International Education Studies; Vol. 16, No. 6; 2023
ISSN 1913-9020 E-ISSN 1913-9039
Published by Canadian Center of Science and Education

From Crisis to Continuity: Exploring Students' Perspectives on the Future of Online Learning Beyond COVID-19

Salma Al-Nabhani[1] & Abdullah Al-Abri[1]

[1] Preparatory Studies Centre, University of Technology and Applied Sciences, Nizwa, Oman

Correspondence: Abdullah Al-Abri, University of Technology and Applied Sciences, Oman

Received: July 9, 2023 Accepted: October 6, 2023 Online Published: November 22, 2023

doi:10.5539/ies.v16n6p45 URL: https://doi.org/10.5539/ies.v16n6p45

Abstract

As we live in the post-COVID-19 era, much research should be devoted to guiding educators and policymakers on what to retain, revise, or even eliminate from the online learning experience. This study aimed to provide a deeper understanding of the students' behavioural intention to continue using technology in the post-COVID-19 era. The study was grounded in a well-known theoretical model for assessing technology adoption, the Technology Acceptance Model (TAM), expanded by adding the following external variables: accessibility (ACC), anxiety (ANX), feedback (FB), computer playfulness (CP) and perceived enjoyment (PNJ). A total of 134 undergraduate students from both public and private universities and colleges in Oman were included in the study. Data was collected through the administration of a Likert-scale questionnaire and analysed using descriptive tests and the Smart-PLS technique. The study's main findings revealed that ACC, ANX, CP, and PNJ had a significant impact on Perceived Ease of Use (PEOU), while no such effect was observed on Perceived Usefulness (PU). Notably, the study concludes that students exhibit a high intention to continue using technology. The study underscores the increasing familiarity of interactive technology tools among teachers and students, a trend accelerated during the pandemic. However, a recommendation is made for the development of a comprehensive framework by educational stakeholders, including policy professionals and teachers, to specify the strategic use of technology and its intended purpose.

Keywords: behavioural intention, e-learning, post-COVID-19 era, Technology Acceptance Model (TAM)

1. Introduction

With the onset of the Coronavirus (COVID-19) pandemic and the increasing prevalence of information technology, integrating technology into teaching and learning processes has become vital. Therefore, online learning tools have been incorporated among universities across the universe as they provide responsive and flexible learning environments (Dimitriadou & Lanitis, 2023; Lee et al., 2005; Sharma & Chandel, 2013). However, "in general, like any information systems, user acceptance and usage are important primary measures of system success" (Saade et al., 2007, p. 176). Hence, students' acceptance of any information system must be considered.

Electronic learning (e-learning) is a platform used by students and teachers to communicate, access, and exchange information anywhere and at any time (Alonso et al., 2005; Jaswal & Behera, 2023). Accordingly, the e-learning system supports learning and teaching processes either inside or outside any higher education institution's campus (anywhere and anytime), as the information and learning instructions can be delivered to learners via the Internet. Many scholars have provided an extensive range of e-learning definitions as these definitions seek to emphasise the correlation between technology and education, learning or training (Alia, 2017).

A respectable amount of literature has demonstrated numerous factors influencing online learning (Jaber, 2016). Therefore, identifying the factors that encourage learners to utilize e-learning is crucial. To do this, researchers have adapted various technology adoption models and theories, including the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Task Technology Fit (TTF) and Theory of Planned Behaviour (TPB). Nevertheless, "TAM is the most common ground theory in e-learning acceptance literature" (Granić & Marangunić, 2019, p. 2575) and has been used in many studies (Davis et al., 1989). In addition, the adaptation and diffusion of information technology have been studied at two levels: organizational and individual levels (Dasgupta et al., 2002). However, the key focus of this study was on the individual level, as there is an emphasis on individuals' acceptance of technology.

Technology Acceptance Model (TAM) "is an intention-based model developed specifically for explaining and/or predicting user acceptance of computer technology" (Hu et al., 1999, p. 93). Previous research has proven that the Technology Acceptance Model (TAM) is utilized to investigate, elucidate, and forecast the behavioural adoption of any technology (Al-Gahtani, 2016).

1.1 The Purpose of the Study

The COVID-19 pandemic has prompted significant changes and disruptions in the education sector. Online and blended learning approaches were swiftly adopted by educational institutions to ensure the continuity of teaching and learning. Various e-learning platforms and tools were integrated into teaching methodologies by educators. However, a gradual return to face-to-face learning has been observed as the pandemic's impact lessens.

The primary objective of this study is to investigate whether students wish to continue using technology after the pandemic. Specifically, the influence of several external factors, including Accessibility (ACC), Anxiety (ANX), Computer Playfulness (CP), Perceived Enjoyment (PNJ), and Feedback (FB), on two crucial factors that shape the behavioural intention of students to continue using technology were assessed: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) of e-learning systems. This study strived to provide a comprehensive understanding of these factors and their implications for e-learning adoption in the post-pandemic educational context.

2. Literature Review

Technology Acceptance Model (TAM), as shown in Figure 1, emphasizes that Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are antecedent determinants that affect learners' Perceived Attitudes (PA) to using technology, which consequently predicts their Behavioural Intention (PI) to utilize the online system and the actual usage of the system (Davis et al., 1989). A number of studies have tested the Technology Acceptance Model (TAM) as a parsimonious, understandable, and reasonable explanatory model. Multiple variables were incorporated into TAM and directly and indirectly, influenced the user's attitude and intention to use the e-learning system. For instance, Venkatesh (2000) expanded the Technology Acceptance Model (TAM2) by including three social instrumental determinants and four cognitive instrumental determinants of Perceived Usefulness. The former includes Subjective Norm, Voluntariness, and Image, whereas the latter is defined by Job Relevance, Outfit Quality, Result Demonstrability and Perceived Ease of Use (Lee et al., 2010).

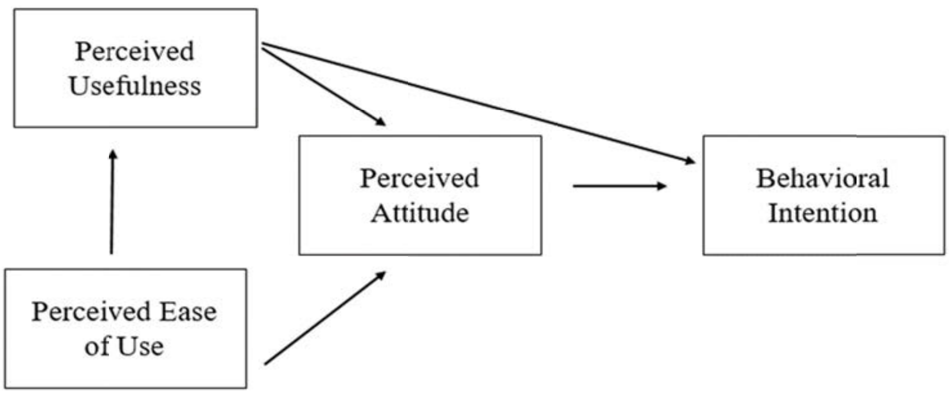

Figure 1. Technology Acceptance Model (TAM)

2.1 Perceived Attitude (PA)

Perceived Attitude (PA) is defined as "a hypothetical construct used to explain the direction and persistence of human behaviour" (Baker, 1992, p. 10). This definition emphasises the role of attitudes in shaping individuals' choices and actions. Basically, attitudes influence the decisions we make and the behaviours we reveal. When an individual perceives a positive attitude towards a particular activity, they are more likely to engage in it, while a negative attitude may lead to avoidance.

Mantle-Bromley's (1995) psychological study further breaks down attitude into three primary components: cognition, affect, and behaviour. These components embrace individuals' preferences, their knowledge about their attitude toward a specific action or object, and, more importantly, their intentions and reactions towards it.

In the context of education, attitudes play a significant role in shaping students' perceptions of curriculum, peers, and teachers (Bailey et al., 2022; Liu, 2014). Attitudes are closely associated with the feelings that guide human behaviour, and individuals can develop either positive or negative attitudes towards various subjects or activities (Edo et al., 2023; Genc & Aydin, 2017).

Perceived attitude's influence extends to e-learning systems. Hussein (2017) emphasized its central role in influencing students' intentions to adopt e-learning. Various studies have supported this finding, highlighting attitude as an effective predictor of students' behavioural intentions (Amali et al., 2022; Sharma & Chandel, 2013a).

Attitudes are also particularly relevant in language learning contexts, where learners often show either positive or negative attitudes towards the target language. Positively inclined learners tend to exhibit higher motivation levels, aiding their learning progress, while those with negative attitudes may experience demotivation and potential neglect (Genc & Aydin, 2017; Maruf, 2022). In light of this background, we propose the following hypothesis:

H1: Perceived Attitude has a positive and significant association with learners' intention to continue using e-learning systems.

2.2 Perceived Usefulness (PU)

Davis (1989, p. 320) defined Perceived Usefulness as "the degree to which a person believes that using a specific system will increase his or her job performance." This concept is not about the general idea of usefulness but is tied to a particular system or technology. It suggests that people evaluate the usefulness of a specific system or tool in achieving a particular purpose. Empirical studies have consistently proved that PU directly influences Perceived Attitude (PA) and, consequently, indirectly affects Behavioral Intention (BI) towards using e-learning websites. The research findings of Al-Adwan (2023), Altawalbeh and Alassaf (2018), Fauzi et al. (2021), and Um (2021) have underscored a significant relationship between Perceived Usefulness (PU) and students' attitudes towards the adoption of e-learning websites.

Furthermore, PU emerges as a critical variable affecting BI. It is well-known that PU plays a crucial role in predicting students' intentions to utilise web-based learning systems (Chang & Im, 2014; Humida et al., 2022). Students are more motivated to accept educational websites when they recognise that these e-learning materials will develop their learning skills and performance. However, it is essential to note that while PU is a prominent influencer of students' intentions to use e-learning systems, some studies, such as those by Saeed and Abdinnour-Helm (2008), Jaber (2016), and M. K. Hsu, Wang, and Chiu (2009), have suggested that PU, while influential, may not be the sole determinant of students' intentions. Therefore, we propose the following two hypotheses:

H2: Perceived Usefulness (PU) has a positive influence on students' Perceived Attitudes (PA) toward the use of internet-based learning.

H3: Perceived Usefulness (PU) has a positive direct effect on students' Behavioural Intention (BI) to use the e-learning system.

2.3 Perceived Ease of Use (PEOU)

The Perceived Ease of Use is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). It suggests the extent to which an individual believes or perceives that using a particular system or technology will involve minimal effort. It is about the subjective perception of ease and convenience in using the system. According to previous research conducted in the past, it has been found that PEOU has both direct and indirect correlations with BI, PU and PA as well.

Several studies have investigated the impact of Perceived Ease of Use (PEOU) on Behavioral Intention (BI) to use e-learning systems. Fan (2023), Hsu et al. (2009), Jaber (2016), and Salloum et al. (2019) have reported a positive effect of PEOU on individuals' intentions to use recent e-learning systems. In contrast, Chesney (2006), Mizher and Alwreikat (2023), and Zhou, Xue, and Li (2022) concluded that PEOU has no significant impact on learners' intentions to use e-learning systems. This disparity highlights the complex nature of the relationship between PEOU and BI, which may vary based on context and system characteristics.

PEOU also has been found to significantly affect Perceived Usefulness (PU) in various studies (Al-Adwan et al., 2013; Amali et al., 2022; Dasgupta et al., 2002; Davis et al., 1989; Salloum et al., 2019; Zhou et al., 2022), emphasising its role in shaping perceptions of a system's utility. Additionally, PEOU is associated with Perceived Attitude (PA) towards using e-learning systems, as evidenced by findings in studies such as Davis et al. (1989) and Salloum et al. (2019). In light of this mixed body of research, we propose the following hypotheses:

H4: Perceived Ease of Use (BEOU) has a positive influence on Perceived Attitude (PA).

H5: Perceived Ease of Use (BEOU) has a direct positive effect on students' Behavioural Intention (BI).

H6: Perceived Ease of Use (BEOU) has a positive effect on Perceived Usefulness (PU).

2.4 Feedback (FD)

Feedback (FD) is defined as "information provided by an agent (e.g., teacher, peer, book, parent, self, experience) regarding aspects of one's performance or understanding" (Hattie & Timperley, 2007, p. 81). Hattie (2008) and Barry (2008) pointed out that FD is a vital factor that influences learning processes. So, in teaching schemes, agent feedback provides learners with information related to the learning process as it will consistently assist students in understanding what they are learning and what they have already learned. Some studies (Petchprasert, 2012) emphasised how FD is closely related to Motivation. Feedback has two side effects on students' motivation in language learning. Receiving feedback can be either in the form of a reward (Deci & Ryan, 1991) or not benefiting from the feedback (Chaudron, 1988). The former exerts a positive impact on enhancing students' learning and performance, whereas the latter's effect stems from students' poor performance on the task. (Petchprasert, 2012). Even though there are several types of FD, this study investigated the general impact of FD on students' behavioural intentions.

Thus far, only a limited number of studies have explored the effect of FD on PU. As an example, Petchprasert (2012) investigated the effects of two types of FD, process and grade-oriented feedback. His findings demonstrated a positive correlation between process-oriented feedback and PU. Petchprasert's (2012) findings are consistent with previous studies' results (Strijbos et al., 2010; Van der Kleij et al., 2012). Therefore, the following is hypothesised:

H7: Feedback is a significant factor in the Perceived Usefulness (PU) of e-learning.

2.5 Accessibility (ACC)

Wixom and Todd (2005, p. 90) defined Accessibility (ACC) as "the ease with which information can be accessed or extracted from the system." It refers to the degree of ease or convenience with which users can access or retrieve information from a particular system. It is all about how straightforward it is for users to get the information they need from the system.

Previous studies, such as those by Park (2009), Saoula et al. (2023), Thong et al. (2002), and Wongvilaisakul and Lekcharoen (2015), have expounded on the significance of ACC in relation to Perceived Ease of Use (PEOU). On the other hand, Teo et al. (2003), Al-Adwan et al. (2013), and Almaiah et al. (2016) have found that ACC considerably affects both Perceived Usefulness (PU) and PEOU in the context of online communities of learning.

Moreover, several literature reviews, including Revythi and Tselios (2019) and Wongvilaisakul and Lekcharoen (2015), have proven a direct relationship between system accessibility and Behavioral Intention (BI). Given that websites primarily serve the function of providing information, it can be argued that the perceived information accessibility of any website significantly influences its Perceived Usefulness (PU) (Bagdi & Bulsara, 2023; Djamasbi et al., 2006). Based on the above literature review, it is assumed that:

H8: Accessibility (ACC) positively correlates with the Perceived Ease of Use (PEOU) of the e-learning system.

H9: Accessibility (ACC) positively correlates with the Perceived Usefulness (PU) of the e-learning system.

H10: Accessibility (ACC) positively correlates with the student's Behavioural Intention (BI) to continue using the e-learning system.

2.6 Anxiety (ANX)

Computer anxiety is defined by Chua, Chen, and Wong (1999, p. 610) as "a fear of computers when using one or fearing the possibility of using it when needed". It involves a sense of fear or apprehension related to computers. Individuals experiencing computer anxiety may feel uneasy, nervous, or even scared when interacting with computer technology. It is worth mentioning that computer anxiety differs from negative attitudes toward utilising computers in an e-learning environment. In addition, it entails feelings and personal beliefs about computers and individuals' emotional reactions toward computer usage (Sam et al., 2005). Individuals with higher levels of technology anxiety become unhappy and tense when they use or intend to use the technology. Besides, they tend to avoid using technology, and therefore, their behaviour is affected (Park et al., 2019). Consequently, individuals with high levels of technology anxiety may encounter difficulties in developing a favourable attitude towards utilizing technology, even if they are aware of its advantages (Cebeci et al., 2019). It was demonstrated in prior research that computer anxiety has a significant negative effect on PEOU (Guo et al., 2013; Hu et al., 1999; Tsai et al., 2020) and PU (Chang & Im, 2014; Hu et al., 1999; Igbaria et al., 1996). On the contrary, there is research evidence showing that ANX has no significant influence on computer usage (Compeau et al., 1999). Therefore, according to the prior research, it is postulated that:

H11: Anxiety (ANX) is negatively associated with Perceived Usefulness (PU).

H12: Anxiety (ANX) negatively corresponds with Perceived Ease of Use (PEOU).

2.7 Computer Playfulness (CP)

Webster and Martocchio (1992, p. 201) defined Computer Playfulness as “the degree of cognitive spontaneity in microcomputer interaction.” It refers to how freely and creatively an individual interacts with a computer. In practical terms, “Computer Playfulness” suggests that some individuals have a greater willingness and ability to explore, experiment, and engage in a creative or spontaneous manner when using microcomputers. Abu-AlSondos et al. (2023) and Al-Aulamie et al. (2012) found that CP has a positive influence on perceived usefulness. Likewise, Adetimirin (2015) indicated that the employment of CP has a favourable impact on the Perceived Ease of Use (PEOU). Therefore, this paper hypothesises the following:

H13: Computer playfulness (CP) is a significant factor in the Perceived Usefulness (PU) of technology.

H14: Computer playfulness (CP) is a significant determinant of the Perceived Ease of Use (PEOU) of e-learning.

2.8 Perceived Enjoyment (PNJ)

Perceived Enjoyment (PNJ) is defined as “the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use’’ (Venkatesh, 2000, p. 351). In other words, individuals find the experience of using the system inherently pleasurable, separate from any functional or performance benefits it might provide. When users perceive a system as enjoyable to use, they are more likely to engage with it, explore its features, and continue using it over time. Many researchers, such as Simonson et al. (1987) and Won et al. (2023), argued that the lack of PNJ might result in a more significant effort to use the system. A considerable amount of prior research has evidenced that PNJ exerts a substantial impact on Perceived Ease of Use (PEOU) (Al-Gahtani, 2016; Kanwal & Rehman, 2017; Zhou et al., 2022) and PU as well (Al-Aulamie et al., 2012; Chang & Im, 2014; Ramírez-Correa et al., 2015). Thus, the following hypotheses were developed:

H15: Perceived Enjoyment (PNJ) is a significant factor in the Perceived Usefulness (PU) of an e-learning system.

H16: Perceived Enjoyment (PNJ) is a significant factor in the Perceived Ease of Use (PEOU) of an e-learning system.

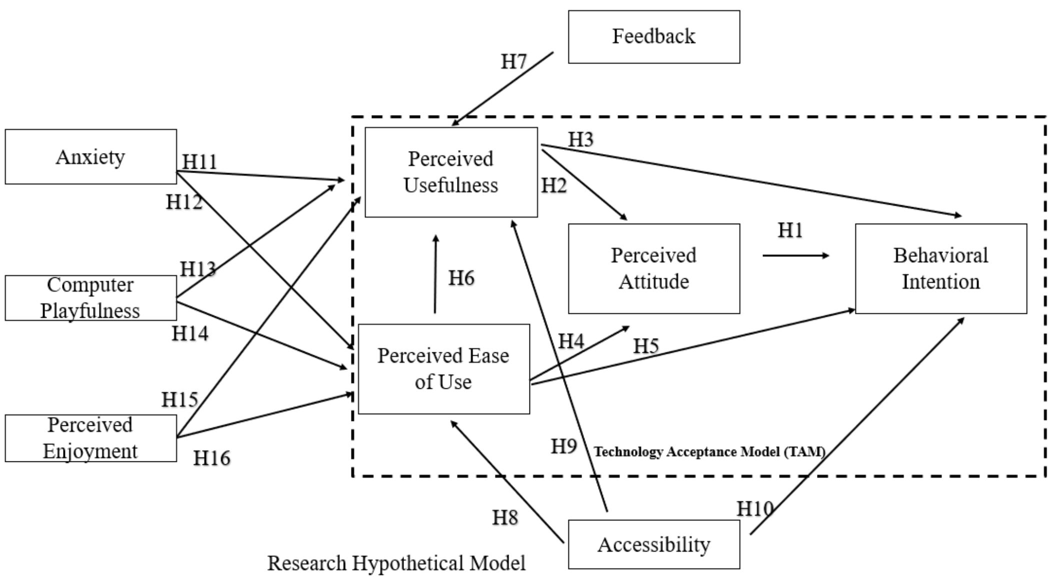

Figure 2. The hypothetical model of the study

3. Method

3.1 Research Design

The present study applied a quantitative research methodology by means of administering a bilingual survey questionnaire. This study explained and predicted the students' intention to continue using technology in the Omani context after COVID-19. Besides, it used a structural equation modelling (SEM) research design in order to test the proposed hypothetical model.

To propose the hypothetical research model, the constructs that have been applied in previous research on the Literature of Information Systems (IS) based on the Technology Acceptance model were reviewed. Then, exploratory factor analysis was conducted to reduce the number of constructs and line the theoretical structure of the variables. Later, the correlation between the items and constructs in the structural model was tested by using confirmatory factor analysis. As indicated in Table 1, the survey included 37 modified items used to examine the constructs developed in the hypothetical framework of this study.

Table 1. Scale items

Constructs	Items	Source
Perceived behavior intention	6	Venkatesh et al. (2003) & Park et al. (2012)
Perceived Attitude	4	Park et al. (2012) & Bender et al. (2012)
Perceived usefulness	4	Venkatesh et al. (2003) & Park et al. (2012)
Perceived Ease of Use	6	Venkatesh et al. (2003), Venkatesh et al. (2000), Park (2010) & Holden and Rada (2011)
Feedback	3	Strijbos et.al, 2010
Anxiety	5	Scott and Timmerman (2005), Venkatesh & Bala (2008) & López-Bonilla and Manuel (2011)
Accessibility	3	Salloum et al. (2019) & Park (2009)
Computer Playfulness	3	Salloum et al., (2019)
Perceived Enjoyment	3	Salloum et al., (2019)

3.2 Sample and Data Collection

The study's data was collected in public and private universities in Oman during the summer semester of the academic year 2021/2022 by distributing a five-point Likert scale survey among the students using a Google form. A total of 134 students completed the survey. As Table 2 illustrates, the participants of this study were undergraduate students who were studying at public and private universities and colleges in Oman, 49 males (62.6%) and 82 females (37.4%). Their age ranged from 17 to 28 years old. Almost half of the respondents (48.1%) were in the foundation stage compared to the diploma students (23.7%), advanced diploma (9.9%) and bachelor (18.3%).

Table 2. Respondents' demographic profile

Item	Category	Frequency	Percent
Gender	Male	49	37.4
	Female	82	62.6
	Total	131	100.0
Age	17-22	121	92.4
	23-28	10	7.6
	Total	131	100.0
Academic Status	Foundation Program	63	48.1
	Diploma	31	23.7
	Advanced Diploma	13	9.9
	Bachelor	24	18.3
	Total	131	100.0
Institution	Public	121	92.4
	Private	10	7.6
	Total	131	100.0

3.3 Research Instrument

A survey was designed and then disseminated among the participants. The survey is composed of two parts. The first part sought to collect participants' demographical information; respondents were asked four questions, including gender, age, academic status and institution. The second part involved the nine variables pertaining to the factors that affect users' intention to continue using online learning. The items in the second section were Behavioural Intention (6 items), Perceived Attitude (4 items), Perceived Ease of Use (6 items), Feedback (3 items), Accessibility (3 items), Anxiety (5 items), Computer Playfulness (3 items) and Perceived Enjoyment (3 items). All of these were measured using 5 Likert-scale items (Strongly agree = 5, and strongly disagree = 1).

3.4 Data Analysis

In this study, the data analysis was conducted using SmartPLS 4, a widely recognized software for structural equation modelling. Various statistical techniques were employed, including the calculation of Cronbach's α for internal consistency assessment, the evaluation of composite reliability (CR), average variance extracted (AVE), and factor loadings to assess the measurement model. Discriminant validity was assessed using the Heterotrait-Monotrait ratio of correlations (HTMT). For hypothesis testing, bootstrapping with 5000 resamples was employed to examine the relationships proposed in the theoretical model. This comprehensive approach allowed for the thorough evaluation of the reliability and validity of the constructs and the testing of hypotheses related to students' technology adoption behaviours and attitudes."

4. Results

4.1 Measurement Model

The measurement model of the proposed theoretical model was assessed by scrutinising the convergent validity and discriminant validity. However, Cronbach's α of each construct was calculated prior to evaluating the convergent validity of the measurement model. Cronbach's α, as seen in Table 3, ranged from 0.718 for Anxiety to 0.941 for Behavioural Intention. Nunnally (1975) suggested 0.70 as a standard value of Cronbach's α, and thus, this proves a high internal consistency of the constructs. Fornell and Larcker (1981) recommend that the convergent validity of the measurement model was evaluated by examining composite reliability (CR), average variance extracted (AVE), and the factor loadings. Fornell and Larcker (1981) explain composite reliability (CR) as the collective variance among variables determining a central construct. As specified by Henseler et al. (2014), the value of CR is recommended to reach 0.70 or higher to confirm the high reliability of the measurement. Therefore, as stated in Table 3, all constructs achieved a high value (ranging from 0.847 to 0.954). Henseler et al. (2014) also recommend a standard value of 0.60 or higher for the Average variance extracted (AVE) of each construct to ascertain the convergent validity of the measurement model, and this has been achieved (ranged from 0.604 to 0.839) as demonstrated in Table 3.

Table 3. Reliability analysis and descriptive statistics

Construct	Indicator	Factor Loading	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
Accessibility	ACC1	0.851	0.837	0.842	0.902	0.754
	ACC2	0.848				
	ACC3	0.905				
Anxiety	ANX1	0.926	0.718	0.819	0.847	0.663
	ANX2	0.933				
	ANX5	0.508				
Computer Playfulness	CP1	0.904	0.941	0.943	0.954	0.774
	CP2	0.88				
Feedback	FB1	0.942				
	FB2	0.913				
	FB3	0.892				
Perceived Attitude	PA1	0.898	0.744	0.75	0.886	0.796
	PA2	0.917				
	PA3	0.878	0.893	0.894	0.934	0.825
	PA4	0.907				
Behavioural Intention	BI1	0.918				

	BI2	0.908	0.904	0.905	0.940	0.839
	BI3	0.897				
	BI4	0.9				
	BI5	0.81	0.922	0.925	0.945	0.811
	BI6	0.841				
Perceived Ease of Use	PEOU1	0.74				
	PEOU2	0.809				
	PEOU3	0.752	0.867	0.876	0.901	0.604
	PEOU4	0.666				
	PEOU5	0.827				
	PEOU6	0.855				
Perceived Enjoyment	PNJ1	0.902				
	PNJ2	0.934				
	PNJ3	0.888	0.900	0.902	0.930	0.769
Perceived Usefulness	PU1	0.838				
	PU2	0.893				
	PU3	0.868				

Savickas et al. (2002) describe discriminant validity as "the degree to which measures of different constructs are unique." Heterotrait-Monotrait ratio of correlations (HTMT) was conducted to evaluate the discriminant validity. The outputs of HTMT (Table 4) indicate that all the HTMT values are under 0.85 (Henseler et al., 2014), and therefore the results confirmed discriminant validity. This means the constructs are accurately distinct from each other.

Table 4. HTMT values

	Accessibility	Anxiety	Behavioural Intention	Computer Playfulness	Perceived Enjoyment	Feedback	Perceived Attitude	Perceived Ease of Use	Perceived Usefulness
Perceived Accessibility									
Anxiety	**0.794**								
Behavioural Intention	0.742	**0.931**							
Computer Playfulness	0.629	0.680	**0.722**						
Perceived Enjoyment	0.532	0.768	0.730	**0.899**					
Feedback	0.546	0.705	0.641	0.489	**0.618**				
Perceived Attitude	0.801	0.909	0.952	0.739	0.706	**0.595**			
Perceived Ease of Use	0.719	0.847	0.814	0.700	0.737	0.641	**0.757**		
Perceived Usefulness	0.668	0.744	0.863	0.614	0.645	0.596	0.782	**0.789**	

4.2 Structural Model: Hypotheses Testing

The next procedure of the SmartPLS 4 analysis was assessing the structural model, which explains the students' intention to continue to use technology in their study. In this part of the analysis, a bootstrapping technique (Figure 3) was performed to check the model hypotheses. Hair et al. (2014) describe bootstrapping as a non-parametric statistical process that generates many sub-samples from the sample data and then observes models for each sub-sample.

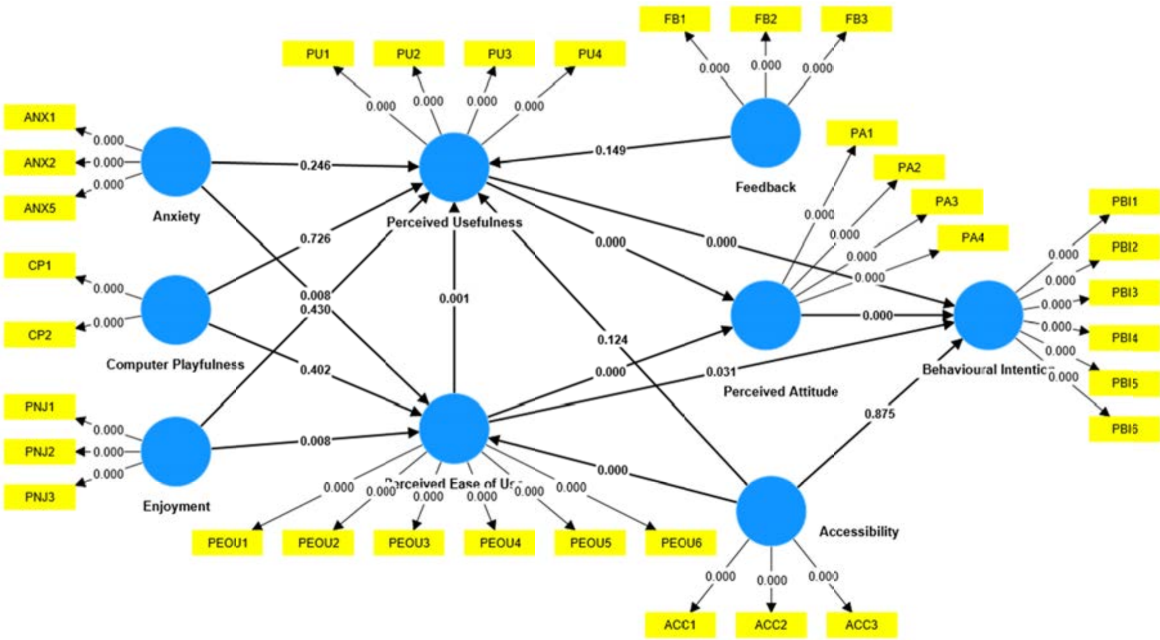

Figure 3. Parameter estimates of the structural model

The SmartPLS 4 bootstrapping technique was run with a resample of 5000 to assess the shape of the sampling distribution with a non-parametric approach, as suggested by Hair et al. (2014). The findings of this analysis showed that Perceived Attitude (β=0.606, t = 10.898, $p<0.05$), Perceived Ease of Use (β=0.145, t = 2.152, $p<0.05$) and Perceived Usefulness (β=0.265, t = 4.473, $p<0.05$) all had a positive significant effect on the Behavioural Intention to continue to use technology in the Post-COVID-19 era. Thus, H1, H3 and H5 were supported, respectively. In contrast, Perceived Accessibility to the used technology (β= -0.008, t = 0.157, $p>0.05$) had no correlation with the students' intention to continue using technology, and thereby H10 was rejected. The results also indicated that Perceived Usefulness (β= 0.468, t = 5.027, $p<0.05$) and Perceived Ease of Use (β= 0.353, t = 4.084, $p<0.05$) both demonstrated a positive influence on the attitude the students perceive towards their intention to continue using technology after COVID-19. Thus, H2 and H4 were accepted.

Table 5. Structural model results

Hypothesis		Path coefficient (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Supported/Not supported
H1	PA -> BI	0.606	0.605	0.056	10.898	0	Supported
H2	PU -> PA	0.468	0.464	0.093	5.027	0	Supported
H3	PU -> BI	0.265	0.264	0.059	4.473	0	Supported
H4	PEOU -> PA	0.353	0.358	0.086	4.084	0	Supported
H5	PEOU -> BI	0.145	0.146	0.067	2.152	0.031	Supported
H6	PEOU -> PU	0.364	0.366	0.105	3.461	0.001	Supported
H7	FB -> PU	0.114	0.110	0.079	1.444	0.149	Not supported
H8	ACC -> PEOU	0.265	0.260	0.071	3.729	0	Supported
H9	ACC -> PU	0.154	0.147	0.10	1.537	0.124	Not supported
H10	ACC -> BI	-0.008	-0.006	0.050	0.157	0.875	Not supported
H11	ANX -> PU	0.144	0.151	0.124	1.161	0.246	Not supported
H12	ANX -> PEOU	0.271	0.272	0.102	2.654	0.008	Supported
H13	CP -> PU	0.040	0.039	0.115	0.350	0.726	Not supported
H14	CP -> PEOU	0.067	0.076	0.080	0.838	0.402	Not supported
H15	PNJ -> PU	0.090	0.092	0.114	0.789	0.430	Not supported
H16	PNJ -> PEOU	0.311	0.310	0.117	2.654	0.008	Supported

Confidence level: $p<0.05$.

Interestingly, the analysis revealed that no construct had an effect on PU in the proposed model except PEOU (β= 0.364, t = 3.461, p<0.05); H6 was supported. This indicates that FB (β= 0.114, t = 1.444, p>0.05), ACC (β= 0.154, t = 1.537, p>0.05), ANX (β= 0.144, t = 1.161, p>0.05), CP (β= 0.040, t = 0.350, p>0.05) and PNJ (β= 0.090, t = 0.789, p>0.05) had no effect on PU Thus, H7, H9, H11, H13, H15, respectively. In contrast, the bootstrapping analysis showed that PEOU was significantly affected by ACC β= 0.265, t = 3.729, p<0.05), Anxiety β= 0.271, t = 2.654, p<0.05), and PNJ (β= 0.311, t = 2.654, p<0.05). As a result, the proposed hypotheses H8, H12 and H16 were supported. However, CP (β= 0.067, t = 0.838, p>0.05) had no effect on PEOU, and thereby H14 was rejected.

5. Discussion

This study utilized a questionnaire to investigate the impact of external variables, including Feedback, Anxiety, Computer Playfulness, Perceived Enjoyment, and Accessibility, on two critical variables of the Technology Acceptance Model (TAM): Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). The primary objective was to understand these factors' influence on students' intentions to adopt e-learning platforms post-COVID-19. Subsequent analysis revealed a significant positive correlation between students' attitudes and their Behavioral Intention (BI), supporting previous research by Amali et al. (2022), Hussein (2017), and Sharma and Chandel (2013a). This finding underscores the idea that a positive attitude towards an e-learning system is a driving force behind a student's intention to continue its use.

The results further underline the significance of PU as a strong determinant, positively impacting both Perceived Ease of Use (PEOU) and Behavioral Intention (BI). These findings resonate with the original Technology Acceptance Model (TAM) proposed by Davis et al. (1989), which suggests that users' acceptance of a learning platform is closely tied to their realization of the system's usefulness and its potential to enhance their performance. The study also showed a significant direct effect of PEOU on Perceived Enjoyment (PA) and Behavioral Intention (BI), aligning with the findings of Salloum et al. (2019). It's evident from these results that users perceiving a digital platform as easy to use or user-friendly are more likely to cultivate a positive attitude and a higher intention to adopt e-learning systems.

Regarding external variables, the study found that Accessibility (ACC) does not have a significant direct effect on Behavioral Intention (BI) to use e-learning systems. This finding diverges from prior studies like Revythi and Tselios (2019) and Wongvilaisakul and Lekcharoen (2015), suggesting that the availability of online learning materials anytime and anywhere does not significantly influence users' behavioural intention. The results also revealed that Feedback (FB), Accessibility (ACC), Anxiety (ANX), Computer Playfulness (CP), and Perceived Enjoyment (PNJ) do not exhibit significant correlations with Perceived Usefulness (PU). These findings contrast with previous research that established positive relationships between FB, CP, and PNJ with PU and negative associations between ANX and PU. This study's outcomes deviate from the existing literature.

Additionally, the study found that Computer Playfulness (CP) does not have a direct impact on Perceived Ease of Use (PEOU), contradicting the findings of Adetimirin (2015). This suggests that users' spontaneous interaction with technology does not necessarily translate to a perception that utilizing an e-learning platform will be straightforward. Despite the disparities observed in this study, there is a consensus among other researchers (Al-Gahtani, 2016; Guo et al., 2013; Hsu, 2019; Kanwal & Rehman, 2017; Park et al., 2019; Park, 2009; Tsai et al., 2020) that quick system access, an enjoyable user experience, and lower levels of technology anxiety contribute to the perception that the e-learning system is easy to use.

6. Conclusion

The two-year COVID-19 era has made policymakers and educators redefine how education is delivered. With the lifting of COVID-19 restrictions worldwide, neglecting the online education experience and returning to full face-to-face classes is not recommended. This paper helps policymakers and educators to understand the students' behavioural intentions on continuing to use technology in the post-COVID-19 era. The key findings of this paper revealed that students' behavioural intention to continue using technology after COVID-19 is high. The findings also confirmed that students' attitudes have a significant positive impact on their Behavioural Intention. It is important to note that this paper proved that Perceived Usefulness is a strong determinant that positively affects both perceived Attitude and Behavioural Intention. There is also a positive relationship between Accessibility, Perceived Enjoyment and Perceived Ease of Use and a negative association between Anxiety and Perceived Ease of Use.

6.1 Implications

The findings of this study have significant practical implications for both e-learning platform developers and educators as they navigate the evolving landscape of online education, especially in the post-COVID-19 era. First, E-learning platform developers should prioritise enhancing the perceived usefulness of their systems. Ensuring that users recognise the value and utility of these platforms is crucial for encouraging their adoption. Furthermore, developers should strive to maintain user-friendly interfaces and easy navigation to improve perceived ease of use. Our results indicate that both PU and PEOU positively influence attitudes and behavioural intentions.

Our findings also underscore the fundamental role of user attitudes in determining their intentions to continue using e-learning systems. Educators and platform developers should focus on creating engaging, interactive, and enjoyable e-learning experiences to cultivate positive attitudes among students. Encouraging positive perceptions of e-learning platforms can contribute to increased user retention and engagement.

While accessibility (ACC) did not emerge as a significant direct determinant of behavioural intention (BI) in our study, it's essential for developers to provide students with the convenience of accessing educational content from anywhere and at any time. This accessibility remains a fundamental aspect of e-learning systems, ensuring that students can seamlessly integrate learning into their daily routines.

Although our study did not find direct correlations between feedback (FB) and perceived enjoyment (PNJ) with perceived usefulness (PU), these aspects should not be overlooked. Feedback mechanisms play a vital role in improving the user experience, and perceived enjoyment contributes to overall satisfaction. Developers should actively seek and respond to user feedback, integrating features that enhance the overall e-learning experience.

6.2 Recommendations

The sudden shift to remote learning during COVID-19 encouraged teachers and students to be familiar with advanced technology tools; however, there was no clear framework that guides teachers and students on how to use the technology tools and for what purpose. This study recommends that policymakers and educators assess the technology used during the pandemic and build a complete framework for how technology might be implemented more efficiently. Students show a high tendency to continue using technology after COVID-19, yet this paper puts forward encapsulating this with a balanced approach that considers Accessibility, Perceived Enjoyment and Perceived Ease of Use.

6.3 Limitations

The study provides insights for future directions. First, this study used the quantitative approach in investigating students' behavioural intention to continue using technology in the post-COVID-19 era; thus, future research may triangulate two data sources: quantitative and qualitative. Second, the present study examines students' behavioural intention to use various digital platforms for learning purposes. Therefore, future research may be narrowed to investigate a specific e-learning system.

References

Abu-AlSondos, I. A., Salameh, A. A., Alkhwaldi, A. F., Mushtaha, A. S., Shehadeh, M., & Al-Junaidi, A. (2023). Evaluating mobile e-learning systems acceptance: An integrated model. *International Journal of Interactive Mobile Technologies, 17*(16), 30-47. https://doi.org/10.3991/ijim.v17i16.42679

Adetimirin, A. (2015). An empirical study of online discussion forums by library and information science postgraduate students using technology acceptance model 3. *Journal of Information Technology Education. Research, 14*, 257-269. https://doi.org/10.28945/2269

Al-Adwan, A. S., Li, N., Al-Adwan, A., Abbasi, G. A., Albelbisi, N. A., & Habibi, A. (2023). Extending the Technology Acceptance Model (TAM) to predict university students' intentions to use metaverse-based learning platforms". *Education and Information Technologies*, 1-33. https://doi.org/10.1007/s10639-023-11816-3

Al-Adwan, A., Al-Adwan, A., & Smedley, J. (2013). Exploring students acceptance of e-learning using Technology Acceptance Model in Jordanian universities. *International Journal of Education Development using ICT, 9*(2), 4-18. Retrieved from https://www.learntechlib.org/p/130283/

Al-Aulamie, A., Mansour, A., Daly, H., & Adjei, O. (2012). *The effect of interinsic motivation on learners' behavioural intention to use e-learning systems.* Paper presented at the Proceedings of International Conference on Information Technology Based Higher Education and Training (ITHET), Istanbul, Turkey. https://doi.org/10.1109/ITHET.2012.6246057

Al-Gahtani, S. S. (2016). Empirical investigation of e-learning acceptance and assimilation: A structural equation model. *Applied Computing and Informatics, 12*(1), 27-50. https://doi.org/10.1016/j.aci.2014.09.001

Alia, A. (2017). *An investigation of the application of the Technology Acceptance Model (TAM) to evaluate* *instructors' perspectives on E-Learning at Kuwait University* (PhD thesis, Dublin City University). Retrieved from https://doras.dcu.ie/21586/

Almaiah, M. A., Jalil, M. A., & Man, M. (2016). Extending the TAM to examine the effects of quality features on mobile learning acceptance. *Journal of Computers in Education, 3*(4), 453-485. https://doi.org/10.1007/s40692-016-0074-1

Alonso, F., López, G., Manrique, D., & Viñes, J. M. (2005). An instructional model for web-based e-learning education with a blended learning process approach. *British Journal of Educational Technology, 36*(2), 217-235. https://doi.org/10.1111/j.1467-8535.2005.00454.x

Altawalbeh, M. A., & Alassaf, H. (2018). Antecedents and consequences of e-learning adoption in Jordanian higher education institutions. *Advances in Social Sciences Research Journal, 5*(5), 378-387. https://doi.org/10.14738/assrj.55.4586

Amali, L. N., Katili, M. R., Suhada, S., Hadjaratie, L., & Mardlatillah, H. (2022). Technology Acceptance Model in government context: A systematic review on the implementation of IT governance in a government institution. *Jurnal Online Informatika, 7*(1), 80-88. https://doi.org/10.15575/join.v7i1.853

Bagdi, H., & Bulsara, H. P. (2023). Understanding the role of perceived enjoyment, self-efficacy and system accessibility: Digital natives' online learning intentions. *Journal of Applied Research in Higher Education*. https://doi.org/ 10.1108/JARHE-09-2022-0302

Bailey, D. R., Almusharraf, N., & Almusharraf, A. (2022). Video conferencing in the e-learning context: explaining learning outcome with the technology acceptance model. *Education and Information Technologies, 27*(6), 7679-7698. https://doi.org/10.1007/s10639-022-10949-1

Baker, C. (1992). *Attitudes and language* (Vol. 83). Multilingual Matters.

Barry, V. J. (2008). Using descriptive feedback in a sixth grade mathematics classroom. Retrieved from https://shorturl.at/dfJ14

Bender, J. L., Wiljer, D., To, M. J., Bedard, P. L., Chung, P., Jewett, M. A., & Gospodarowicz, M. (2012). Testicular cancer survivors' supportive care needs and use of online support: a cross-sectional survey. *Supportive care in cancer, 20*, 2737-2746. https://doi.org/10.1007/s00520-012-1395-x

Cebeci, U., Ince, O., & Turkcan, H. (2019). Understanding the intention to use Netflix: An extended technology acceptance model approach. *International Review of Management and Marketing, 9*(6), 152-157. https://doi.org/10.32479/irmm.8771

Chang, S. J., & Im, E.-O. (2014). A path analysis of internet health information seeking behaviors among older adults. *Geriatric Nursing, 35*(2), 137-141. https://doi.org/10.1016/j.gerinurse.2013.11.005

Chaudron, C. (1988). *Second Language Classrooms. Research on Teaching and Learning*. ERIC. https://doi.org/10.1017/CBO9781139524469

Chesney, T. (2006). An acceptance model for useful and fun information systems. *Human Technology: An Interdisciplinary Journal on Humans in ICT Environments*, 225-235. https://doi.org/10.17011/ht/urn.2006520

Chua, S. L., Chen, D.-T., & Wong, A. F. (1999). Computer anxiety and its correlates: a meta-analysis. *Computers in human behavior, 15*(5), 609-623. https://doi.org/10.1016/S0747-5632(99)00039-4

Compeau, D., Higgins, C. A., & Huff, S. (1999). Social cognitive theory and individual reactions to computing technology: A longitudinal study. *MIS quarterly*, 145-158. https://doi.org/10.2307/249749

Dasgupta, S., Granger, M., & McGarry, N. (2002). User acceptance of e-collaboration technology: An extension of the technology acceptance model. *Group Decision Negotiation, 11*(2), 87-100. https://doi.org/10.1023/A:1015221710638

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science, 35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

Deci, E. L., & Ryan, R. M. (1991). A motivational approach to self: integration in personality. 237. Retrieved from bit.ly/40wOLlz

Dimitriadou, E., & Lanitis, A. (2023). A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. *Smart Learning Environments, 10*(1), 12. https://doi.org/10.1186/s40561-023-00231-3

Djamasbi, S., Tullis, T., Girouard, M., Hebner, M., Krol, J., & Terranova, M. (2006). Web accessibility for visually impaired users: Extending the Technology Acceptance Model (TAM). *AMCIS Proceedings*, 367. Retrieved from https://aisel.aisnet.org/amcis2006/367

Edo, O. C., Ang, D., Etu, E. E., Tenebe, I., Edo, S., & Diekola, O. A. (2023). Why do healthcare workers adopt digital health technologies-A cross-sectional study integrating the TAM and UTAUT model in a developing economy. *International Journal of Information Management Data Insights, 3*(2), 100186. https://doi.org/10.1016/j.jjimei.2023.100186

Fan, C. (2023). English learning motivation with TAM: Undergraduates' behavioral intention to use Chinese indigenous social media platforms for English learning. *Cogent Social Sciences, 9*(2), 2260566. https://doi.org/10.1080/23311886.2023.2260566

Fauzi, A., Wandira, R., Sepri, D., & Hafid, A. (2021). Exploring students' acceptance of google classroom during the covid-19 pandemic by using the technology acceptance model in West Sumatera Universities. *Electronic Journal of e-Learning, 19*(4), 233-240. https://doi.org/10.34190/ejel.19.4.2348

Fornell, C., & Larcker, D. F. (1981). *Structural equation models with unobservable variables and measurement error: Algebra and statistics*. In: Sage Publications Sage CA: Los Angeles, CA. https://doi.org/10.1177/002224378101800313

Genc, Z. S., & Aydin, F. (2017). An analysis of learners' motivation and attitudes toward learning English language at tertiary level in Turkish EFL context. *English Language Teaching, 10*(4), 35-44. https://doi.org/10.5539/elt.v10n4p35

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology, 50*(5), 2572-2593. https://doi.org/10.1111/bjet.12864

Guo, X., Sun, Y., Wang, N., Peng, Z., & Yan, Z. (2013). The dark side of elderly acceptance of preventive mobile health services in China. *Electronic Markets, 23*(1), 49-61. https://doi.org/10.1007/s12525-012-0112-4

Hair Jr, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European business review*, 106-121. https://doi.org/10.1108/EBR-10-2013-0128

Hattie, J. (2008). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement*. London: Routledge. https://doi.org/10.4324/9780203887332

Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of educational research, 77*(1), 81-112. https://doi.org/10.3102/003465430298487

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., . . . Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational research methods, 17*(2), 182-209. https://doi.org/10.1177/109442811452692

Holden, H., & Rada, R. (2011). Understanding the influence of perceived usability and technology self-efficacy on teachers' technology acceptance. *Journal of Research on Technology in Education, 43*(4), 343-367. https://doi.org/10.1080/15391523.2011.10782576

Hsu, H.-C. (2019). Wiki-mediated collaboration and its association with L2 writing development: an exploratory study. *Computer Assisted Language Learning, 32*(8), 945-967. https://doi.org/10.1080/09588221.2018.1542407

Hsu, M. K., Wang, S. W., & Chiu, K. K. (2009). Computer attitude, statistics anxiety and self-efficacy on statistical software adoption behavior: An empirical study of online MBA learners. *Computers in human behavior, 25*(2), 412-420. https://doi.org/10.1016/j.chb.2008.10.003

Hu, P. J., Chau, P. Y., Sheng, O. R. L., & Tam, K. Y. (1999). Examining the technology acceptance model using physician acceptance of telemedicine technology. *Journal of management information systems, 16*(2), 91-112. https://doi.org/10.1080/07421222.1999.11518247

Humida, T., Al Mamun, M. H., & Keikhosrokiani, P. (2022). Predicting behavioral intention to use e-learning system: A case-study in Begum Rokeya University, Rangpur, Bangladesh. *Education and Information Technologies, 27*(2), 2241-2265. https://doi.org/10.1007/s10639-021-10707-9

Hussein, Z. (2017). Leading to Intention: The Role of Attitude in Relation to Technology Acceptance Model in E-Learning. *Procedia Computer Science, 105*, 159-164. https://doi.org/10.1016/j.procs.2017.01.196

Igbaria, M., Parasuraman, S., & Baroudi, J. J. (1996). A motivational model of microcomputer usage. *Journal of management information systems, 13*(1), 127-143. https://doi.org/10.1080/07421222.1996.11518115

Jaber, O. A. (2016). *An examination of variables influencing the acceptance and usage of E-learning systems in Jordanian higher education institutions.* Cardiff Metropolitan University. Retrieved from https://shorturl.at/wPRUZ

Jaswal, P., & Behera, B. (2023). Blended matters: Nurturing critical thinking. *E-Learning and Digital Media*, 20427530231156184. https://doi.org/10.1177/20427530231156184

Kanwal, F., & Rehman, M. (2017). Factors affecting e-learning adoption in developing countries-empirical evidence from Pakistan's higher education sector. *IEEE access, 5*, 10968-10978. https://doi.org/10.1109/ACCESS.2017.2714379

Lee, M. K. O., Cheung, C. M. K., & Chen, Z. (2005). Acceptance of Internet-based learning medium: the role of extrinsic and intrinsic motivation. *Information & Management, 42*(8), 1095-1104. https://doi.org/10.1016/j.im.2003.10.007

Lee, Y.-C., Li, M.-L., Yen, T.-M., & Huang, T.-H. (2010). Analysis of adopting an integrated decision making trial and evaluation laboratory on a technology acceptance model. *Expert Systems with Applications, 37*(2), 1745-1754. https://doi.org/10.1016/j.eswa.2009.07.034

Liu, Y. (2014). Motivation and attitude: Two important non-intelligence factors to arouse students' potentialities in learning English. *Creative Education, 5*, 1249-1253. https://doi.org/10.4236/ce.2014.514140

López-Bonilla, & Manuel, J. (2011). Validation of an information technology anxiety scale in undergraduates. *British Journal of Educational Technology, 43*(2), E56-E58. https://doi.org/10.1111/j.1467-8535.2011.01256.x

Mantle-Bromley, C. (1995). Positive attitudes and realistic beliefs: Links to proficiency. *The Modern Language Journal, 79*(3), 372-386. https://doi.org/10.1111/j.1540-4781.1995.tb01114.x

Maruf, Z., Pratolo, B. W., Sari, O. W., & Ardinengtyas, A. (2022). Undiscovered Voices: Motivation and Demotivation Factors in Learning English among Indonesian Orphan Students. *International Journal of Evaluation and Research in Education*, *11*(1), 441-448. https://doi.org/10.11591/ijere.v11i1.21262

Mizher, R. A., & Alwreikat, A. A. (2023). EFL Students' Use of E-Books for E-Learning: Applying Technology Acceptance Model (TAM). *Journal of Language Teaching and Research, 14*(1), 153-162. https://doi.org/10.17507/jltr.1401.16

Nunnally, J. C. (1975). Psychometric Theory—25 Years Ago and Now. *Educational Researcher, 4*(10), 7-21. https://doi.org/10.3102/0013189x004010007

Park, J., Ahn, J., Thavisay, T., & Ren, T. (2019). Examining the role of anxiety and social influence in multi-benefits of mobile payment service. *Journal of Retailing and Consumer Services, 47*, 140-149. https://doi.org/10.1016/j.jretconser.2018.11.015

Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Journal of Educational Technology & Society, 12*(3), 150-162. Retrieved from https://www.jstor.org/stable/jeductechsoci.12.3.150

Petchprasert, A. (2012). Feedback in second language teaching and learning. *US-China Foreign Language, 10*(4), 1112-1120. Retrieved from https://shorturl.at/eWY78

Ramírez-Correa, P. E., Arenas-Gaitán, J., & Rondán-Cataluña, F. J. (2015). Gender and acceptance of e-learning: a multi-group analysis based on a structural equation model among college students in Chile and Spain. *PLoS one, 10*(10), Article e0140460. https://doi.org/10.1371/journal.pone.0140460

Revythi, A., & Tselios, N. (2019). Extension of technology acceptance model by using system usability scale to assess behavioral intention to use e-learning. *Education and Information Technologies, 24*(4), 2341-2355. https://doi.org/10.1007/s10639-019-09869-4

Saadé, R., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: an extension of the technology acceptance model. *Information & Management, 42*(2), 317-327. https://doi.org/10.1016/j.im.2003.12.013

Saadé, R., & Bahli, B. (2005). The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: an extension of the technology acceptance model. *Information management, 42*(2), 317-327. https://doi.org/10.1016/j.im.2003.12.013

Saeed, K. A., & Abdinnour-Helm, S. (2008). Examining the effects of information system characteristics and perceived usefulness on post adoption usage of information systems. *Information & management, 45*(6), 376-386. https://doi.org/10.1016/j.im.2008.06.002

Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE access, 7*, 128445-128462. https://doi.org/10.1109/ACCESS.2019.2939467

Sam, H. K., Othman, A. E. A., & Nordin, Z. S. (2005). Computer self-efficacy, computer anxiety, and attitudes toward the Internet: A study among undergraduates in Unimas. *Journal of Educational Technology and Society, 8*(4), 205-219. Retrieved from https://www.jstor.org/stable/jeductechsoci.8.4.205

Saoula, O., Shamim, A., Mohd Suki, N., Ahmad, M. J., Abid, M. F., Patwary, A. K., & Abbasi, A. Z. (2023). Building e-trust and e-retention in online shopping: the role of website design, reliability and perceived ease of use. *Spanish Journal of Marketing-ESIC, 27*(2), 178-201. https://doi.org/10.1108/SJME-07-2022-0159

Savickas, M. L., Taber, B. J., & Spokane, A. R. (2002). Convergent and discriminant validity of five interest inventories. *Journal of Vocational Behavior, 61*(1), 139-184. https://doi.org/10.1006/jvbe.2002.1878

Scott, C. R., & Timmerman, C. E. (2005). Relating computer, communication, and computer-mediated communication apprehensions to new communication technology use in the workplace. *Communication research, 32*(6), 683-725. https://doi.org/10.1177/0093650205281054

Sharma, S. K., & Chandel, J. K. (2013a). Technology Acceptance Model for the Use of Learning Through Websites Among Students. *International Arab Journal of e-Technology, 3*(1), 44-49. Retrieved from https://search.emarefa.net/detail/BIM-334678

Sharma, S. K., & Chandel, J. K. (2013b). Technology Acceptance Model For The Use Of Learning Through Websites Among Students In Oman. *Int. Arab. J. e Technol., 3*(1), 44-49. Retrieved from https://shorturl.at/hknov

Simonson, M. R., Maurer, M., Montag-Torardi, M., & Whitaker, M. (1987). Development of a standardized test of computer literacy and a computer anxiety index. *Journal of educational computing research, 3*(2), 231-247. https://doi.org/10.2190/7CHY-5CM0-4D00-6JC

Strijbos, J.-W., Narciss, S., & Dünnebier, K. (2010). Peer feedback content and sender's competence level in academic writing revision tasks: Are they critical for feedback perceptions and efficiency? *Learning and instruction, 20*(4), 291-303. https://doi.org/10.1016/j.learninstruc.2009.08.008

Teo, H.-H., Chan, H.-C., Wei, K.-K., & Zhang, Z. (2003). Evaluating information accessibility and community adaptivity features for sustaining virtual learning communities. *International Journal of Human-Computer Studies, 59*(5), 671-697. https://doi.org/10.1016/S1071-5819(03)00087-9

Thong, J. Y., Hong, W., & Tam, K.-Y. (2002). Understanding user acceptance of digital libraries: what are the roles of interface characteristics, organizational context, and individual differences? *International journal of human-computer studies, 57*(3), 215-242. https://doi.org/10.1016/S1071-5819(02)91024-4

Tsai, T.-H., Lin, W.-Y., Chang, Y.-S., Chang, P.-C., & Lee, M.-Y. (2020). Technology anxiety and resistance to change behavioral study of a wearable cardiac warming system using an extended TAM for older adults. *PLoS one, 15*(1), e0227270. https://doi.org/10.1371/journal.pone.0227270

Um, N. (2021). Learners' Attitude toward E-Learning: The Effects of Perceived System Quality and E-Learning Usefulness, Self-Management of Learning, and Self-Efficacy. *International Journal of Contents, 17*(2), 41-47.

Van der Kleij, F. M., Eggen, T. J., Timmers, C. F., & Veldkamp, B. (2012). Effects of feedback in a computer-based assessment for learning. *Computers Education, 58*(1), 263-272. https://doi.org/10.1016/j.compedu.2011.07.020

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information systems research, 11*(4), 342-365. https://doi.org/10.1287/isre.11.4.342.11872

Webster, J., & Martocchio, J. J. (1992). Microcomputer playfulness: Development of a measure with workplace implications. *MIS quarterly*, 201-226. https://doi.org/10.2307/249576

Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information systems research, 16*(1), 85-102. https://doi.org/10.1287/isre.1050.0042

Won, D., Chiu, W., & Byun, H. (2023). Factors influencing consumer use of a sport-branded app: The technology acceptance model integrating app quality and perceived enjoyment. *Asia Pacific Journal of Marketing and Logistics, 35*(5), 1112-1133. https://doi.org/10.1108/APJML-09-2021-0709

Wongvilaisakul, W., & Lekcharoen, S. (2015). *The acceptance of e-Learning using SEM approach: A case of IT Literacy development for PIM students*. Paper presented at the 12th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Hua Hin, Thailand. https://doi.org/10.1109/ECTICon.2015.7207117

Zhou, L., Xue, S., & Li, R. (2022). Extending the Technology Acceptance Model to explore students' intention to use an online education platform at a University in China. *SAGE Open, 12*(1), 1-6. https://doi.org/10.1177/21582440221085259

Acknowledgments

Our great gratitude to the students from public and private universities in Oman for their vital contributions to this research project. Their participation significantly enriched the quality of this study.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Canadian Center of Science and Education.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.