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Acceptance of e-learning and associated factors among postgraduate medical and health science students at first generation universities in Amhara region, 2023: using modified technology acceptance model

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Abstract

Background Electronic learning is the process of remote teaching and learning through the use of electronic media. There is a dearth of research on the factors influencing e-learning acceptance in Ethiopia using the modified technology acceptance model (TAM). Previous research appears to have overlooked the mediating impact of factors on e-learning acceptability Therefore, the present study aimed to assess the acceptance of e-learning and its associated factors among postgraduate medical and health science students by applying TAM at first-generation universities in the Amhara region.

Methods This institutional-based cross-sectional study was conducted from March 15 to April 20, 2023, at Amhara First Generation University, Ethiopia. A total of 659 students participated in the study. A self-administered questionnaire in the Amharic language was used to collect the data. SEM analysis was employed to test the proposed model and the relationships among factors using SPSS version 25 and AMOS version 26.

Results The proportion of postgraduate students who agreed to use e-learning was 60.7%, 95% CI (56.9–64.4). SEM analysis revealed that perceived ease of use ($\beta = 0.210$, $p < 0.001$), attitude ($\beta = 0.377$, $p < 0.001$) and perceived usefulness ($\beta = 0.330$, $p < 0.001$) had positive direct relationships with acceptance of e-learning. Perceived usefulness ($\beta = 0.131$, $p < 0.001$), and perceived ease of use ($\beta = 0.029$, $p < 0.01$) significantly mediate the relationship between self-efficacy, and acceptance of e-learning. Accessibility had a positive indirect effect on acceptance of e-learning through perceived ease of use ($\beta = 0.040$, $p < 0.01$). Facilitating condition had a positive indirect on acceptance of e-learning through perceived ease of use ($\beta = 0.070$, $p < 0.01$), and perceived usefulness ($\beta = 0.084$, $p < 0.001$).

Conclusion and recommendation Overall, the proportion of postgraduate students who accepted e-learning is promising. Perceived ease of use perceived usefulness, and attitude had positive direct effects on the acceptance of

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e-learning. Facilitating conditions and self-efficacy had positive indirect effects on the acceptance of e-learning. Thus, implementers need to prioritize enhancing the provision of devices, students' skills, and knowledge of e-learning by providing continuous support to improve students' acceptance of the use of e-learning.

Keywords Acceptance, E-learning, Postgraduate students, Medical and health science, Modified TAM, Ethiopia

Introduction

E-learning is defined as "learning that is enabled electronically". 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]. 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. Globally, the higher education sector has demonstrated a proclivity to use technology-based learning to innovate the teaching and learning process [3, 4].

Educational practices and methodologies are shifting toward collaborative, online and offline computer-supported learning as a result of modern digital technologies. In the twenty-first century, the use of e-learning systems in higher education was necessary. Students and adults in higher education rely heavily on massive online educational platforms and self-directed learning via their own smart and mobile devices [5].

Compared to developed countries, developing countries face many challenges in applying e-learning, including poor internet connections, insufficient knowledge about the use of information and communication technology, and weak content development [6]. Many higher education institutions in African countries, including Ethiopia, have made investments in e-learning content development and timely updates, salaries and incentives for direct and indirect e-learning staff involved in e-learning system implementations, e-learning infrastructure such as dedicated e-learning labs and e-studios, relevant e-learning software such as authoring systems, and data centers [7]. 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 [8].

Globally, between 2011 and 2021, the number of massive open online courses (MOOCs) increased from 300,000 to 220 million learners [9]. In the fall of 2020, approximately 8.6 million college students in the United States were enrolled solely in distance education courses through postsecondary 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 through the use of e-learning [10]. According to the e-Learning Statistics 2022 report, 27% of European citizens aged 16 to 74 reported taking an online course or using online learning material in 2021, up from 23% in 2020. In 2021, Ireland had the highest percentage of citizens aged 16 to 74 years who were enrolled in online courses or who used online learning resources (46%). Finland and Sweden came in second with 45% each, followed by the Netherlands with 44%.

In Egypt, the e-learning system implemented has a high acceptance level [11]. In developing countries, a recent study indicated that the magnitude of intention to use e-learning systems in higher education institutions is low [12–14]. In Ethiopia, a recent study indicated that the magnitude of intention to use e-learning systems in higher education institutions is low (19%) for teachers [15]. 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 [16].

The modified TAM is the most commonly used theory in existing e-learning technology studies for understanding the acceptance of e-learning. 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 [11]. Developing countries have limited resources, inadequate administrative and technical support, and inadequate staff development, all of which prevent them from implementing e-learning systems [17, 18]. In Ethiopia, the intention to use e-learning systems in higher education institutions is affected by infrastructure problems, a lack of awareness and motivation, a lack of ICT skills, a lack of training, a lack of administrative management and technical support, and the resistance of individuals to change [17].

Facilitating conditions, computer self-efficacy and accessibility are external variables that affect perceived usefulness and perceived ease of use [19–24]. The perceived ease of use (PEOU) and perceived use (PU) are the most important TAM constructs for predicting user acceptance or rejection of technologies [25–27]. PEOU, PU and attitude toward using e-learning are the main predictors (constructs) affecting the acceptance of e-learning. Previous studies conducted on e-learning acceptance have several limitations, including the previous studies has only reported the direct relationship

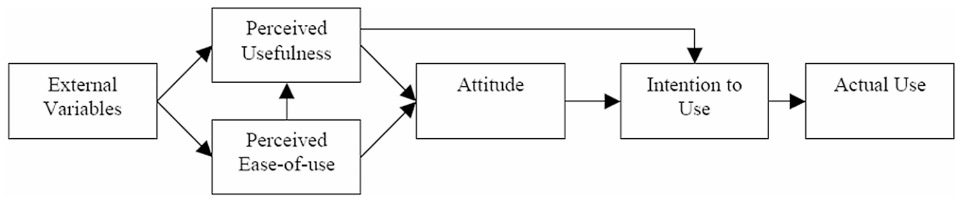

Fig. 1 The original technology acceptance model (TAM 1) [31, 32]

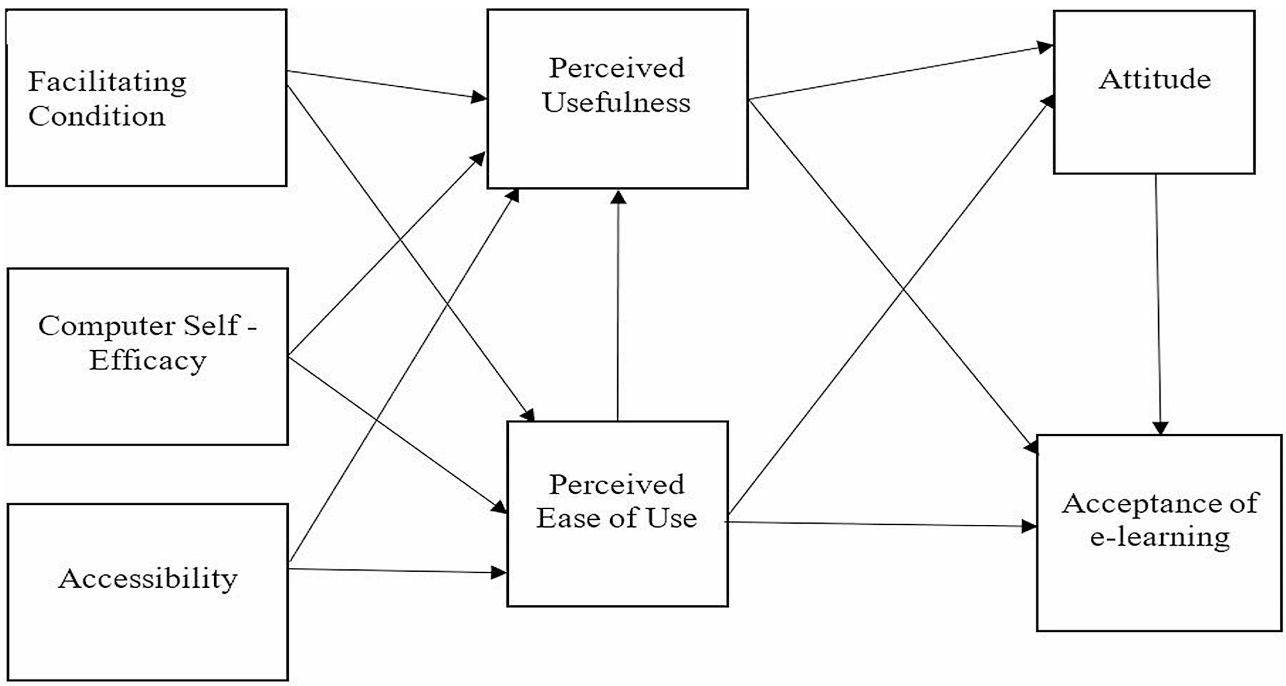

Fig. 2 The proposed model based on the above TAM model

between TAM constructs and acceptance of e-learning [20, 28–30]. Such analysis also has no ability to incorporate latent variables and indirect effects into the analysis. As with my literature search 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 for filling these research 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) identifying factors associated with e-learning acceptance among postgraduate medical and health science students in the College of Medicine and Health Sciences by using a structural equation modeling at first-generation universities in the Amhara region.

Theoretical background and hypothesis

The Technology Acceptance Model (TAM) was originally proposed by F. D. Davis in 1986 [31] and later revised in 1989 [32]. The TAM provides a foundation for tracing how external variables influence perceptions, attitudes, intentions to use a specific technology, and actual technology use (Fig. 1).

TAM has been extensively researched and accepted as a valid model for predicting individual acceptance behavior across a wide range of technologies and users [32, 33]. Despite the large body of existing TAM research, there is lack of evidence on e-learning using TAM in Ethiopia. This study was conducted with modified TAM (TAM2). Factors such as perceived usefulness and perceived ease of use in the TAM model are influenced by external factors [34]. The external factors for this study are facilitating conditions, computer self-efficacy, and accessibility. There are different mediation hypotheses for the modified TAM (Fig. 2).

Facilitating conditions

The degree of accessibility to the means and possessions needed to complete a task is defined as a facilitating condition [35]. A supportive external environment includes adequate infrastructure and organizational resources [36, 37]. They also identified adequate computer availability, network reliability, and access to online repositories as supportive conditions for e-learning. A study conducted in Bangladesh revealed that facilitating conditions significantly affect perceived ease of use [38]. In East Africa's higher education, facilitating conditions had a statistically significant impact on students' acceptance of mobile learning solutions [39].

Two hypotheses can be generated from the aforementioned arguments.

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

H1b Facilitation conditions will have a significant influence on PU.

Computer self-efficacy

Computer Self-Efficacy (CSE) refers to a person's ability to perform information technology-related activities on a computer system. 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 more effort to overcome difficult obstacles than people with low CSE [40]. The findings revealed that self-efficacy influenced both the PEOU and BIU [41].

Two hypotheses can be generated from the aforementioned arguments.

H2a Computer self-efficacy will significantly influence perceived ease of use (PEOU).

H2b Computer self-efficacy will have a significant influence on 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" [42]. According to a study conducted among university students in UAE, the perceived ease of use of an e-learning system is greatly influenced by system accessibility [43]. Two hypotheses can be generated from the aforementioned arguments.

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

H3b Accessibility will have a significant influence on PU.

Perceived usefulness

According to studies performed at the University of Huddersfield (UK) [19], at King Abdulaziz University (Saudi Arabia) [44], Haryana (India) [34] and Addis Ababa University (Ethiopia) [45], perceived usefulness affects learners' intention to use e-learning systems and affects attitude.

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 attitudes toward using e-learning systems.

Perceived ease of use

According to a study performed at the University of Huddersfield (UK), perceived ease of use significantly affects perceived usefulness and attitude, but it does not significantly affect the intention to use an e-learning system [19]. A study performed at Abu Dhabi University (United Arab Emirates) revealed that perceived ease of use significantly affects the intention to use e-learning systems [20]. 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 [45]. In agreement with the findings above, we would like to broaden the hypotheses by testing the following hypotheses:

H5a Perceived ease of use will significantly influence 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 users' attitudes toward e-learning.

Attitudes toward 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 [46]. In studies conducted at the University of Huddersfield (UK) [19], Kuwait University [41], Pakistan [22], and Colombia [47], attitudes toward the use of e-learning systems significantly affect intentions to use such systems. In light of the preceding findings, the following hypotheses are tested in this study:

H6a Attitudes toward e-learning will have a significant influence on the acceptance of e-learning systems.

Methods and materials

Study area and period

The study was carried out at first-generation universities in Northwest Ethiopia in 2023. The two first-generation universities in the Amhara region, Northwest Ethiopia, are the University of Gondar and Bahir Dar University. In this region, there are ten universities: the 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).

We chose two universities from among 10 located in the Amhara region based on the following criteria. First, the two institutions can enroll more students than other second and third-generation universities in the Amhara region. Second, because the two universities have adequate infrastructure such as internet connectivity in various buildings, computers, computer rooms, servers, and human resources, they can adopt e-learning across all departments. Gondar University offers services through five campuses and two institutions, and Bahir Dar University offers services through five campuses. The two universities serve a total of 7,155 postgraduate students. During the study period, there were 2,376 postgraduate medical and health sciences students at College of medicine and Health Sciences (CMHS) at the universities.

Study design

This study used a quantitative research method with an institution-based cross-sectional approach 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 the Amhara region by applying a modified technology acceptance model.

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 were the source population.

Study population

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

Eligibility criteria

Inclusion criteria

- Postgraduate medical and health science students who were enrolled in first-generation universities in the Amhara region available during the academic year 2023 were included.

Exclusion criteria

Those students who were unable to participate in the study due to physical or mental illness, and students who were withdrawn from university at the time of data collection were excluded from the study. Due of political uncertainty, some students transferred from Mekele University and other locations during the 2023 academic year. Transferred students do not represent the selected universities. These students' e-learning acceptance level reflects their prior universities. Furthermore, there are differences in infrastructure, computer access, and personnel availability between selected universities and Mekele University. As a result, we excluded students who were transferred in. Some students who fill out the withdrawal form or who withdraw might stay at university for several weeks or days until they are ready to leave the campus owing to a financial constraint to travel. We excluded those students since students who have withdrawn from university may remain on campus for several weeks or days.

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 by considering 32 variances of the independent variables, 3 covariances between independent variables, 18 factor loadings between latent variables and latent variable indicators, and 12 direct effects of regression coefficients between unobserved latent variables. Finally, 65 free parameters were estimated. However, 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 the latent and its indicator for the independent latent variables (Fig. 3).

To estimate the sample size based on the number of free parameters in the hypothetical model, a 1:10 ratio of respondents to free parameters to be estimated was

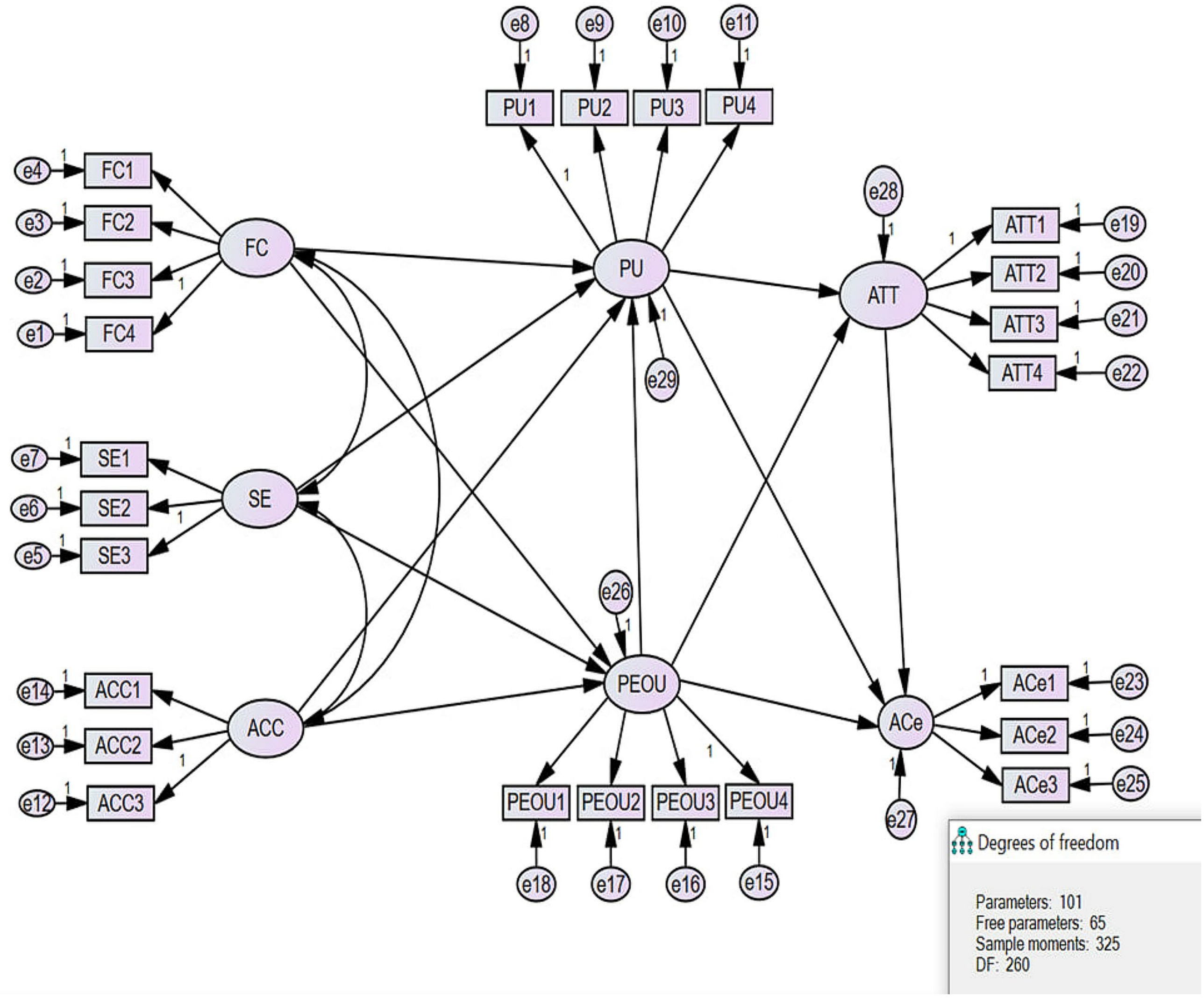

Fig. 3 Sample size determination using the modified model

suggested. As a result, the minimum sample size required was 650, based on the 65 parameters that needed to be estimated and a free parameter ratio of 10. Because the computed sample size considered a 10% nonresponse rate, the final sample size was 715. A direct effect is the immediate influence one variable has on another in the model. An indirect impact is the influence one variable has on another via a third variable (or group of variables) in the model [48] .

Sampling procedure

A stratified simple random sampling method was used. Once the sample was stratified based on the department and year of study, the sample was allocated in each stratum proportionally. Then, a simple random sampling technique was used to select the study subjects in each department Sampling frame were taken from the CMHS registrar's office.

Operational definitions

- The acceptance of e-learning is defined as the user's likelihood of using electronic learning for easy improvements in education. When a student agrees to use a technology measurement and scores median and above, the median is accepted for use; otherwise, they are not accepted for use on a five-point Likert scale with three questions [49].

Data collection tool and procedures

A structured questionnaire was developed after reviewing literatures on the subject [41, 50–53]. The structured questionnaire was divided into two sections: the first contained socio-demographic questions, and the second contained elements related to model constructs such as original TAM constructs (perceived ease of use, perceived usefulness, attitude toward use and intention to use) as well as additional elements that are included in the modified TAM, such as computer self-efficacy, facilitating conditions and accessibility. The questionnaire was written in English and then translated into Amharic. The data were collected using a self-administered questionnaire. A questionnaire was constructed to test the formulated hypotheses.

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 conditions, 3 items for self-efficacy, 4 items for perceived usefulness, 4 items for perceived ease of use, 4 items for attitude and 3 items for acceptance of e-learning. All the items used to measure the constructs were measured by using a Likert scale ranging from 1 to 5 (1 = strongly disagree, and 5 = strongly agree). The dependent variable was students' acceptance of e-Learning Systems. Socio-demographic characteristics of the students, perceived Usefulness, perceived ease of use, facilitating conditions, computer self-efficacy, accessibility, and attitude toward e-learning were the independent variables. Two days of training was given to the data collectors and supervisors.

Data quality assurance

Two days of training were given for the 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, such as storing data in multiple locations and creating hard and soft copies of the data, were carried out to prevent data loss. The data collection instruments were pre-tested at Addis Ababa University on 5% of the total sample size prior to the data collection period to ensure answer accuracy, language clarity, and tool suitability. The essential alteration for the actual research was made following the pretest. The internal consistency was checked by computing Cronbach's α from the pretest data. The pre-test indicated that the Cronbach's α was >0.7 for each constructs. We used expert reviews, and pilot testing to evaluate content validity of the data collection tools. Experts assessed the relevance, clarity, and comprehensiveness of the items.

Data processing and analysis

The respondent data were entered into Epi Data version 4.6 before being exported to SPSS version 25 for descriptive data analysis, Student's t test and correlation analysis. The Kaiser–Meyer–Olkin (KMO) measure of sample adequacy and Bartlett's test of sphericity were computed at the start of the SEM analysis. SEM analysis was carried out in two stages. In the first stage, the model constructs were evaluated via structural equation modeling (SEM) analysis using the Analysis of Moment Structure (AMOS) version 26 software. Confirmatory factor analysis (CFA) with standardized data was used for the test measurement model. Confirmatory factor analysis was used to assess correlations between constructs that were less than 0.8 and factor loadings that were greater than 0.6 for each item [54]. The average variance extracted (AVE) approach was used to assess convergent validity, while the square root of the AVE in the Furnell Larcker criterion was used to assess diverging validity, with values less than 0.9 [32, 49]. In the second stage, the final SEM analysis was performed using the seven-factor model to validate the relationships and associations among the exogenous, mediating, and endogenous variables. To assess the goodness of fit, the chi-square ratio (≤5), Tucker–Lewis index (TLI > 0.9), comparative fit index (CFI > 0.9), goodness-of-fit index (GFI > 0.9), adjusted goodness-of-fit index (AGFI > 0.8), root mean square error approximation (RMSEA < 0.08), and root mean square of the standardized residual (RMSR < 0.08) were used [32, 55, 56]. The dataset's missing values were managed, and data normality was evaluated using multivariate kurtosis < 5 and a critical ratio between −1.96 and +1.96.

Multicollinearity was also tested with a VIF < 10 and tolerances > 0.1, as well as a correlation between exogenous constructs of less than 0.8. The internal consistency reliability of each construct was assessed by calculating Cronbach's alpha. The path coefficient was used to analyze the relationship between exogenous and endogenous variables to evaluate the 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 participated in this study, including 519 males (78.8%) and 140 females (21.2%). Approximately 54.6% of the study participants were 25–29 years old, and approximately 0.9% of the study participants were 40 years old or older. Approximately 51.4% of participants had incomes between 10,000 and 15,000 ETB. The majority of respondents (54.8%) had less than 2 years of work experience. Approximately 29.7% of the respondents were second-year postgraduate health science students. A total of 5.6% of the respondents were resident 4 (R4) medicine specialty students (Table 1). The greatest percentages of respondents (10.2%) were from the gynecology department, and the smallest percentages of respondents (0.2%) were from the integrated emergency surgery and obstetrics department. .

Table 1 Demographic profile of respondents who were postgraduate medical and health science students at first-generation universities in the 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 10,000 and 15,000 ETB	339	51.4
Above 15,000 ETB	10	1.5
Age		
21 _ 24	22	3.3
25 _ 29	360	54.6
30 _ 39	271	41.1
>= 40 years	6	0.9
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

Table 2 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

Multicollinearity test

SEM analysis was used to evaluate the hypotheses after evaluating the measurement model's validity and ensuring that there were no strong relationships between the exogenous constructs and that collinearity was assessed. Multicollinearity was found to be nonexistent in this investigation (Table 2).

Measurement model assessment

Evaluation of the measurement model involves checking the model fit, internal consistency, discriminant validity, and convergent validity of indicators/items using CFA (Fig. 4).

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 greater than the other values in the columns, and the raw and HTMT ratios are less than 0.9. As a result, the discriminant validity of the model's constructs has been achieved (Tables 3 and 4).

Table 5 shows that the Cronbach's alpha and composite reliability are greater than 0.70 for all the constructs. The AVE values are greater than 0.70 for all the constructs. All of the constructs, therefore, had strong convergent validity.

Kaiser–Meyer–Olkin test and Bartlett's test of sphericity

We examined the findings of Bartlett's sphericity test and the Kaiser-Meyer-Olkin (KMO) sample adequacy assessment. The total KMO (0.89) shows excellent partial correlation, and the Bartlett's test of sphericity is significant.

Goodness of fit statistics for path analysis

The results in Table 6 show that the values of the fitness model met the required level.

Experience with using the internet, smartphones and computers

Approximately 83.8% of the 659 respondents had more than 6 years, and approximately 2.3% of the study participants had between 1 and 3 years of experience using mobile devices. Approximately 76.8% of the participants owned computer/laptop, smartphone and tablet ICT devices, and 0.8% of the students owned tablets. Approximately 75.1% of respondents used mobile data. Additionally, a minimum of 24.9% of respondents used broadband internet for internet connections. Approximately 93.2% of the respondents were comfortable using a computer, laptop, smartphone, tablet, or web application, and 6.8% of the respondents were not comfortable (Table 7).

Acceptance of using e-learning

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

Factors associated with acceptance of using e-learning

Exogenous constructs such as self-efficacy, accessibility and facilitating conditions explained 35.0% of the perceived ease of use construct, which has an R^2 of 0.35. Self-efficacy, accessibility, facilitating conditions and

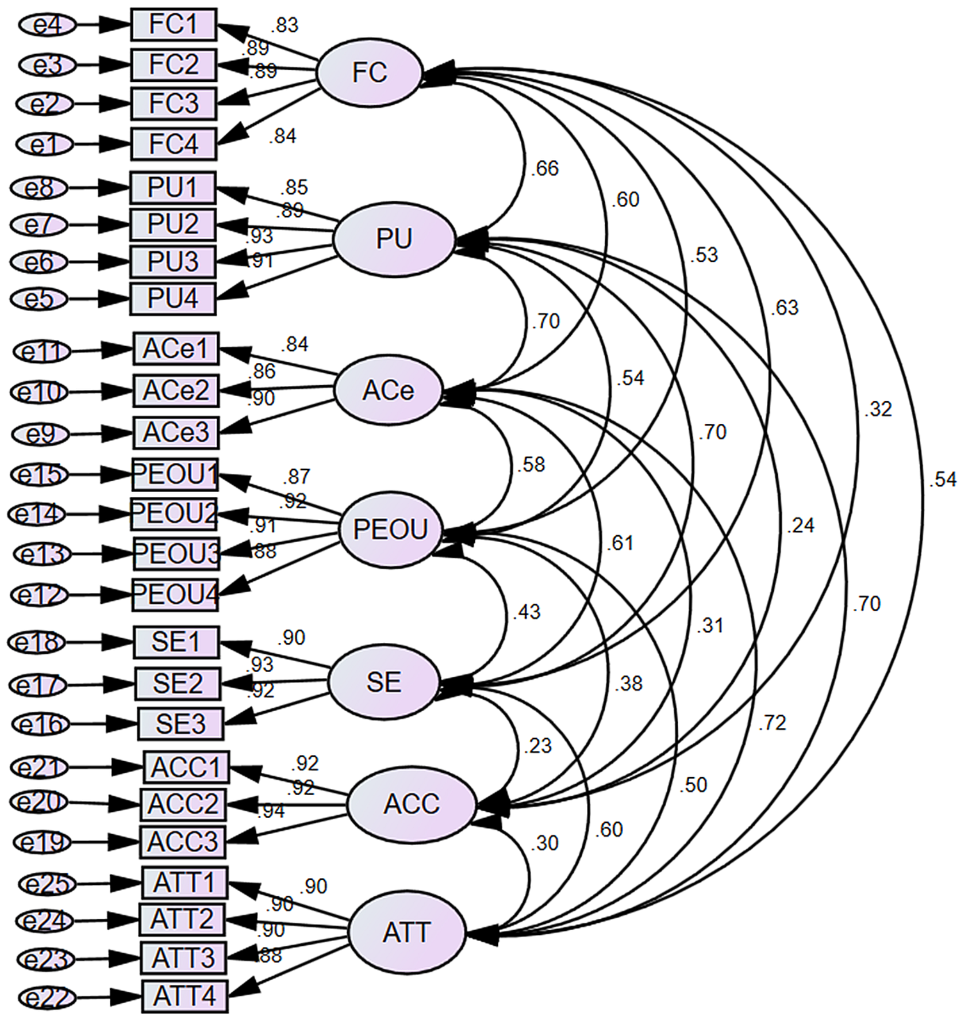

Fig. 4 Confirmatory factor analysis

Table 3 Discriminant validity of respondents among postgraduate medical and health science students in first-generation universities in the 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 Heterotrait-Monotrait ratio of correlations

	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	

Table 5 Convergent validity and reliability test

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

perceived ease of use explained 61.1% of the variance in perceived usefulness, for which the R^2 value was 0.61. Perceived usefulness and perceived ease of use explained 52.0% of the variance in the attitude construct, with an R^2 of 0.52. perceived usefulnessfulness, perceived ease of use and attitude explained 63.0% of the endogenous construct (acceptance to use the e-learning construct), with an R2 of 0.63. According to the R^2 value is considered 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 8).

The aforementioned hypotheses were tested together using structural equation modeling (SEM). SEM analysis revealed that attitude had the most substantial effect on the intention to use e-learning, which was greater than the effects of the other predictors, and facilitating conditions had the most substantial effect on the perceived ease of use of e-learning. Additionally, 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 toward the use of e-learning among students (Fig. 5).

The results showed that accessibility ($\beta=0.231$, 95% CI: [0.154, 0.308], $p<0.01$), self-efficacy ($\beta=0.156$, 95% CI: [0.042, 0.269], $p<0.01$) and facilitating conditions ($\beta=0.361$, 95% CI: [0.246, 0.472], $p<0.01$) had direct effects on students' perceived ease of use, supporting hypotheses **H1a, H2a and H3a**, respectively. Additionally,

Table 7 Experience using the internet, smartphones, and computers among postgraduate medical and health science students at first-generation universities in the 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
Smartphone	67	10.2
Tablet	5	0.8
Computer/Laptop, Smartphone, 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

Table 8 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

Table 6 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

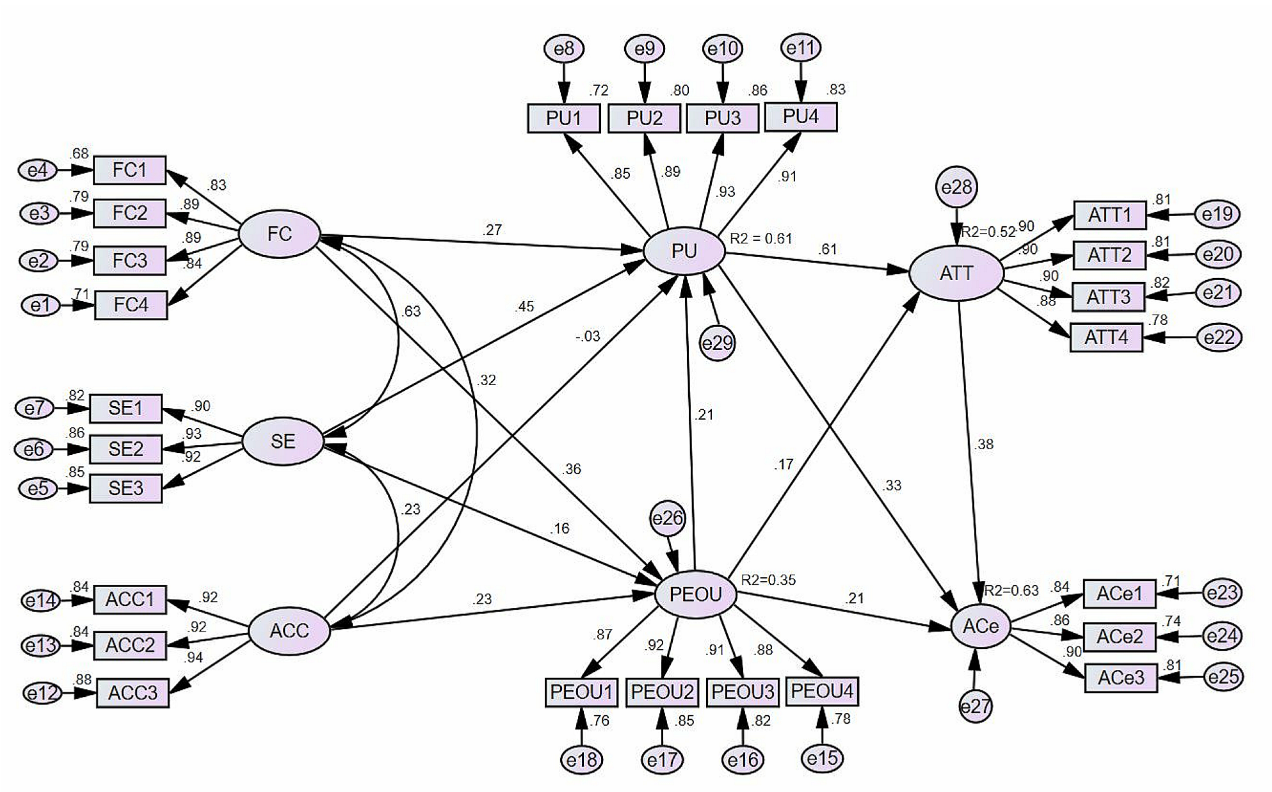

Fig. 5 SEM for predictors of acceptance of using e-learning among postgraduate medical and health science students at first-generation universities in the Amhara region, Ethiopia, 2023

facilitating conditions (β=0.274, 95% CI: [0.179, 0.381], $p<0.01$), self-efficacy (β=0.451, 95% CI: [0.346, 0.547], $p<0.01$) and perceived ease of use (β=0.212, 95% CI: [0.127, 0.304], $p<0.01$) had direct effects on students' perceived usefulness, which supports hypotheses **H1b**, **H2b and H5a**, respectively. In Contrast Accessibility (β = -0.030, 95% CI: [-0.087, 0.026], p value=0.280) had no direct effect on students' perceived usefulness, and Hypothesis **H3b** was not supported.

PEOU (β=0.167, 95% CI: [0.078, 0.255], $p<0.01$) and PU (β=0.613, 95% CI: [0.521, 0.699], $p<0.01$) had direct effects on students' attitude, which supports hypotheses **H5b** and **H4b**, respectively. PEOU (β=0.210, 95% CI: [0.118, 0.299], ATT (β=0.377, 95% CI: [0.255, 0.496], $p<0.01$) and PU (β=0.332, 95% CI: [0.209, 0.455], $p<0.01$) had direct effects on students' acceptance of e-learning, supporting hypotheses **H5b**, **H6a** and **H4a**, respectively (Table 9).

Mediating effects

Table 10 was generated by estimating the specific indirect effect path estimand algorithm feature in AMOS software. There are three mediators, PU, PEOU and ATT, among the 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 to be no significant 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 to be positive. Perceived usefulness (β=0.131, $P<0.001$), and perceived ease of use (β=0.029, $P<0.01$) significantly mediate the relationship between self-efficacy, and acceptance of e-learning. Accessibility had a positive indirect effect on acceptance of e-learning through perceived ease of use (β=0.040, $p<0.01$). Facilitating condition had a positive indirect on acceptance of e-learning through perceived ease of use (β=0.070, $p<0.01$), and perceived usefulness (β=0.084, $p<0.001$). Perceived ease of use had a positive indirect effect on acceptance of e-learning through perceived usefulness (β=0.062, $p<0.001$). Perceived ease of use had also a positive indirect effect on acceptance of e-learning through attitude (β=0.055, $p<0.001$). Perceived usefulness had also a positive indirect effect on acceptance of e-learning through attitude (β=0.214, $p<0.001$).

In most cases, PU alone does not have the ability to mediate the relationships between accessibility (ACC) and attitude (ATT), between accessibility (ACC) and attitude (ATT) and acceptance of e-learning (ACe), or

Table 9 SEM analysis of factors related to the acceptance of using e-learning

Hypothesis	Estimate	S.E.	C.R.	P - Value	95% Confidence Interval		Result
					Lower	Upper	
ACC ◊ PEOU	0.230	0.039	6.271	***	0.154	0.308	Supported
SE ◊ PEOU	0.156	0.057	3.368	**	0.042	0.269	Supported
FC ◊ PEOU	0.361	0.059	7.312	***	0.246	0.473	Supported
FC ◊ PU	0.274	0.052	6.530	***	0.179	0.381	Supported
SE ◊ PU	0.451	0.051	11.430	***	0.346	0.547	Supported
PEOU ◊ PU	0.212	0.045	5.988	***	0.127	0.304	Supported
ACC ◊ PU	-0.030	0.029	-0.985	0.280	-0.087	0.026	Not Supported
PEOU ◊ ATT	0.167	0.045	4.478	***	0.078	0.255	Supported
PU ◊ ATT	0.613	0.045	14.979	***	0.521	0.699	Supported
PEOU ◊ ACe	0.210	0.046	5.868	***	0.118	0.299	Supported
ATT ◊ ACe	0.377	0.062	8.600	***	0.255	0.496	Supported
PU ◊ ACe	0.332	0.063	7.225	***	0.209	0.455	Supported

** significant at $P<0.01$, *** significant at $P<0.001$

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

between accessibility (ACC) and acceptance of e-learning (ACe) (Table 10).

Discussion

This study investigated the acceptance of e-learning and associated factors among postgraduate medical and health science students at first-generation universities in the Amhara region. The study revealed that postgraduate students' acceptance of e-learning was 60.7%; 95% CI: [56.9–64.4]). This revealed that more than half of postgraduate students agreed to use e-learning. This result is less than that of a study conducted in Egypt, where 79.8% of the participants agreed to use e-learning [57]. This difference could be the result of Egypt having more advanced technological development than Ethiopia. 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 was 16.7% of the total population at the start of 2023 [58]. The accessibility of gadgets used for e-learning technology may also be another cause for the discrepancies.

Our proposed model explains 63% of the variance ($R^2=0.63$) in the acceptance of postgraduate students to use e-learning. In our investigation, acceptance of the use of e-learning was significantly associated with perceived ease of use, perceived usefulness and attitude toward use, indicating that 3 out of 3 path relationships in the proposed model were directly associated with acceptance of the use of e-learning. Accordingly, hypotheses **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 in which perceived ease of use had a direct significant effect on perceived usefulness and acceptance of e-learning [45]. In the United Arab Emirates, perceived ease of use had a direct significant effect on perceived usefulness, and acceptance of e-learning and perceived ease of use had significant direct effects on acceptance of e-learning [20].

According to our study, the 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 studies show that when the facilitating conditions for postgraduate students to use e-learning are strong, the perceived ease of use of e-learning and the perceived usefulness of e-learning are also high. This 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 those of previous studies in Bangladesh [38] and East Africa [39]. Accordingly, **H1a** and **H1b** are supported. Although facilitating conditions had significant effects on behavioral intention to use e-learning technology, these effects were mediated by attitude toward usage, perceived usefulness, and perceived ease of use. The findings of this research are consistent with those of previous studies in Singapore [59]. The possible reason is that facilitating conditions make it convenient for students to use e-learning systems, which can significantly improve their acceptance of e-learning without affecting their specific use behavior because the channels for accessing information and knowledge are diverse [60]. Moreover, 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 studies show that when the computer self-efficacy of postgraduate medical and health science students in using e-learning is strong, the perceived ease of use and perceived usefulness of e-learning

Table 10 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

are also high. This finding is consistent with other studies performed in Malaysia [61], Azerbaijan [21], and Kuwait [41]. Accordingly, hypotheses **H2a** and **H2b** are supported. Although computer self-efficacy had significant effects on acceptance of the use of e-learning technology, these effects were mediated by attitude toward usage, perceived usefulness, and perceived ease of use. The possible reason might be that postgraduate students currently have their own computers. In other studies, computer self-efficacy did not significantly affect perceived usefulness [21].

Accessibility had a direct effect on postgraduate students' perceived ease of use (β=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 simple to use. This is consistent with studies conducted in Greece [62], the UAE [43], and Iran [63]. The availability of information technologies for sharing knowledge via Zoom and other communication channels among students in modern society may be a possible reason. However, accessibility did not significantly influence perceived usefulness. Therefore, this study's findings for accessibility are consistent with the findings of other studies [20, 64]. Therefore, **H3a** is supported, and **H3b** is not supported.

According to our study, perceived usefulness had a direct effect on postgraduate students' attitudes toward using e-learning systems (β=0.606, $p<0.001$). In other words, these studies show that when the perceived usefulness of e-learning for postgraduate medical and health science students is strong, the attitude toward using e-learning systems is also high. The possible reason might be that postgraduate students currently have a good attitude toward the use of e-learning after COVID-19 [65]. Therefore, **H4b** is supported. This finding is consistent with those of previous studies conducted in Pakistan [22] and Iran [66].

Strengths of the study

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

Limitations of the study

In this study, the sample was recruited only from first-generation universities in the Amhara regional state. Only a quantitative technique was used to conduct the investigation. To strengthen their conclusions, future research studies should consider including a qualitative approach. Additionally, the study was only carried out in first-generation universities, which may limit the applicability of the findings in other contexts.

Implications of the findings

Our study's objective is to assess students' acceptance of e-learning by applying the TAM, which has implications for both policy and practice. Policymakers (ministry of education and ministry of health) can use our findings to advocate for investments in digital infrastructure within educational institutions. This supports broader initiatives to enhance digital literacy and access to technology. Understanding e-learning acceptance can influence curriculum development policies, ensuring that digital learning tools are integrated effectively into educational programs. Policies can be shaped to promote digital inclusion by addressing barriers identified in TAM research. This might include ensuring access to devices, internet connectivity, and training for students from diverse socioeconomic backgrounds. Policymakers can establish guidelines and regulations based on TAM research to protect student data privacy and ensure the security of e-learning platforms.

By understanding students' acceptance through TAM, educators and designers can tailor e-learning platforms to better meet user expectations. This includes enhancing usability, user interface design, and content delivery. Universities can provide targeted training and support based on factors identified by TAM that influence acceptance, such as perceived usefulness and ease of use. This ensures students can effectively use e-learning tools and resources. TAM insights can guide strategies to increase student engagement with e-learning materials. For example, highlighting the relevance of content or enhancing interactive features based on perceived ease of use. Schools can allocate resources more efficiently by investing in technologies that align with students' acceptance factors. This can include budgeting for upgrades or new tools that better match user preferences.

Conclusions and recommendations

Our study showed that more than half of postgraduate students accepted the e-learning system, Perceived usefulness, and perceived ease of use significantly mediate the relationship between self-efficacy, and acceptance of e-learning. Accessibility had a positive indirect effect on acceptance of e-learning through perceived ease of use. Facilitating condition had a positive indirect effect on acceptance of e-learning through perceived ease of use, and perceived usefulness. BDU and UoG are better positioned to raise awareness and make more informed decisions for health science students by delivering education and training on e-learning as an educational instrument to facilitate their learning process and increase efficiency. We recommend that more large-scale research involving first-generation, second-generation, and third-generation colleges be conducted for increased generalizability. Furthermore, a qualitative study is required to explore the acceptance of e-learning in in-depth from different perspectives. Sufficient computers, internet, and online repository access should be made available by the ministries of health and education in order to facilitate e-learning.

Abbreviations and acronyms

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

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Author contributions
AB 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 AD, AK, TA, HA, BW and GS. AB, BW, and AD 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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Data availability
The datasets generated and/or analyzed during the current study will be available upon reasonable request from the corresponding author.

Declarations

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

Consent for publication
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Competing interests
The authors declare no competing interests.

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