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Student Adoption of E-Learning in Higher Education Institutions in Saudi Arabia:
Opportunities and Challenges

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ABSTRACT

This study aims to explore the various factors influencing students in adopting e-learning in educational institutions in Saudi Arabia and analyze the relationship between factors of students' adoption of e-learning and student behavior intention. The study also analyzes perceived opportunities and challenges faced by students in adopting an e-learning system in higher education. A well-structured questionnaire was developed, and information was collected from 509 respondents. The study found that students' behavioral intention to adopt e-learning is highly influenced by performance expectancy, effort expectancy, social influence, facilitating conditions, computer self-efficacy, and internet knowledge. The study confirms the mediating role of student engagement that can act as an alternate path for strengthening the relationship between factors of adoption of e-learning and behavioral intention. In addition, several implications and new lines of investigation are recommended for meeting the educational transformation needs and future sustainability.

KEYWORDS

Behavior Intention, E-Learning, Student Engagement, Sustainability

INTRODUCTION

The rapid development of digital technologies is reshaping our economies as well as our entire administrative and educational systems. Education is seen as a critical component of gaining a competitive advantage in today's technological era because it encompasses teaching and learning. ICT improves educational standards by using technology to help students learn more effectively. Understanding the difficulties students confront and their incentives for using e-learning in order to support long-term adoption is critical. The Kingdom of Saudi Arabia is constantly improving education by adopting a contemporary and sustainable e-learning system and combining cutting-edge educational technology. There are 27 public universities, 36 private universities, and 25 institutes geographically

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dispersed across several parts of the Kingdom. There are 75,807 faculty members in public and private universities and 1,383,882 students enrolled in public and private colleges and affiliated institutions in Saudi Arabia, of which 95.1% of students are Saudi students. Under the guidance of 31 cultural missions, more than 53,000 Saudi students are finishing their scholarships in 57 different nations. Exactly 20,676 international students on Saudi scholarships are enrolled in Saudi colleges from 163 different nations. The modern educational technology for facilitating e-learning was started in 2020, with the spread of the Covid-19 pandemic crisis (Saleh et al., 2022). Due to unfamiliarity and lack of comprehension of the technology, students, educators, and school administrators expressed their discontent with the e-learning educational system in Saudi Arabia. Technological adoption in the educational system by students and instructors needs to be explored extensively to find its usefulness in improving people's comprehension and understanding of e-learning sustainability.

This study is undertaken in the context of students' adoption of e-learning in Saudi Arabia. Saudi Arabia is a large country with a significant and growing higher education system. The Saudi government has been proactive in supporting the development of e-learning for both students in traditional courses and those engaged in distance-learning courses. Only three studies have attempted to identify the CSFs for e-learning in Saudi Arabia (Alhomod & Shafi, 2013; Altameem, 2013; Fryan & Stergioulas, 2011). The purpose of this study is to identify the factors that affect e-learning and how they are viewed in Saudi Arabia. The Unified Theory of Acceptance and Use of Technology (UTAUT), a well-known theoretical framework, is used in this study as a basis for adoption. The primary focus is on exploring factors of e-learning adoption among students of higher educational institutions in Saudi Arabia. In addition, the study attempts to analyze students' perception of perceived opportunities and challenges they face in adopting an e-learning system and how far e-learning adoption affects their engagement and behavior intention towards e-learning adoption in higher educational institutions. Researchers also try to explore and analyze the opportunity, challenges, and problems faced by students in adapting the e-learning system in the higher education system.

The Technology Acceptance Model (TAM) is a popular method for evaluating the adoption of innovations by users (Alharbi & Drew, 2014; Binyamin et al., 2017; Mohammadi, 2015). TAM has been cited in approximately 36,000 publications according to Google Scholar. The model describes how users interact with technology and identifies perceived utility, attitude toward use, and behavioral intention to use as the three main factors that influence the adoption of emerging technologies (Holden & Rada, 2011). TAM is one of the few theories that have successfully combined psychological and technological frameworks, making it a valuable tool for researchers (Holden & Rada, 2011).Qazi et al. (2021) and Habib et al. (2022) investigate the level of acceptance of e-learning systems using the expanded model of UTAUT2. The findings show that behavioral intention is positively related to performance expectancy, effort expectancy, social influence, enabling situations, habit, knowledge acquisition, and information sharing. Alhabeeb and Rowley (2017), in their study on critical success factors for e-learning in Saudi Arabian universities, aim to provide insights into the growth of e-learning systems in three significant Saudi universities. The study outcome indicates student and instructor qualities were crucial success variables and participants valued technological infrastructure, student and teacher computer literacy, and instructor familiarity with learning tools as significant success enablers. Clarity of learning objectives and content quality are considered to be key components of instructional design.

BACKGROUND

Performance Expectancy

An important factor in the adoption and use of information systems is performance expectation. It is one of the concepts included in the UTAUT model's unified theory of acceptance and usage of technology (Khayati & Zouaoui, 2013; Tossy, 2014; Venkatesh et al., 2003; Wijaya et al., 2022). The performance expectations have a direct bearing on how postgraduate students utilize smartphones for mobile study. Performance expectation measures how much a person believes that utilizing a system will improve his or her ability to succeed at work (Venkatesh et al., 2003). It may also be characterized as the chance that utilizing smartphones would help postgraduate students do better in their academic endeavors. These arguments lead to the following hypothesis:

H1: Performance expectancy has a significant influence on students' adoption of e-learning in higher educational courses.

Effort Expectancy

The idea that there are linkages between the effort put forth at work, the outcomes gained because of that effort, and the benefits earned as a result of the effort form the basis of effort expectation (Al-Rahmi et al., 2018; Ghalandari, 2012; Meet et al., 2022; Teo & Zhou, 2014). Postgraduate students' use of smartphones for mobile learning and effort expectations are closely connected. This is due to the likelihood that the ease or complexity of quickly retrieving pertinent information using smartphones will affect how postgraduate students use them for mobile study. Consequently, if graduate students discover that it is incredibly simple to utilize their smartphones for mobile learning, they might not refrain from using them. These arguments lead to the following hypothesis:

H2: Effort expectancy has a significant influence on students' adoption of e-learning in higher educational courses.

Social Influence

The concept of social influence is crucial in helping people adopt information technology, which was proven to have a favorable impact on playing online games (Malhotra & Galletta, 1999). The variable motivation in the context of 'e-service usage' was discovered to have the biggest impact on 'e-service usage', contributing both directly and indirectly to e-service utilization (Kala & Chaubey, 2023; Urumsah, 2015). Social influence plays an important role in both embracing online learning and promoting the benefits of various e-learning platforms (Meet et al., 2022). Similar to other developing countries, in KSA the majority of people are cautious about using online learning platforms. The study's goal is to discover how social influence influences students' behavioral intentions to adopt online learning. These arguments lead to the following hypothesis:

H3: Social influence has a significant influence on students' adoption of e-learning in higher educational courses.

Facilitating Conditions

The concept of facilitating conditions in UTAUT refers to the level of belief that postgraduate students have in the availability of organizational resources (both human and material) and technical infrastructure to support the effective use of smartphones for mobile learning. This belief can determine whether or not they will choose to use their smartphones for mobile learning. (Ghalandari, 2012; Habib et al., 2022; Wut et al., 2022). The review of these studies leads to the following hypothesis:

H4: Facilitating conditions have a significant influence on students' adoption of e-learning in higher education courses.

Computers Self-Efficacy

The first and most widely utilized vector to extend TAM in the field of e-learning is computer self-efficacy (Abdullah & Ward, 2016). Venkatesh and Davis (1996) presented this factor as a predictor of self-efficacy. CSE is a test that evaluates an individual's ability to use computer technology (Compeau & Higgins, 1995). As a result, whether or not a person feels he or she has a high potential for using computer technology will determine if they are more inclined to do so. For this report, CSE refers to students' confidence in their ability to use the e-learning system provided by their university. CSE has been observed to influence students' PEOU and PU of TAM-based e-learning systems in Saudi Arabia (Al-Mushasha, 2013). Venkatesh's model and the TAM3 model (Venkatesh & Bala, 2008) researched CSE, and it was suggested that CSE affected PEOU. In Saudi Arabia, TAM3 (Al-Gahtani, 2016) was utilized to explain this hypothesis:

H5: Computer self-efficacy has a significant influence on students' adoption of e-learning in higher education courses.

Technical Knowledge and Support

Technological knowledge and support is an important component for making online education more effective and for obtaining greater student engagement. Higher education institutions are contending with the challenge of developing resilient infrastructure that is both competitive and suitable for the external environment as well as to internal user requirements. Every e-learning system requires the establishment of a basic 'infrastructure' of computers, networks, communications, and a technical department staffed by ICT specialists. Several researchers support this view that greater technical knowledge and support results in the better adoption of e-learning systems into the academic curriculum. (Alhabeeb & Rowley 2017; Qazi et al., 2021; Nawaz et al., 2012). These arguments lead to the following hypothesis:

H6: Technical knowledge and support have a significant influence on students' adoption of e-learning in higher education courses.

E-Learning Adoption and Students' Engagement

The relationship between e-learning adoption and students' engagement has been explored by several researchers who found a significant correlation between these two constructs (Benson & Brack, 2009; McPherson & Nunes, 2004).

Several authors indicated that teacher presence, feedback, support, time invested, content expertise, and information and communications technology skills are some of the key drivers of student engagement with their teachers (Beer et al., 2010; Quin, 2017; Ma et al., 2015; Zepke & Leach, 2010; Zhu, 2006). For instructional activities, the quality, design, difficulty, relevance, amount of necessary cooperation, and use of technology can influence students' interaction and affect their engagement (Almarghani & Mijatovic, 2017; Bundick et al., 2014; Coates, 2007; Xiao, 2017; Zepke & Leach, 2010; Zhu, 2006). Online learning may take several forms, including entirely synchronous learning, totally asynchronous learning, and hybrid learning. Each has a unique set of problems and opportunities in terms of technical convenience, time management, community, and pace. Students may feel alone in all online modes, and professors and students must devote more time and effort to fostering community. Collaboration can be done synchronously or asynchronously, and both are effective. The teacher may have to adjust their teaching designs because of hybrid learning. Some students feel more detached from the instructor and one another in hybrid learning contexts, and active class involvement is challenging (Bülow, 2022; Fadde & Vu, 2014; Gillett-Swan, 2017). Although Bülow's (2022) review focused on the challenges and opportunities of designing effective hybrid learning environments for teachers, students participating in various environments also need to adapt to foster effective active participation environments that include both local and remote learners. These arguments lead to the following hypothesis:

H7: Students' adoption of e-learning in higher education courses has a significant influence on their level of engagement in classes.

Student Engagement and Behavioral Intention Towards E-Learning

The relationship between students' engagement in e-learning and behavior intention towards adopting an e-learning system is critical since it is related to their participation and engagement towards an online teaching-learning environment. This issue was extensively researched by several authors including Azizi et al. (2020), Mohammadi (2021), and Wut et al. (2022), and most of the researchers indicated a positive association between these two constructs. Azizi et al. (2020) designed a model based on the Unified Theory of Acceptance and Use of Technology (UTAUT2); it has good potential for identifying the factors influencing the use of blended learning in medical education. Performance expectancy, effort expectancy, social influence, facilitation conditions, hedonic motivation, price value, and habit constructs had a significantly positive effect on the student's intention to use blended learning. In a survey of 152 graduate and postgraduate students from Jeddah, Saudi Arabia, it was found that personal, social, and emotional factors positively impact the students' cognitive engagement and behavioral intention towards e-learning. These factors are important for students to consider during disruptions as witnessed during the COVID-19 pandemic period. Wut et al. (2022) investigate factors affecting university students' participation in the discussion forum of electronic learning platforms of teacher-student interaction. A combined model based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and DeLone and McLean models serves as a research framework. One way to enhance students' academic discussion is to establish a closed university social media site with a chatbot included. This argument leads to the following hypotheses:

H8: Students' engagement in e-learning has a positive and significant influence on users' behavior intention.
H9: Students' engagement in e-learning mediates the relationship between factors of adoption of e-learning and students' behavior intention to adopt e-learning in higher educational courses.

METHODOLOGY

The research methodology for this study aims to explore the factors that affect students' adoption of e-learning in Saudi Arabia's higher education institutions. The study will use a mixed-methods approach, combining both quantitative and qualitative research methods, to provide a comprehensive understanding of the research problem. The research design for this study is a sequential explanatory design, where the quantitative data was collected first, followed by qualitative data to explain and elaborate on the findings from the quantitative data. Primary data was collected from the university student by using a survey method to frame the empirical part of the study. A well-structured questionnaire covering different dimensions of the study objective was prepared. The questionnaire was operationalized by adapting measuring scales from previous research; it was carried out to identify the constructs predicting students' adoption of e-learning (Farooq et al., 2017; Gunasinghe et al., 2020; Meet et al. 2022; Venkatesh et al., 2003). Student engagement and its measurement variable were developed based on previous studies by Perets et al. (2020) and Kala and Chaubey (2023). The measurement variable for measuring behavioral intention towards adopting e-learning was developed based on Gillett-Swan (2017). Following the development of the survey instrument, a pilot survey of 30 respondents was conducted. The pilot test findings indicated no issues with the reading of the questionnaire statement. The original questionnaire was evaluated by academics and industry specialists to verify content validity. Cronbach's alpha for all of the study's constructs was determined to be 0.930 for the full survey. This suggests that the questionnaire was trustworthy.

The information was gathered by convenience and justified sampling methods. The online questionnaire, created with Google forms, was given to prospective students, and additional responders were encouraged to spread it to their known peers. Prospective respondents' replies were also gathered through various social media platforms. The questionnaire was written in English. Data were collected during 20 weeks, from February 2022 to July 2022. All of the items were scored on a five-point Likert scale, with 1- indicating strongly disagree and 5- indicating strongly agree. A total of 550 responses were received. After editing, 509 responses (excluding 41 incomplete questionnaires) were considered appropriate for use in the study and were used. The material obtained was meticulously arranged, tallied, and examined. SPSS 22 and Smart PLS software were used for data analysis. Because this study involves examining the relationship between several constructs as dependent and independent variables, structural equation modeling (SEM) was believed to be an appropriate method. Confirmatory factor analysis was carried out using Cronbach's alpha, composite reliability, AVE, and convergent validity. The fitness of a structural model was determined using the Variance Inflation Factor (VIF), R2, and standardized path coefficients (Hair et al., 2019). The demographic characteristics of respondents are shown in Table 1.

Table 1. Demographic characteristics of respondents (N=529)

Categories	Description	Frequency	Percentage
Age	Up to 18 Years	154	30.3
	19-22 Years	119	23.4
	23-25 Years	107	21.0
	26-30 Years	78	15.3
	More Than 30 Years	51	10.0
Gender	Male	323	63.5
	Female	186	36.5
Marital Status	Married	16	3.1
	Un-Married	493	96.9
Nature of Course	Graduation Courses	210	41.3
	Post-Graduation Courses	218	42.8
	Doctoral/Post-Doctoral	56	11.0
	Courses	25	4.9
Specialization	Engineering/Science	120	23.6
	Courses	88	17.3
	Arts/Humanities courses	178	35.0
	Management/Humanities	36	7.1
	Medical/Paramedical	24	4.7
	Courses	57	11.2
	Legal Studies	6	1.2

RESULTS

The information presented in Table 1 indicates the demographic characteristics of respondents. It is observed that 154 (30.3%) respondents were in the age group of up to 18 years. Another 119 (23.4%) respondents were in the age group of 19-22 years. Another 107 (21.0%) respondents were in the age group of 23-25 years. An additional 78 (15.3%) respondents were in the age group of 26-30 years, and the remaining 51 (10.0%) respondents fell into the more than 30 years age group. Looking at the gender categories of respondents, it is observed that 323 (63.5%) were males and the remaining 186 (36.5%) respondents were females. Most of the respondents 493 (96.9%) were unmarried, and very few of the group 16 (3.1%) were married. Looking at the nature of courses, it is observed that 210 (41.3%) were pursuing graduation, 218 (42.8%) were pursuing postgraduation, 56 (11.0%) were pursuing doctoral/post-doctoral courses, and the remaining 25 (4.9%) respondents were from others courses. Regarding specialization, it was observed that 120 (23.6%) were from the Engineering/ Science discipline, 88 (17%) were from the Arts/Humanities discipline, 178 (35.0%) were from the Management/Humanities discipline, 36 (7.1%) were from the Medical/Paramedical discipline, 24 (4.7%) were from Legal Studies, 57 (11.2%) were from the Social Science/Education discipline, and the remaining 6 (1.2%) were from other disciplines.

The information presented in Table 2 indicates the descriptive statistics of all the measurement variables of each construct under investigation. It is observed from Table 2 that students have given the highest rating to Facilitating Condition with a mean of 3.8448, SD of 0.75681, and variance (σ) of 0.573. Dependent variable 'Behavior Intention' has a scored mean of 3.8912, SD of 0.46620 and variance (σ) of 0.217. The mediating variable 'Student Engagement' has a scored mean of 3.9893, SD of 0.67034, and variance (σ) of 0.449.

E-Learning Adoption and Emerging Challenges

The provision and usage of online and e-learning systems are becoming the main challenge for many universities. There is a lack of agreement about the critical challenges and factors that shape the successful usage of e-learning systems during this pandemic; a clear gap has been identified. The findings of Amin et al. (2022 offer useful suggestions for policymakers, designers, developers and researchers, which will enable them to get better acquainted with the key aspects of succesful e-learning system usage during this pandemic. For developing countries, adopting e-learning has always been a challenge because of the lack of mechanisms due to the resistance of teachers and students. Saleh et al. (2022) in their study on sustainable adoption of e-learning from the TAM perspective indicated lack of internet connection, ICT skills, and technology capabilities as the main issues. Based on these findings and another literature survey, some measurement variables were developed, and students were asked to rate them on a scale of 1 to 5 (see Table 3). It is observed that statements like 'It is tough to hold learners accountable for putting what they have learned into practice' scored the highest mean of 3.943 with an SD of 0.70898 and variance (σ) of 0.503. This was followed by the statement 'e-learning may encourage the cheating culture' with a mean of 3.9253, SD of 0.8195, and variance (σ) of 0.672 and 'e-learning quickly becomes obsolete and requires periodic updates' with a mean of 3.9155, SD of 0.53124, and variance (σ) of 0.282.

MEASUREMENT MODEL

The measurement model is the model that relates the latent variable to its multiple indications. It aids in testing the number of latent variables underlying the measurements and allows for evaluations of the indicators' quality. The model fit in the PLS-SEM measurement model was evaluated using Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE) (Table 4). Note that, α: values for all constructs were far above the ideal value of 0.70, and CR: all constructs ranges from 0.750 (Perceived Ease of Use) to 0.935 (Facilitating Conditions). In addition, AVE is a convergent validity

Table 2. Factors of e-learning adoption, student engagement, behavior intention (N=509)

Constructs and Items	Mean	SD	Variance
Performance Expectancy	3.7343	0.70152	0.492
Using an e-learning system will help me do better in my higher education classes.	3.6876	0.99737	0.995
I find the e-learning system valuable in my learning activities.	3.7780	0.85333	0.728
I complete my task quickly by adapting the e-learning system.	3.7407	0.98189	0.964
My learning quality and efficacy improved as a result of adopting the e-learning system.	3.7308	0.94757	0.898
Effort Expectancy	3.7141	0.68775	0.473
I worked hard and put in more effort to create an up-to-date e-learning system for higher education courses.	3.7819	0.96268	0.927
My interactions with the e-learning system are straightforward.	3.6306	0.91635	0.840
It will be simple for me to learn how to use the e-learning system in higher education.	3.7564	0.82742	0.685
I find the e-learning system to be user-friendly and simple to utilize.	3.6876	0.97945	0.959
Social Influence	3.7583	0.64909	0.421
People who influence my behavior think that I should use an e-learning system in my higher education learning.	3.6817	0.88784	0.788
This course's instructor has been quite helpful in utilizing e-learning technology.	3.7210	0.88556	0.784
Students in my class who utilize an e-learning system have more status than those who do not.	3.6974	0.81013	0.656
Students' academic standing improves when they use an e-learning system.	3.9332	0.95749	0.917
Facilitating Conditions	3.8448	0.75681	0.573
The institute provided the necessary knowledge needed to adopt an e-learning system in my academic program.	3.8959	1.01318	1.027
My resources are compatible with adopting the e-learning system of other academic learning programs I use.	3.5874	1.02081	1.042
Institutions provide competent and dedicated staff to assist with e-learning system issues.	3.6974	1.13412	1.286
Computer Self-Efficacy	3.6103	0.70579	0.498
I am comfortable with the e-learning system even though I have not used it in the past.	3.6660	0.89972	0.809
I am capable of using an e-learning system without the assistance of others.	3.6189	0.91150	0.831
I feel comfortable utilizing an e-learning system if someone explains to me how to utilize it.	3.5462	0.85593	0.733
Internet Knowledge	3.5108	0.92910	0.863
I spend many hours on the Internet to improve my e-learning experience.	3.4008	1.15377	1.331

continued on following page

Table 2. Continued

Constructs and Items	Mean	SD	Variance
I regularly use the Internet for e-learning courses.	3.6130	0.99284	0.986
I have used the Internet for e-learning courses for many years.	3.5187	1.03013	1.061
Technical Support	3.7597	0.83194	0.692
When there is a technical difficulty with one of my online courses, I receive virtual technical help.	3.6149	1.02000	1.040
When there is a technical problem with a higher education e-learning system, there are several online support systems accessible.	3.8684	0.95590	0.914
I receive technical support when utilizing an e-learning system.	3.7957	1.02791	1.057
Student Engagement	3.9893	0.67034	0.449
I am very much excited about e-learning classes.	3.8134	1.10053	1.211
I am completely involved in e-learning classes.	3.9961	0.85573	0.732
I participate(d) actively in e-learning classes.	3.9332	0.93038	0.866
I used to visit the course website regularly.	4.0255	0.84726	0.718
I am having a strong desire to learn the course material.	3.9214	0.90369	0.817
I give/gave a great deal of effort in the online classes.	3.9018	0.95889	0.919
I am connected personally via online means with my classmates.	4.0884	0.83598	0.699
I share(d) personal concerns with others.	4.0413	0.85359	0.729
I am very much concerned and committed to engaging in online classes with my classmates to help each other.	4.1827	0.77104	0.595
Behavior Intention	3.8912	0.46620	0.217
I intend to study higher education courses using an e-learning system.	3.8664	0.62260	0.388
I aim to use an e-learning system to study other topics.	3.8959	0.59440	0.353
In the future, I intend to use an e-learning system more frequently.	3.9882	0.60823	0.370
In future sessions, I plan to use an e-learning system.	3.6385	0.64826	0.420
I hope that in the future, e-learning apps in higher education will become a mainstream manner of instruction.	4.0668	0.70394	0.496

indicator that examines the amount of variation captured by a concept in terms of measurement error. In general, an AVE of 0.5 or higher is required; otherwise, the error variance exceeds the variance explained, which is undesirable. In our case, AVEs ranging from 0.551 (Performance Expectancy) to 0.832 (Facilitating Conditions) demonstrated the model's convergent validity, suggesting that the components in each category were substantially correlated with one another.

Discriminant validity is a subtype of construct validity that shows how effectively a test evaluates the issue for which it was prepared (Table 5). Discriminant validity examines whether two concepts that should not be linked are, in fact, unconnected. It compares one concept's Square Root of AVE to the correlation between that construct and others. The Square Root of AVE is typically thought to be bigger than the construct's relationship with others; if not, the individual construct does not provide much discrimination (i.e., unique explanatory power). Figure 1 shows that all variables in each construct had loading factors greater than 0.5, hence no variable was eliminated from the model. The loading factor should be statistically significant and higher than 0.5, preferably higher than 0.7.

Table 3. Student adoption of e-learning: Perceived challenges

Items	Mean	SD	Variance
In creating e-learning courses for various generations	3.8016	0.57671	0.333
the greatest issue is a lack of focus and learner engagement, and motivation is lacking.	3.8173	0.59195	0.350
Keeping up with contemporary technologies.	3.7819	0.66225	0.439
It is difficult to keep learners interested in their e-learning courses.	3.7544	0.85838	0.737
It is tough to hold learners accountable for putting what they have learned into practice.	3.9430	0.70898	0.503
E-Learning quickly becomes obsolete and requires periodic updates.	3.9155	0.53124	0.282
The greatest hurdles in reaching the goal of e-learning are technological ones.	3.7367	0.74072	0.549
Establishing social interaction in an e-learning environment is difficult. E-learning may develop social isolation.	3.7308	0.78886	0.622
It is challenging for me to manage screen time for a longer period.	3.8139	0.55241	0.305
Users' interphase is a challenge because of the non-responsive e-learning system.	3.7878	0.54775	0.300
E-Learning may encourage the cheating culture.	3.9253	0.81950	0.672
It is a challenge to meet the objective of e-learning due to the large coverage of subjective matters.	3.4774	0.93803	0.880

Table 4. Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	Collinearity Statistics
Behavior Intention (BI)	0.786	0.795	0.540	
Computer Self-Efficacy (CSE)	0.704	0.733	0.623	1.164
Effort Expectancy (EE)	0.736	0.757	0.552	1.073
Facilitating Conditions (FC)	0.933	0.935	0.832	1.003
Internet Knowledge (IK)	0.850	0.854	0.770	1.213
Performance Expectancy (PE)	0.673	0.688	0.607	1.114
Social Influence (SI)	0.724	0.828	0.595	1.218
Student Engagement (SE)	0.902	0.904	0.561	1.603
Students' Adoption of e-Learning (SSeL)	0.789	0.807	0.138	1.603
Technical Support (TS)	0.776	0.778	0.692	1.233

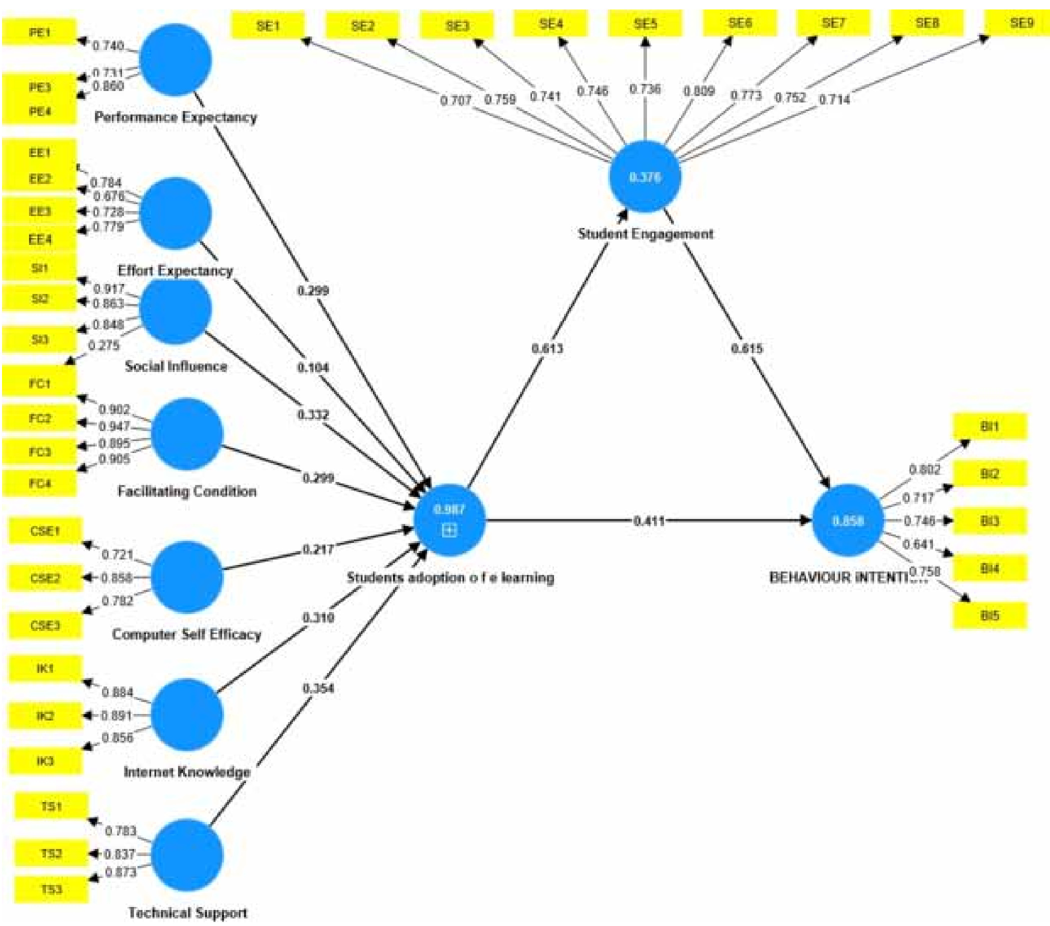
Structural Model

The structural model is assessed in terms of the estimates and hypothesis tests for the causal relationships between exogenous and endogenous variables given in the route diagram. SmartPLS's bootstrapping option estimates standard errors and t-test statistics for the relevant parameters.

Table 5. Discriminant validity: Fornell-Larcker criterion

	BI	CSE	EE	FC	IK	PE	SI	SE	TS
Behavior Intention	0.735								
Computer elf-Efficacy	0.299	0.789							
Effort Expectancy	0.112	0.174	0.743						
Facilitating Condition	0.248	-0.006	-0.017	0.912					
Internet Knowledge	0.472	0.099	0.086	-0.002	0.877				
Performance Expectancy	0.468	0.223	0.138	0.040	0.085	0.742			
Social Influence	0.419	0.219	0.207	-0.007	0.318	0.242	0.772		
Student Engagement	0.867	0.266	0.082	0.026	0.345	0.433	0.298	0.749	
Technical Support	0.578	0.283	0.047	0.031	0.296	0.228	0.098	0.570	0.832

Figure 1. Structural model and hypothesis testing



Subsamples are randomly selected observations from the original set of data in bootstrapping (with replacement). The PLS path model is then estimated using each subsample. This procedure is continued until a large number of random subsamples have been generated (e.g., 5,000). The variance among these numerous (e.g., 5,000) bootstrap subsample estimations is utilised to calculate standard errors for the PLS-SEM results. Standard errors, Beta coefficients, t-values, and p-values may be generated using this information to evaluate the PLS-SEM estimate outcomes. According to the findings as presented in Table 6, performance expectancy, effort expectancy, social influence, facilitating condition, computer self-efficacy, internet knowledge, and technical support strongly predict students' adoption of e-learning. VIFs should be less than 5.0, R2 should be within acceptable bounds, and standardized path coefficients should be statistically significant to rule out factor multicollinearity. All these over 1.0 are observed, with the maximum VIF of 2.514 being within the acceptable range of 3.0. It demonstrated that multicollinearity was not a problem. The remaining structural model components were responsible for 85.8% of behavioral intention and 37.6% of student engagement. All the standardized path coefficients were statistically significant at the 0.01 level according to R^2 estimations. When these criteria were combined, they demonstrated the structural model's fit to the data.

The PLS-SEM algorithm generates model associations (path coefficients) between constructs, which indicate the predicted relationships between the constructs. Table 6 displays the path coefficients, t-statics, and p-values for all proposed hypotheses. Statistical results in Table 6 refer for each of the following for Performance Expectancy -> Students' Adoption of e-Learning (β=0.299, t=9.583,

Table 6. Path coefficients, mean, STDEV, t-values, p-values

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-Statistics (|O/STDEV|)	P-Values
Computer Self-Efficacy -> Students's Adoption of e-Learning	0.217	0.211	0.027	7.967	0.000
Effort Expectancy -> Students' Adoption of e-Learning	0.104	0.102	0.037	2.777	0.006
Facilitating Conditions -> Students' Adoption of e-L'earning	0.299	0.282	0.127	2.363	0.018
Internet Knowledge -> Students' Adoption of e-Learning	0.310	0.304	0.036	8.701	0.000
Performance Expectancy -> Students' Adoption of e-Learning	0.299	0.293	0.031	9.583	0.000
Social Influence -> Students' Adoption of e-Learning	0.332	0.325	0.031	10.562	0.000
Student Engagement -> Behavior Intention	0.615	0.619	0.025	24.930	0.000
Students' Adoption of e-Learning -> Behavior Intention	0.411	0.404	0.035	11.916	0.000
Students' Adoption of e-Learning -> Student Engagement	0.613	0.616	0.036	17.089	0.000
Technical Support -> Students' Adoption of e-Learning	0.354	0.349	0.031	11.465	0.000
Students' Adoption of e-learning -> Student Engagement -> Behavior Intention	0.377	0.381	0.027	13.939	0.000

p-value =0.000, p-value ≤0.05), Effort Expectancy -> Students' Adoption of e-Learning (β=0.104, t=2.777, p- value =0.006, p-value ≤0.05), Social Influence -> Students; Adoption of e-Learning (β=0.332, t=10.562, p-value =0.000, p-value ≤0.05), Facilitating Condition -> Students' Adoption of e-Learning (β=0.299, t=2.636, p-value =0.018, p-value ≤0.05), Computer Self-Efficacy -> Students' Adoption of e-Learning (β=0.217, t=7.967, p-value =0.000, p-value ≤0.05), Internet Knowledge -> Students' Adoption of e-Learning β=0.310, t=8.710, p-value =0.000, p-value ≤0.05), and Technical Support -> Students' Adoption of e-Learning (β=0.354, t=11.465, p-value =0.000, p-value ≤0.05); they are significant except for Perceived Ease of Use. Hence, test statistics support research hypotheses 1-7. The path coefficient between Students' Adoption of e-Learning -> Student Engagement (β=0.613, t=17.089, p-value=0.000, p-value≤0.05) is significant, indicating a positive relationship between them. Hence, the finding supports research hypothesis 7. The standardized path coefficient from Student Engagement -> Behavior Intention (β=0.615, t=24.930, p-value =0.000, p- value ≤0.05) is significant and supports research hypothesis 8.

A mediation model in statistics aims to discover and explain the mechanism or process underlying an observed association between an independent variable and a dependent variable by incorporating a third hypothetical variable. A mediation model proposes that the independent variable influences the mediator variable, which in turn influences the dependent variable, rather than there being a direct causal relationship between the independent and dependent variables. In the present study, researchers analyzed student engagement as a mediator in the relationship between factors of e-learning adoption and behavior intention. Bootstrapping using SmartPLS was carried out to measure the direct and indirect effects. It is hypothesized that there are direct relationships between students' adoption of e-learning and their behavioral intention towards e-learning in higher educational courses. The outcome of the data as presented in Table 6 indicates the direct impact of factors of adoption of e-learning on behavior intention to adopt e-learning. The path coefficient between factors of students' adoption of e-learning on behavior intention is significant – Students' Adoption of e-Learning -> Behavior Intention (β=0.411, t=11.916, p-value =0.000, p-value ≤0.05) – which indicates a positive and significant relationship between them. Hence, the finding supports the research hypothesis. The mediation test was a performance in a two-step. The impact of students' adoption of e-learning on student engagement was calculated and was found to be significant – Students' Adoption of e-Learning -> Student Engagement (β=0.613, t=17.089, p-value =0.000, p-value ≤0.05) – and further the impact of students' engagement on behavior intention was found to be significant – Student Engagement -> Behavior Intention (β=0.615, t=24.930, p-value =0.000, p-value ≤0.05). The specific indirect effect of Students' Adoption of e-Learning -> Student Engagement -> Behavior Intention is found to be β=0.377, t=13.939, p-value =0.000) as p- value is ≤0.05) indicating that students level of engagement in improving the relationship between factors of adoption of e learning and behaviour intention is significant. It is found that the inclusion of student engagement reduces the variance from 0.035 to 0.027 from the direct effect of the factor of adoption of e-learning on behavior intention to an indirect effect via student engagement. Thus, student engagement mediates the relationship between factors of student adoption of e-learning and behavior intention toward e-learning in higher education courses and thus supports hypothesis 9.

DISCUSSION

The research supports and contradicts several relationships in the UTAUT model. The hypothesized relationships between Students' Adoption of e-Learning, Student Engagement, and Behavior Intention are statistically significant (β=0.377, t=13.939, p-value =0.000, p-value≤0.05); similarly, the impact of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Perceived Usefulness, Computer Self-Efficacy, Internet Knowledge, and Technical Support on student adoption of e-learning is statistically significant and strongly predict Students' Adoption of e-Learning.

The outcome of the present study indicates that the Performance Expectancy (PE) was the strongest determinant – Performance Expectancy -> Students' Adoption of e-Learning (β=0.299, t=9.583, p-value =0.000) – followed by Social Influence – Social Influence -> Students' Adoption of e-Learning (β=0.332, t=10.562, p-value =0.000) – within the proposed model. The present finding is in conformance with the previous research work (Tarhini et al., 2013; These findings are consistent with the previous research finding of Fouad et al. (2021), Abusalim et al. (2020), Al-Maiah (2019), and Tarhini et al. (2016). Venkatesh & Zhang, 2010; Venkatesh et al., 2012). As a result, when students see a system as beneficial, they are more likely to have a positive opinion of utilizing technology. Therefore, to draw in more users and satisfy their expectations and demands, practitioners should enhance the quality of information systems based on user comments. To do this, policymakers should offer users a manual that includes comprehensive instructions regarding the advantages of the system, such as services that enable students to attend academic courses from anywhere at any time.

Although users are not affected by referent groups but by individuals' necessity in a voluntary context (Venkatesh et al., 2003), our results indicate that SI has a significant positive influence on BI which is consistent with the majority of previous studies (Foon & Fah, 2011; Tarhini et al. 2014). In this context, it is advised that practitioners should persuade earlier adopters of the system to help in promoting it to other users. In such environments, consumers may be influenced by positive word-of-mouth from their referent peers. To attract more users, the use of social websites and communities should be employed. This will affect customers' decisions to adopt and accept the technology. Several researchers point to the importance of facilitating conditions (FC) in real technology usage behavior, and the results of this study support those findings when seen in the context of e-learning adoption in higher education services (Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Yu, 2012). To better serve their students, an institution in association with the government should spend more on ICT infrastructure and offer all educational services for the betterment of students.

The study reported that the hypothesized paths between facilitating conditions (FC) and e-learning adoption are statistically significant. Such results are consistent with studies conducted by Elie-Dit-Cosaque et al. (2011), Lau (2011), Meet et al. (2022), Habib et al. (2021) and Kala and Chaubey (2023. The study also confirmed the relationships between the UTAUT constructs: social influence and facilitating condition and perceived behavior. The study has substantiated and refuted several relationships in the UTAUT model. SI has been confirmed as the strongest predictor of e-learning adoption followed by EE and FC. Findings suggest that educational institutions should focus on factors influencing teachers' and students' attitudes toward adopting and using e-learning services. The system features, internet experience, and computer self-efficacy were the major obstacles to effective adoption in Pakistan (Kanwal & Rehman, 2017). In impoverished nations, 45% of e-learning initiatives are complete failures, 40% are partial failures, and only 15% are successful. An Al-Arabi et al. (2019) study supports this. Numerous IS/IT experts, such as Al-Arabi et al. (2019), Esterhuyse and Scholtz (2015), and Islam et al. (2015), have conducted a study to look at the challenges that must be overcome for such projects to be effective.

CONCLUSION

E-learning has evolved alongside the advancement of information and communication technologies (ICT). It is widely used by educational institutions and other professionals in the educational systems. The e-learning market is highly diverse; Blended learning, gamification, micro learning, MOOCs, Software as a Service (e-learning in the cloud), personalized learning, continuous learning, and other trends are dominating. The goal of the study was to identify the most important aspects influencing learners' behavioral intentions in Saudi Arabia which in turn drive their usage behavior. The study has concentrated on figuring out a different route for Saudi Arabia to adopt e-learning. A learner's desire to adopt online learning is mostly dependent on the technical skills and aptitude that they have since poor online learning skills can lead to poor adoption behavior, which can make it difficult for learners to embrace e-learning. However, people who currently use a variety of technology-driven goods and services to perform their everyday tasks may have high levels of technical abilities, which may boost their inclination to accept online learning. In general, the majority may encounter adoption difficulties, whereas fewer may adopt online learning while getting beyond the obstacles. We thus suggest that educators should concentrate on increasing learners' perceived behavioral control or self-efficacy needed to handle online learning when developing institutional solutions. With this in mind, general policies may be pushed to improve the necessary abilities required to function in the environment.

E-learning is becoming increasingly important in modern academic education and corporate training, and it is critical to maintain and monitor the quality of online training programmes in order to make it the most effective and engaging. It is also necessary to consider the complexities of e-learning-related issues, such as increasing trainers' and designers' IT literacy; developing complex digital curricula; and collaborating with various players such as academia, instructional designers, and learning practitioners as well as IT and platform providers. To use technology, trainers and course designers must have technical and pedagogical skills as well as their full support, commitment, time, and experience.

The study found that learners' behavioral intention to accept e-learning in Saudi Arabia is highly influenced by these factors: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Computer Self-Efficacy, Internet Knowledge, and Technical Support. Since e-learning is not widely used in Saudi Arabia and is seen to be technical and difficult, an institution needs to focus on some issues, such as: it is tough to hold learners accountable for putting what they have learned into practice, there exists the fear that e-learning may encourage the cheating culture, and there exists the fear that e-learning quickly becomes obsolete and requires periodic updates. Managing these issues may influence learners' belief systems more favourably and lead to an increase in acceptance.

Students' engagement can act as an alternate path for strengthening the relationship between factors of adoption of e-learning and behavioral intention to adopt e-learning in Saudi Arabia. By far, adoption behavior is related to the level of confidence that the person possesses in dealing with technology-enabled platforms. In most cases, learners are not provided with any sort of hands-on training on the issues. According to the study, the factors of Performance Expectancy, Social Influence, and Internet Knowledge all work together to shape behavioral intentions (BI) to adopt online learning. The association between the elements influencing the adoption of e-learning and the behavior intention to embrace it has been strengthened by the researchers' use of student engagement as a mediator. Although all moderators were removed from the study, the findings may have been more intriguing if they had been examined in regards to specific moderators, including age, gender, internet proficiency, and self-expertise.

More research on the topic is recommended, such as conducting separate surveys of students and professors on the effectiveness of e-learning verse blended learning approaches, overall satisfaction with each method, the applicability of the knowledge received, and the extent to which knowledge "sticks" to the learner when delivered through the e-learning channel; research into the specific "ideal" characteristics for IT platforms and hardware is also recommended. According to current research, e-learning is most effective in developing technical skills and delivering the learning curriculum, whereas the digital learning environment is best for developing "soft" skills. Future studies on these topics can be carried out to clarify the problems and produce insightful study results.

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