,155 students in postgraduate programs. During the study period, there are 2,376 postgraduate medical and health sciences students at CMHS in the universities.

Source and study population

Source population

All Amhara region first generation universities (Bahir Dar University and University of Gondar) college of medicine and health sciences postgraduate students in the academic year of 2023 was the source population.

Study population

All selected medical and health sciences postgraduate students who were enrolled in first-generation Universities in Amhara region available during the data collection period.

Eligibility criteria

Inclusion Criteria

All postgraduate medical and health science students who were enrolled in first-generation Universities in Amhara region available during the academic year of 2023 was included.

Exclusion criteria

All postgraduate medical and health science students who were not physically or mentally capable of being interviewed at the period of data collection was excluded from the study. Students who were transferred in or out and withdraw from university during the academic year in which the study was taken place also excluded.

Variables

Dependent Variables

Acceptance of e-Learning Systems

Independent Variables

- Students Socio demographic characteristics
- Perceived Usefulness
- Perceived Ease of Use
- Facilitating condition
- Computer self-efficacy
- Accessibility
- Attitude towards e-learning

Acceptance of e-learning: is defined as the user's likelihood to use electronic learning for easy improvements of education. Items for the Likert scale was transformed into dichotomized as "Yes" or "No." Like strongly agree and agree was classified as "Yes" while strongly disagree, disagree, and neutral was classified as "No". When a student rates accepted to use a technology measurement and scores median and above the median is accepted to use else not accepted to use with a five-point Likert scale of three questions(66).

Sample size determination and sampling procedure

Sample size determination

The sample size was estimated based on structural equation modeling assumptions of determining model-free parameters using the modified TAM model (Fig. 3) by considering 32 variances of the independent variables, 3 covariances between independent variables, 18 factors loading between latent variables and latent variable indicators, 12 direct effects of regression coefficients between unobserved latent variables were estimated. finally, 65 free parameters were estimated. But the variances of dependent variables, the covariance between dependent variables, and the covariance between dependent and independent variables are never parameters (as would be explained by other parameters), and for each latent variable, its metric must be set: Set its variance to a constant (typically 1) and fix a load factor between latent and its indicator for independent latent.

To estimate the sample size based on the number of free parameters in the hypothetical model, a 1: 10 ratios of respondents to free parameters to be estimated was suggested(67). As a result, the minimum sample size required were 650, based on the 65 parameters that were needed to be estimated and a free parameter ratio of 10. Because the computed sample size considers the 10% non-response rate, the final sample size was 715.

Figure 3. sample size determination using modified model

sampling procedure

The sampling method preferred for this study was simple random sampling technique. the total sample size proportionally allocated to each university and participants was selected by simple random sampling. Then, a simple random sampling technique was done to select the study subjects in each university. Study participants was selected using a simple random sampling using sampling frame from the two universities. Sampling units were taken from the CMHS registrar's office (Fig 4).

Figure 4. Schematic presentation of sampling procedure

Data Collection Tool and Procedures

A structured questionnaire was developed after reviewing several works of literature on the subject(47, 68-71). The structured questionnaire was divided into two sections: the first was contain socio-demographic questions, and the second was contain elements related to model constructs such as original TAM constructs (perceived ease of use, perceived usefulness, attitude towards use and Intention to use) as well as additional elements which are included in modified TAM such as computer self-efficacy, facilitating condition and accessibility. The questioner was be written in English and then translated into Amharic. The data was gathered using a self-administered questioner. The questionnaire was constructed to test the formulated hypothesis. For the second section, a total of 25 questions were used for the model constructs such as 3 items for Accessibility, 4 items for facilitating condition, 3 items for Self-efficacy, 4 items for Perceived Usefulness, 4 items for Perceive Ease of Use, 4 items for Attitude and 3 items for acceptance of e-learning. All the items used to measure the constructs was measured by using a Likert scale ranging from 1 to 5 (1 = strongly disagree, and 5 = strongly agree). two-day training was given to the data collectors and supervisors.

Data quality Assurance

Two days of training were given for data collectors and supervisors on the objective of the study, data collection procedures, data collection tools, the respondents approach, data confidentiality, and the respondent's rights before the data collection date. The completeness of the questionnaire was checked every day by the supervisors. Data backup procedures was carried out to prevent data loss, such as storing data in multiple locations and creating hard and soft copies of the data. A pre-test was done at Addis Ababa University with 5% of the total estimated sample units to check the readability, and consistency of the tool. Based on the feedback from the respondents, the questions were modified with their wording by language experts. The original data collection process is then started.

Data Processing and Analysis

Respondent data was entered into Epi data version 4.6 before being exported to SPSS version 25 for descriptive data analysis, student t-test and correlation analysis. The Kaiser-Meyer-Olkin (KMO) measure of sample adequacy and Bartlett's test of sphericity was computed at the start of the SEM analysis. The SEM analysis was carried out in two stages. In the first stage, model constructs were evaluated using structural equation modeling (SEM) analysis using the Analysis of Moment Structure (AMOS) version 26 software. Confirmatory factor analysis (CFA) with standardized data was used on the test measurement model. Confirmatory factor analysis was look at correlations between constructs that are less than 0.8 and factor loadings that are greater than 0.6 for each item(72). The Average Variance Extracted (AVE) approach was used to assess converging validity, while the square root of AVE in the Furnell Larcker criterion was used to assess diverging validity, with values less than 0.9(38, 66). In the second stage, the final SEM analysis was performed using the seven-factor model to validate relationships and associations among exogenous, mediating, and endogenous variables. To assess the goodness of fit, the chi-square ratio ($\leq$5), the tucker-lewis index (TLI>0.9), the comparative fit index (CFI>0.9), the goodness of fit index (GFI >0.9), the adjusted goodness of fit index (AGFI >0.8), the root means square error approximation (RMSEA<0.08), and the root mean square of the standardized residual (RMSR<0.08) was used(38, 73, 74). The dataset's missing values was managed, and data normality was evaluated using multivariate kurtosis <5 and the critical ratio between - 1.96 and + 1.96. Multicollinearity was also tested with VIF <10 and tolerances >0.1, as well as a correlation between exogenous constructs of less than 0.8, and there were no issues.

The path coefficient was used to analyze the relationship between exogenous and endogenous variables in order to evaluate a structural model. The statistical significance of the predictors was determined using a p-value less than 0.05.

RESULTS

Socio-demographic characteristics

A total of 659 (92.17% response rate) Postgraduate medical and health science students, were participated in this study and consists of 519 males (78.8%) while the rest (140) were females (21.2%). About 54.6% (360/659) of the study participants were 25 _ 29 years and about 0.9% (6/659) of the study participants were 40 and more than 40 years. Age is categorized based on the study done in postgraduate students in Ethiopia(75). About 51.4% (339/659) participants income were between 10,000 and 15,000 ETB. The majority of respondents (54.8%) were less than 2 year of work experience. About 29.7% (196/659) of respondent's year of study were second year postgraduate health science students. 5.6% respondents were resident 4(R4) medicine specialty students (table 1). From 44 department students the highest number of respondents (10.2%) were from gynecology department and the minimum number of respondents (0.2%) were from integrated emergency surgery and obstetrics department.

Table 1: Demographic profile of respondent among Postgraduate medical and health science students in first generation universities in Amhara region, 2023.

Demographic Profile (N=659)	Frequency	Percent
university		
UOG	399	60.5
BDU	260	39.5
Gender		
Male	519	78.8
Female	140	21.2
Monthly Income		
Bellow 10,000 ETB	310	47.0
Between 10000 and 15000 ETB	339	51.4
Above 15000 ETB	10	1.5
Age		
21 _ 24	22	3.3
25 _ 29	360	54.6
30 _ 39	271	41.1
>= 40 years	6	.9
Year of Study		
1st Year (Masters)	150	22.8
3rd Year (Masters)	39	5.9
R1 (Medicine)	93	14.1
R3 (Medicine)	56	8.5
2nd Year (Masters)	196	29.7
R2 (Medicine)	88	13.4
R4 (Medicine)	37	5.6
Work Experience		
Less than 2 Year	361	54.8
2-3 Year	88	13.4
4-5Year	97	14.7
Above 5 year	113	17.1

Experience on Using Internet, Smartphone & Computer

From 659 respondents about 83.8% (552/659) were greater than 6 years and about 2.3% (15/659) of the study participants were between 1 and 3 years of experience in using mobile devices. About 76.8% (506/659) participants were owned computer/laptop, smart phone and tablet ICT devices and 0.8 % students were owned tablet. About 75.1% (495/659) of respondent's Type of Internet connection used were Mobile data. Also, minimum respondents 24.9% respondents Type of Internet connection used were broadband internet. About 93.2% (614/659) of respondents were comfortable when using a computer, laptop, smartphone, tablet, or web application and 6.8% of respondents were not comfortable (table 2).

Table 2: Experience on using internet, smartphone, and computer among Postgraduate medical and health science students in first generation universities in Amhara region, 2023.

Demographic Profile (N=659)	Frequency	Percent
Experience in using mobile devices		
Between 1 and 3 Years	15	2.3
Between 3 and 5 years	92	14.0
Greater than 6 Years	552	83.8
Type of ICT devices owned by students		
Computer/Laptop	81	12.3
Smart Phone	67	10.2
Tablet	5	.8
Computer/Laptop, Smart Phone, Tablet	506	76.8
Type of Internet connection used by student		
Mobile data	495	75.1
Broadband	164	24.9
Comfortability using a computer, laptop, smartphone, tablet, or web application		
Yes	614	93.2
No	45	6.8
The usefulness of computer, laptop, smartphone, tablet, or web applications for educational purposes		
Yes	647	98.2
No	12	1.8

Acceptance to use e-learning

In this study, 400 (60.7%; 95% CI: [56.9–64.4], P-value=0.001) postgraduate medical and health science students scored above the median. Three questions with five Likert scales were used to assess acceptance of e-learning, and the median score was 12 with a standard deviation of 2.95. The score range was 3 to 15, with 15 being the highest possible. So, 60.7% students had accepted to use e-learning system.

Measurement model assessment

Evaluation of the measurement model involves checking the model fit, internal consistency, discriminant validity, and convergent validity of indicators/items using confirmatory factor analysis (CFA) (Figure 5).

Figure 5: Confirmatory Factor Analysis

In this study, multivariate kurtosis value is >5 (kurtosis= 315.43) and multivariate critical ratio not range between -1.69 and +1.69 (CR=110.19). In this case, the nonparametric test of bootstrapping methods aids non-normal data by resampling the data that assumes a normal distribution was used, and it estimates the significance of the path coefficients, standard errors, and confidence intervals(76, 77). Thus, 5000 bootstrap samples of 95% bias-corrected confidence interval in AMOS were applied.

Reliability and validity of the construct

The results shown in table 3 are the square root of the AVE of the construct, and other values refer to the significant correlation between constructs. The values in bold (diagonal values) are higher than other values in its column, and the raw, and HTMT ratio is less than 0.9 (Table 3 and Table 4), As a result, the model's constructs' discriminant validity has been achieved.

Table 3: Discriminant validity of respondents *among Postgraduate medical and health science students in first generation universities in Amhara region, 2023.*

Construct	FC	PU	ACe	PEOU	SE	ACC	ATT
FC	**0.862**						
PU	0.657	**0.897**					
ACe	0.596	0.703	**0.868**				
PEOU	0.531	0.545	0.576	**0.896**			
SE	0.634	0.701	0.611	0.435	**0.917**		
ACC	0.321	0.235	0.307	0.379	0.229	**0.925**	
ATT	0.541	0.697	0.716	0.498	0.600	0.298	**0.897**

Table 4: HTMT Analysis

	FC	SE	PU	PEOU	ATT	ACC	ACe
FC							
SE	0.634						
PU	0.657	0.701					
PEOU	0.531	0.435	0.545				
ATT	0.541	0.600	0.697	0.498			
ACC	0.321	0.229	0.235	0.379	0.298		
ACe	0.596	0.611	0.703	0.576	0.716	0.307	

In the results shown in table 5, Cronbach's alpha and composite reliability have values above 0.70 for all the constructs. In the case of AVE have values above 0.70 for all the constructs. All of the constructs, therefore, had strong convergent validity.

Table 5: Convergent validity

Construct	Indicators / Items	Factor loading	CR	Cronbach alpha	AVE
Facilitating Condition	FC1	0.83	0.920	0.920	0.74
	FC2	0.89			
	FC3	0.89			
	FC4	0.84			
Perceived Usefulness	PU1	0.85	0.943	0.942	0.80
	PU2	0.89			
	PU3	0.93			
	PU4	0.91			
Intension to Use	BI1	0.84	0.902	0.901	0.75
	BI2	0.86			
	BI3	0.90			
Perceived Ease of Use	PEOU1	0.87	0.942	0.942	0.80
	PEOU2	0.92			
	PEOU3	0.91			
	PEOU4	0.88			
Self Efficacy	SE1	0.90	0.940	0.940	0.84
	SE2	0.93			
	SE3	0.92			
Accessibility	ACC1	0.92	0.947	0.947	0.86
	ACC2	0.92			
	ACC3	0.94			
Attitude	ATT1	0.90	0.943	0.943	0.80
	ATT2	0.90			
	ATT3	0.90			
	ATT4	0.88			

CR: Composite reliability, AVE: Average Variance Extracted

Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity

Furthermore, the construct validity of the underlying structure of the TAM questionnaire was calculated through a factor analytic approach (Table 6). Sampling adequacy was investigated using the Kaiser-Meyer-Olkin (Kaiser, 1974) measure. Overall sampling adequacy was 0.940 which indicated the research sample sufficiency to carry out a factor analysis.

Table 6: Sampling Adequacy (Validity) Based on Kaiser-Meyer-Olkin Measure

Construct	Kaiser-Meyer-Olkin	Bartlett’s Test of Sphericity	DF	p-value
Accessibility	0.773	1890.7	3	0.000
Self-efficacy	0.771	1762.48	3	0.000
Facilitating condition	0.852	1939.27	6	0.000
Perceived ease of use	0.852	2453.50	6	0.000
Perceived usefulness	0.860	2458.74	6	0.000
Attitude	0.850	2458.59	6	0.000
Acceptance of e-learning (ACe)	0.751	1242.18	3	0.000

Goodness of fit

The results in table 7 show that the values of the fitness model met the required level.

Table 7: Model fit indices

Fit indices	Threshold Value	Sources	Results obtained	Conclusion
Chi-square/degree of freedom	<5	Gaskin, J. & Lim, J. (2016)	2.52	Accepted
Goodness-of-fit-index (GFI)	>0.9	Gaskin, J. & Lim, J. (2016)	0.93	Accepted
Adjusted goodness-of-fit-index (AGFI)	>0.8	Gaskin, J. & Lim, J. (2016)	0.90	Accepted
Comparative fit index (CFI)	>0.95	Gaskin, J. & Lim, J. (2016)	0.98	Accepted
Root means square error of approximation (RMSEA)	<0.06	Gaskin, J. & Lim, J. (2016)	0.05	Accepted
standardized root mean squared residual (SRMR)	<0.08	Gaskin, J. & Lim, J. (2016)	0.025	Accepted

Structural equation model assessment

SEM analysis was used to evaluate the hypotheses after evaluating the measurement model's validity and making sure there were no strong relationships between exogenous constructs, collinearity was assessed. Collinearity may affect the interpretation and can be assessed by the variance inflation factor (VIF) and tolerance, which suggest the possibility of multicollinearity exists when they are above 10 and below 0.1 respectively. Proving that multicollinearity was nonexistent in this investigation (table 8).

Table 8: Multicollinearity test

Exogenous Construct	Tolerance	Variance Inflation Factor
Accessibility (ACC)	0.802	1.247
Self-Efficacy (SE)	0.394	2.541
Perceived Ease of Use (PEOU)	0.562	1.778
Perceived Usefulness (PU)	0.290	3.444
Facilitating Condition (FC)	0.414	2.414
Attitude (ATT)	0.423	2.366

Factors associated with Acceptance to use e-learning

The exogenous constructs such as Self-Efficacy, Accessibility and facilitating condition explained 35.0 % of the Perceived ease of use construct, which has an R^2 of 0.35. The constructs such as Self-Efficacy, Accessibility, facilitating condition and Perceived ease of use explained 61.1 % of the Perceived usefulness construct, which has an R^2 of 0.61. The constructs such as Self-Efficacy, Accessibility, facilitating condition, perceived usefulness and Perceived ease of use explained 52.0 % of the Attitude construct, which has an R^2 of 0.52. The constructs such as Self-Efficacy, Accessibility, facilitating condition, Perceived Usefulness, Perceived ease of use and Attitude explained 63.0 % of the endogenous construct (intention to use the e-learning construct), which has an R^2 of 0.63. In accordance with the advice given by (78), the R^2 value is viewed as high when it is greater than 0.67, moderate when it is between 0.33 and 0.67, and weak when it is between 0.19 and 0.33. table 9 shows R^2 of the endogenous latent variables

Table 9: R^2 of the endogenous latent variables

Constructs	R^2	Results
Perceived Usefulness (PU)	0.61	Moderate
Perceived Ease of Use (PEOU)	0.35	Moderate
Attitude (ATT)	0.52	Moderate
Acceptance of e-learning (ACe)	0.63	Moderate

The aforementioned hypotheses were put to the test together using the structural equation modelling (SEM) method. SEM analysis found that Attitude had the most substantial effect on the intention to use e-learning, which was larger than the effects of other predictors and facilitating condition had the most substantial effect on the perceived ease of use of e-learning. And also, self-efficacy had the most substantial effect on the perceived usefulness of e-learning and perceived usefulness had the most substantial effect on the attitude towards use of e-learning among students (figure 6).

Figure 6: SEM for predictors of acceptance to use e-learning among Postgraduate medical and health science students in first generation universities in Amhara region, Ethiopia, 2023.

The results showed that Facilitating condition (β=0.381, 95% CI: [0.259, 0.499cc), Self-efficacy (β=0.156, 95% CI: [0.046, 0.271], p-value<0.01) and Accessibility (β=0.216, 95% CI: [0.142, 0.292], p-value<0.01), had direct effect on students perceived ease of use supporting hypothesis **H1a, H2a and H3a** respectively. And also, facilitating condition (β=0.274, 95% CI: [0.176, 0.380], p-value<0.01), Self-efficacy (β=0.426, 95% CI: [0.325, 0.528], p-value<0.01) and perceived ease of use (β=0.201, 95% CI: [0.124, 0.284], p-value<0.01) had direct effect on students perceived Usefulness which support hypotheses **H1b, H2b and H5a** respectively. in Contrast Accessibility (β= -0.026, 95% CI: [-0.077, 0.023], p-value=0.280) had no direct effect on students perceived Usefulness and Hypothesis **H3b** is not supported.

PU significantly influenced ATT (β= 0.606, 95% CI: [0.497, 0.709], P <0.01) and BI (β= 0.307, 95% CI: [0.193, 0.429], P <0.01) supporting hypothesis H4b and H4a respectively. The results also revealed that PEOU significantly influenced BI (β= 0.307, 95% CI: [0.193, 0.429], P <0.01) and ATT (β= 0.156, 95% CI: [0.074, 0.244], P <0.01) supporting hypothesis **H5b** and **H5c** respectively. ATT significantly influenced BI (β= 0.353, 95% CI: [0.234, 0.461], P <0.01) supporting hypothesis H6a. A summary of the hypotheses testing results is shown in Table 10.

Table 10: SEM analysis of factors of acceptance to use e-learning

Hypothesis	Estimate	S.E.	C.R.	P - Value	95% Confidence Interval		Result
					Lower	Upper	
ACC → PEOU	0.216	0.034	6.271	***	0.142	0.292	Supported
SE → PEOU	0.156	0.046	3.368	**	0.046	0.271	Supported
FC → PEOU	0.381	0.052	7.312	***	0.259	0.499	Supported
FC → PU	0.274	0.042	6.530	***	0.176	0.380	Supported
SE → PU	0.426	0.037	11.430	***	0.325	0.528	Supported
PEOU → PU	0.201	0.034	5.988	***	0.124	0.284	Supported
ACC → PU	-0.026	0.027	-0.985	0.280	-0.077	0.023	Not Supported
PEOU → ATT	0.156	0.035	4.478	***	0.074	0.244	Supported
PU → ATT	0.606	0.040	14.979	***	0.497	0.709	Supported
PEOU → ACe	0.183	0.031	5.868	***	0.101	0.266	Supported
ATT → ACe	0.353	0.041	8.600	***	0.234	0.461	Supported
PU → ACe	0.307	0.043	7.225	***	0.193	0.429	Supported

****** significance at P< 0.01, ******* significance at P< 0.001

C.R: critical ratio S.E: standard error

Mediating Effects

Table 11 has been generated using *estimating SpecificIndirecteffect_path* estimand algorithm feature in AMOS software. there are three mediators: PU, PEOU and ATT among seven variables used in the proposed research model. The table shows that there are 35 indirect effects. In three cases (ACC → PU → ATT, ACC → PU → ATT → ACe and ACC → PU → ACe), mediating effects were found insignificant in predicting acceptance of e-learning among postgraduate medical and health science university students in the context of e-learning. On the other hand, 32 indirect effects were found positive. In most cases, PU alone does not have the ability to mediate the relationship between accessibility (ACC) and attitude (ATT), accessibility (ACC) and attitude (ATT) to acceptance of e-learning (ACe), accessibility (ACC) and acceptance of e-learning (ACe). In other cases, PU, PEOU and ATT have the ability to mediate the relationship with acceptance of e-learning. Detail information about mediating effect showed in (table 11).

Table 11: Mediating effects

Parameter	Estimate	95% Confidence Interval		P-Value	Decision
		Lower	Upper		
ACC –> PEOU –> PU	0.043	0.023	0.069	0.001	Supported
ACC –> PEOU –> PU –> ATT	0.026	0.014	0.042	0.001	Supported
ACC –> PEOU –> PU –> ATT –> ACe	0.009	0.004	0.016	0.001	Supported
ACC –> PEOU –> PU –> ACe	0.013	0.006	0.023	0.001	Supported
ACC –> PEOU –> ATT	0.034	0.014	0.059	0.001	Supported
ACC –> PEOU –> ATT –> ACe	0.012	0.005	0.022	0.001	Supported
ACC –> PEOU –> ACe	0.040	0.019	0.064	0.001	Supported
ACC –> PU –> ATT	-0.016	-0.047	0.014	0.280	Not Supported
ACC –> PU –> ATT –> ACe	-0.006	-0.018	0.005	0.280	Not Supported
ACC –> PU –> ACe	-0.008	-0.026	0.007	0.280	Not Supported
SE –> PEOU –> PU	0.031	0.008	0.062	0.007	Supported
SE –> PEOU –> PU –> ATT	0.019	0.005	0.037	0.007	Supported
SE –> PEOU –> PU –> ATT –> ACe	0.007	0.002	0.014	0.007	Supported
SE –> PEOU –> PU –> ACe	0.010	0.002	0.021	0.007	Supported
SE –> PEOU –> ATT	0.024	0.005	0.054	0.007	Supported
SE –> PEOU –> ATT –> ACe	0.009	0.002	0.019	0.007	Supported
SE –> PEOU –> ACe	0.029	0.007	0.058	0.007	Supported
SE –> PU –> ATT	0.258	0.182	0.341	0.001	Supported
SE –> PU –> ATT –> ACe	0.091	0.054	0.135	0.001	Supported
SE –> PU –> ACe	0.131	0.076	0.194	0.001	Supported
FC –> PEOU –> PU	0.076	0.041	0.119	0.001	Supported
FC –> PEOU –> PU –> ATT	0.046	0.024	0.076	0.001	Supported
FC –> PEOU –> PU –> ATT –> ACe	0.016	0.007	0.029	0.001	Supported
FC –> PEOU –> PU –> ACe	0.023	0.012	0.040	0.001	Supported
FC –> PEOU –> ATT	0.059	0.027	0.096	0.001	Supported
FC –> PEOU –> ATT –> ACe	0.021	0.008	0.037	0.001	Supported
FC –> PEOU –> ACe	0.070	0.035	0.107	0.001	Supported
FC –> PU –> ATT	0.166	0.106	0.236	0.001	Supported
FC –> PU –> ATT –> ACe	0.058	0.033	0.091	0.001	Supported
FC –> PU –> ACe	0.084	0.043	0.142	0.001	Supported
PEOU –> PU –> ATT	0.122	0.073	0.179	0.001	Supported
PEOU –> PU –> ATT –> ACe	0.043	0.021	0.072	0.001	Supported
PEOU –> PU –> ACe	0.062	0.033	0.099	0.001	Supported
PEOU –> ATT –> ACe	0.055	0.023	0.092	0.001	Supported
PU –> ATT –> ACe	0.214	0.138	0.296	0.001	Supported

Discussion

This study investigates the Acceptance of e-learning and associated factors among postgraduate medical and health science students at first generation universities in Amhara region. The study revealed that postgraduate students' acceptance of e-learning was 400 (60.7%; 95% CI: [56.9–64.4]). This revealed that more than half of postgraduate students had accepted to use e-learning. This result is less than that of a research conducted in Egypt, where 79.8% of the participants accepted to use e-learning(79). This difference can be the result of Egypt's more advanced technological development than Ethiopia's. The lack of widespread acceptance of e-learning in Ethiopia compared to Egypt may be the other factor and the availability of resources needed to use e-learning but

Ethiopia's internet penetration rate stood at **16.7 percent** of the total population at the start of 2023(80). The accessibility of gadgets used for e-learning technology may also be another cause for the discrepancies.

Our proposed model explains 63% variance ($R^2 = 0.63$) in the acceptance of postgraduate students to use e-learning. In our investigation, the acceptance to use e-learning was significantly associated with perceived ease of use, perceived usefulness and attitude towards use, indicating that 3 out of 3 path relationships in the proposed model were directly associated with the acceptance to use e-learning. Accordingly, hypothesis **H4a**, **H5b** and **H6a** were supported. The following insights are described, based on the results, to enhance the acceptance of e-learning by postgraduate students in Ethiopia. This evidence is consistent with previous similar studies' conducted in Ethiopia perceived ease of use had a direct significant effect to perceived ease of use and acceptance of e-learning(62), conducted in United Arab Emirates perceived ease of use had a direct significant effect to perceived ease of use and acceptance of e-learning and perceived ease of use had significant direct effect to acceptance of e-learning(27).

According to our study, Facilitating Condition had a direct effect on postgraduate students perceived ease of use ($\beta = 0.381$, $p < 0.001$) and perceived usefulness ($\beta = 0.274$, $p < 0.01$). In other words, these study shows that when the facilitating condition of postgraduate students to use e-learning is strong, the perceived ease of use e-learning and perceived usefulness of e-learning is also high. The result implies that the availability of resources, support, and knowledge is necessary to motivate postgraduate students to use e-learning. The findings of this research are consistent with previous studies in Bangladesh (50) and East Africa(51). Accordingly, **H1a** and **H1b** are supported. Although facilitating conditions had significant effects on behavioral intention to use e-learning technology, that were mediated by attitude toward usage, perceived usefulness, and perceived ease of use. The findings of this research are consistent with previous studies in Singapore(81). The possible reason is that facilitating conditions will make it convenient for students to use the e-learning system which can significantly improve their acceptance of e-learning without affecting the specific use behavior due to the channels to access information and knowledge are diverse(82). computer self-efficacy had a direct effect on postgraduate students perceived ease of use ($\beta = 0.156$, $p < 0.01$) and perceived usefulness ($\beta = 0.426$, $p < 0.001$). In other words, these study shows that when the computer self-efficacy of postgraduate medical and health science students to use e-learning is strong, the perceived ease of use and perceived usefulness of e-learning is also high. it is consistent with other studies done in Malaysia(48), Azerbaijan(30), Kuwait(47). Accordingly, hypothesis **H2a** and **H2b** are supported. Although computer self-efficacy had significant effects on acceptance to use e-learning technology, that were mediated by attitude toward usage, perceived usefulness, and perceived ease of use. The possible reason might be that nowadays postgraduate students have their own computer. In other studies computer self-efficacy is not significantly affects perceived usefulness(30). Accessibility had a direct effect on postgraduate students perceived ease of use ($\beta = 0.\ 0.216$, $p < 0.001$). This means that when e-learning is strongly accessible to postgraduate medical and health science students, e-learning is also strongly recognized as being simple to use. This is consistent with studies conducted in previous studies in Greece(57),UAE(6), Iran(60). The availability of information technologies for sharing knowledge via zoom and other communication channels among students in modern society may be the possible reason. but, accessibility did not influence significantly the perceived usefulness. Therefore, this study's findings for accessibility only comply with the finding of other studies(27, 83). So, **H3a** is supported and **H3b** is not supported.

According to our study, Perceived usefulness had a direct effect on postgraduate students' attitude towards using e-learning systems ($\beta = 0.606$, $p < 0.001$). In other words, these study shows that when the Perceived usefulness of postgraduate medical and health science students to use e-learning is strong, the attitude towards using e-learning systems is also high. The possible reason might be that nowadays postgraduate students have good attitude for to use e-learning after covid-19(84). So **H4b** is supported. This is consistent with studies conducted in previous studies in Pakistan(31), Iran(85).

Strength and limitations of the study

Strength of the study

This study evaluated postgraduate students' intention to use e-learning using a standardized instrument (modified TAM model). The current study additionally used multivariate analysis (SEM), which allows for the simultaneous examination of several variables, accounts error terms and asses correlation between exogenous variables. We also evaluated the mediator's impacts on the latent variables.

Limitation of the study

In this study, the sample was recruited only from first generation universities in Amhara regional state. Only a quantitative technique was used to conduct the investigation. To strengthen their conclusions, future research studies should think about including a qualitative approach. Additionally, the study is only carried out in first-generation universities, which may limit the applicability of the findings in other contexts. It would be preferable for future works to include locations other than first-generation universities.

Conclusion and recommendation

Conclusion

The major objective of this study was to assess the acceptance of e-learning systems and its associated factors among postgraduate Medical and health science students in first generation universities. This study demonstrates that more than half of postgraduate students(60.7%) were accepted e-learning system and the modified TAM model with the inclusion of the most commonly used external factors explains and predicts the acceptance of postgraduate students to the use of e-learning as an educational tool, to facilitate their learning process and increase efficiency. Facilitating condition, computer self-efficacy and accessibility were significantly affects' perceived ease of use. except accessibility other external variables had significant effect on perceived usefulness.

perceived ease of use, perceived usefulness, and attitude were mediation variables to predict behavioral intension to use e-learning among postgraduate medical and health science students. So those mediator variables had significant effect to behavioral intention to use e-learning.

Recommendation

Based on the study findings, the following recommendations are suggested to manage acceptance of e-learning among postgraduate medical and health science students.

For the ministry of health: The ministry shall emphasize the advantages of e-learning for the students for better management of the class with the collaboration of the ministry of education. Finally, it is an insight for rational discussion about how to adopt e-learning to increase postgraduate students.

For researcher: We suggest that further studies should be done with a large-scale study that includes first generation, second generation, and third generation universities for more generalizability, beyond quantitative it is better to support with qualitative study, moreover enjoyment, experience and other external predictors are required for more explained the intention to use e-learning.

For BDU and UOG: It is better to create awareness and more informed decisions for health science students through delivering education and providing training, related to how to use e-learning as an educational tool, to facilitate their learning process and increase efficiency.

Abbreviations

ACC	Accessibility
ACe	Acceptance of e-learning
AGFI	Adjusted Goodness of Fit Index
AMOS	Analysis of Moment Structure
ATT	Attitude
AVE	Average Variance Extracted
BDU	Bahir Dar University
CFI	Comparative Fit Index
CMHS	College of medicine and Health Sciences
CR	Composite Reliability
CSE	Computer Self Efficacy
e-Learning	Electronic Learning
FC	Facilitating condition
FC	Facilitating condition
GFI	Goodness of Fit Index
ICT	Information Communication Technology
IS	Information system
KMO	Kaiser-Mayer-Olkin
MOOCs	massive open online courses
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
RMSEA	Root mean square error approximation
RMSR	Root mean square residual
SEM	Structural Equation Model
TAM	Technology Acceptance Model
TLI	Trucker Lewis Index
UOG	University of Gondar
VIF	Variance Inflation Factor

Declarations

Ethics approval and consent to participate

The Ethical Review Committee of Bahir Dar University School of Public Health was provided ethical approval with ethical reference number 683/2023. Written informed consent was obtained from each study participant. To keep the confidentiality of the information provided by the study subjects, the data collection procedure was anonymous. Additionally, this study was conducted according to the Helsinki. Declaration.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and/or analyzed during the current study will be available upon reasonable request from the corresponding author.

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Authors' contributions

ABM was responsible for a significant contribution to the conceptualization, study selection, data curation, formal analysis, funding acquisition, investigation, methodology, and original draft preparation. Project administration, resources, software, supervision, validation, visualization, and reviewing are all handled by **ADW**, **AK**, **TA**, **HA**, **BW** and **GS**. **ABM, BW,** and **ADW** wrote the final draft of the manuscript, and the final draft of the work was read, edited, and approved by all writers.

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Declaration of competing interest

The authors declare that there is no conflict of interest.

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Figures

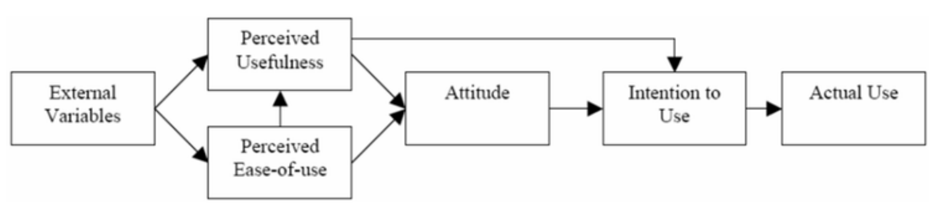

Figure 1

The original Technology Acceptance Model (TAM 1)(37, 38)

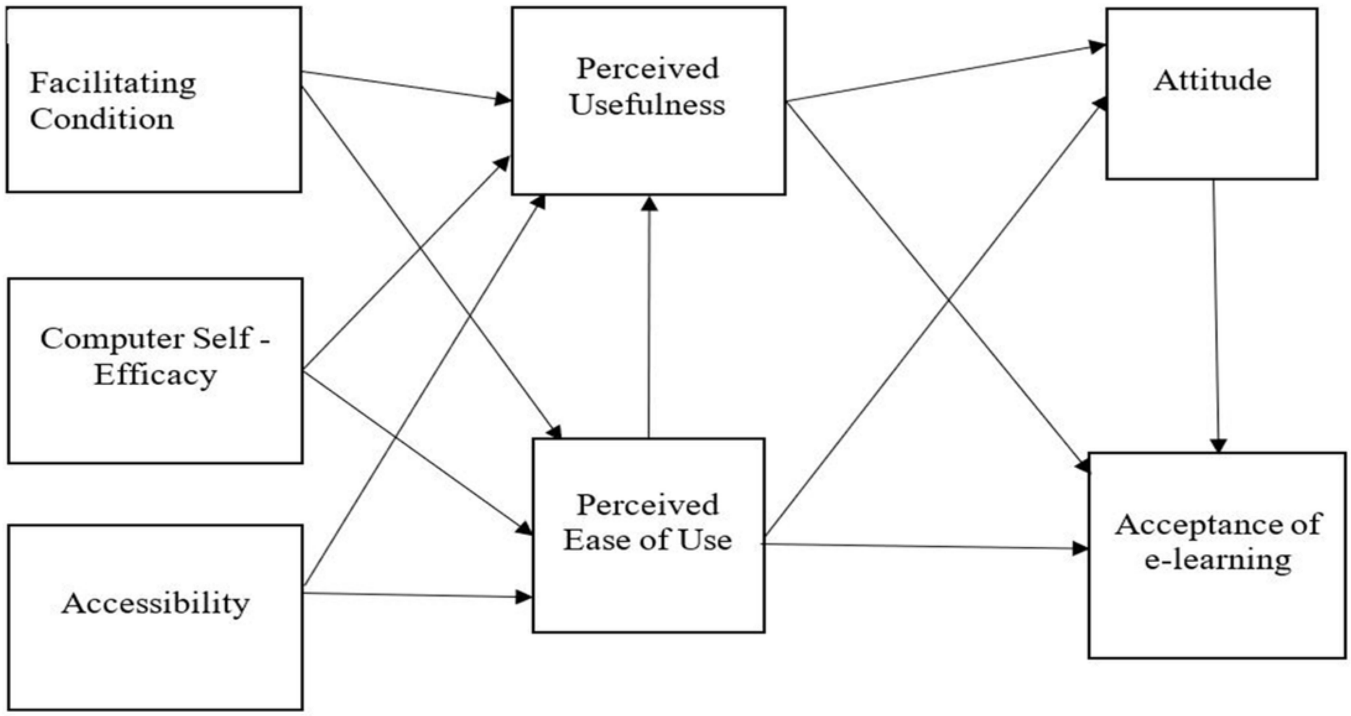

Figure 2

The proposed model

Based on the above actual UTAUT model, the following hypothesis was developed.

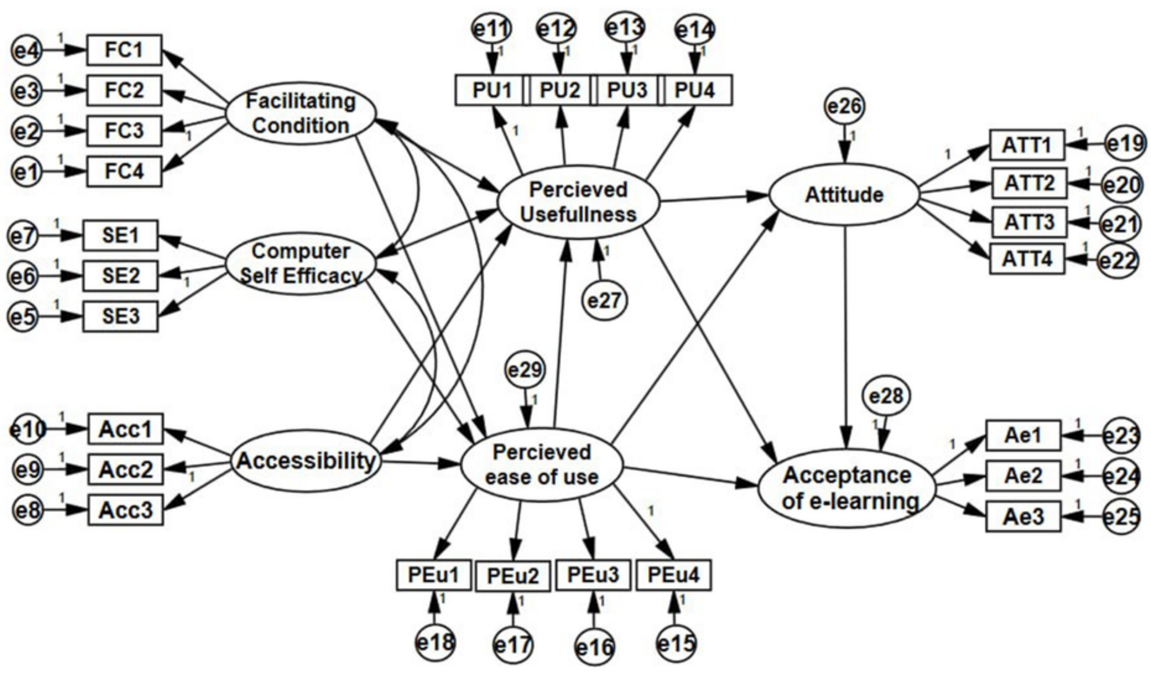

Figure 3

sample size determination using modified model

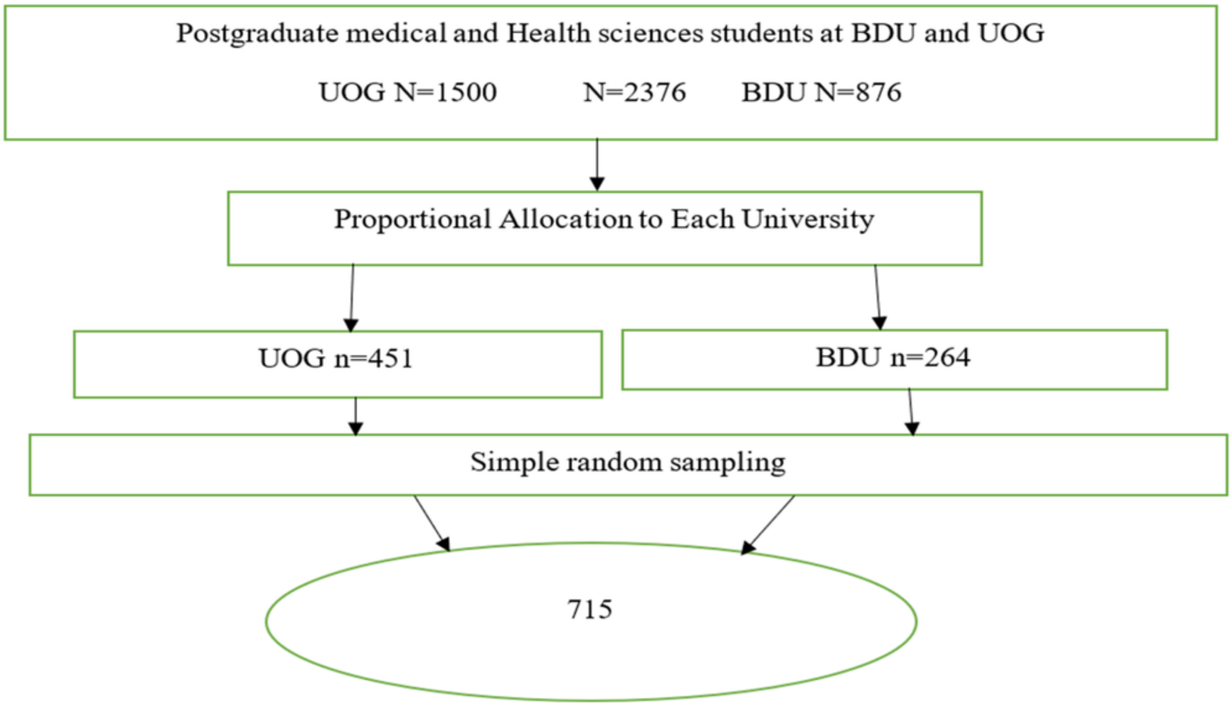

Figure 4

Schematic presentation of sampling procedure

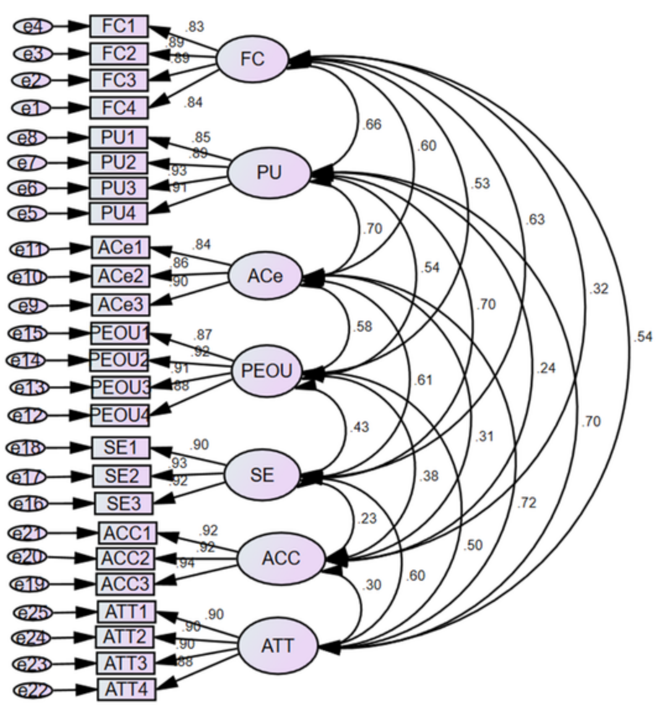

Figure 5

Confirmatory Factor Analysis

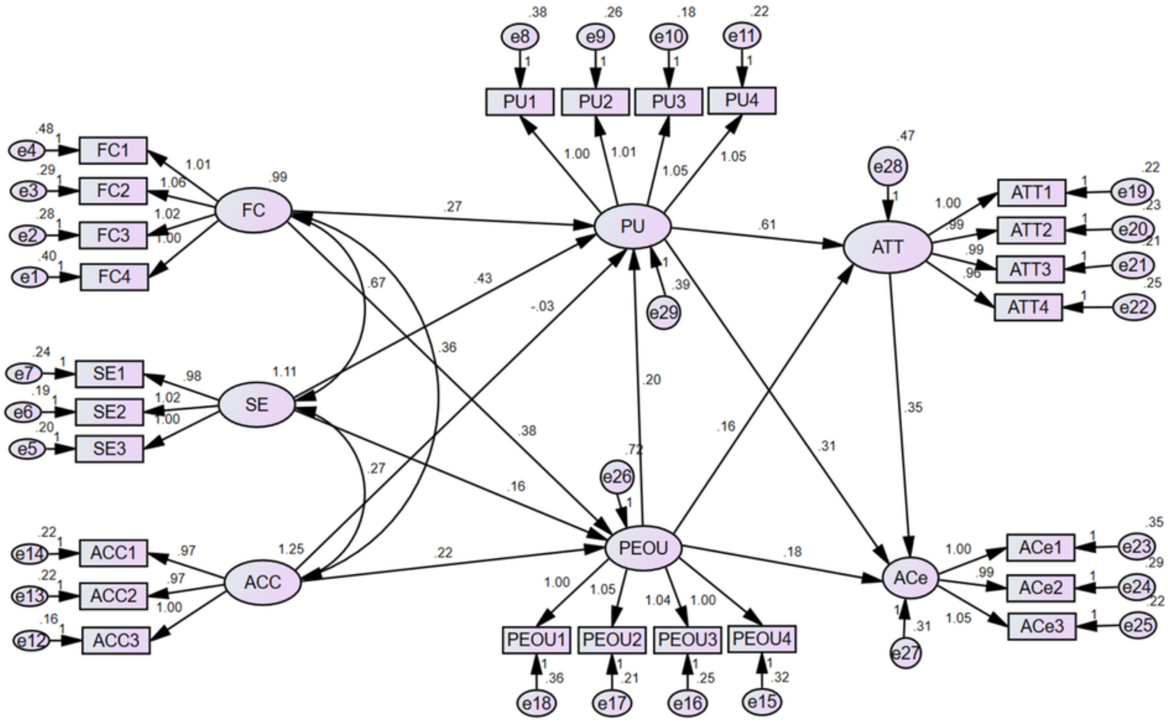

Figure 6

SEM for predictors of acceptance to use e-learning among Postgraduate medical and health science students in first generation universities in Amhara region, Ethiopia, 2023.