Breaking Barriers in Higher Education: How Students are Embracing Mobile Learning in the Post-COVID Era

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Abstract

Emerging technologies have caused significant changes in many aspects of our lives, particularly in the education sector, which has undergone tremendous changes during COVID-19. Even after the era of COVID-19, the positive use of smartphones in learning has increased dramatically, and these portable internet-enabled devices have been used immensely for learning. Mobile learning is imperative for students in a higher education institution even after the COVID-19 pandemic, as it assists students in studying and exchanging information constructively with the help of the internet. The objective of the current research study is to explore the influence of Perceived ease of use, Social influence, Task-technology fit, and Student satisfaction on the Actual use of mobile learning and to investigate the mediating role of Student satisfaction and Task-technology fit in the stated variables in higher educational institutions based on the Technology Acceptance Model. The data was collected from 440 Pakistani students through the survey of self-administered questionnaires using the convenience sampling technique. SPSS 24.0 and Smart PLS 3.0 were used to analyze and study the hypotheses. The results supported the significant positive impact of Perceived ease of use, Social influence, Student satisfaction, and Task-technology fit on the Actual use of mobile learning. In addition, Student satisfaction partially mediates between Perceived ease *of use and Actual use of mobile learning, and Task-technology fit partially mediates between Social influence and Actual use of mobile learning. The findings provided significant implications by highlighting students the importance and acceptance of mobile learning in higher education institutions. This study necessitated that*

higher education institutions pay attention to and improve their mobile learning strategies and policies.

Keywords: Actual Use of Mobile Learning, Technology Acceptance Model, Educational Institutions. Pakistan.

Introduction

There has been an escalation in the usage of emergent internet technologies in higher education (Ifinedo and Usoro, 2016). The COVID-19 pandemic increased apprehensions to the extreme level by creating an environment of lockdowns, and almost all productive activities (business, social, official, or educational) suffered severely. The pandemic shut down countless worldwide activities and postures a hazard to humans and educational activities (Maatuk *et al*., 2022). It has exposed the growing flaws of the education structure in the world and motivates societies to adopt strong and flexible education systems (Ali, 2020). There has been an immense rise in the usage of emergent internet technologies in the higher education segment (Ifinedo and Usoro, 2016). Educational institutions were forced to switch to e-learning as it was the best solution to lessen the influence of the pandemic. Online learning or education is inevitable during the COVID-19 pandemic, and it also delivers robust support for more research in the future (Ali, 2020). Mobile learning or M-learning assists digital, internet, computer-assisted, and interactive learning (Aljawarneh, 2020; Lara *et al*., 2020). Technology usage was rapidly enhanced due to pandemic circumstances in higher educational institutions for innovative educational methods (Alismaiel, 2021; Cifuentes-Faura *et al*., 2021). Information and Communications Technology (ICT) provides an innovative approach to learning and teaching people, organizations, and societies. With the support of ICT, more creative educational policies and strategies can be devised to motivate an innovative and ground-breaking educational environment in higher education institutions (Abdullah *et al*., 2019). Many universities in developing countries adopt the ICT approach, and more consideration is made towards such an innovative teaching methodology (Maatuk *et al*., 2022). The students realize that the mobile interface is easy and friendly for learning, and they use mobiles for learning purposes (Almaiah *et al*., 2019; Sung *et al*., 2015).

The use of mobile phones has been rapidly developing even after the COVID-19 pandemic, as reported by the Pakistan Telecommunication Authority (PTA). PTA faced the incurable anxieties of the pandemic but developed the blustery year by providing excellent services in the Information and Communications Technology field. It acts as an enabler with the government to expedite the administration to curb the effects of COVID-19 in a better approach. One hundred million broadband and mobile subscribers prevail in Pakistan. Almost 89% of Pakistan's population uses ICT or broadband services, generating revenues

of Rs.644 billion (Pakistan Telecommunication Authority. Annual Report, 2021). It allows students and educators to exchange their views through the internet. It permits and facilitates the students to cooperate, study, and discuss scholastic information using technology. Owing to the constant use of M-learning, smartphones are exhausting as educational tools around the globe because of their innovative characteristics (mobility, lightweight, easy connectivity, and inexpensive). M-learning links humans and technology at the same time (Alturki and Aldraiweesh, 2022). M-learning is anticipated to escalate due to COVID-19 spreading as a mutual elegance of learning and distance learning became a compulsion in lockdowns (Ali, 2020). M-learning inventiveness created M-learning apps. These apps are admired and famous in the existing educational systems of modern years (Al-Rahmi *et al*., 2022). Therefore, recognizing M-learning is crucial and imperative for faculty and students in this age of high technology (Alturki and Aldraiweesh, 2022).

In the M-learning system or Actual use of mobile learning, Perceived ease of use (PEOU) provides less complicated academic situations for educational reasons (Alturki and Aldraiweesh, 2022). Perceive ease of use focuses on the perception that the end user is anxious about how complex the technology is and that the particular technology does not require much effort to complete the task. Both types of perception determine whether the end user will continue using the particular technology (Sun *et al*., 2008). Students use mobiles for knowledge purposes as this service is easy to use, and PEOU validated the students' views about M-learning as user-friendly (Mutambara and Bayaga, 2020). Social influence (SI) is clients' opinion that all friends and family trust that they must practice technology (Venkatesh *et al*., 2003). Other people discourage students from making decisions regarding using specific technology, and these beliefs are imperative in their lives (Lutfi, 2022). Therefore, students are impressed by others about using M-learning technology (Arain *et al*., 2019).

M-learning provides ease to the users by teaching actions with knowledge. Therefore, M-learning technology is essential to produce by assimilating task technology fit (TTF), which is the degree to which a specific technology supports the task (Al-Rahmi *et al*., 2021; Goodhue and Thompson, 1995; Qashou, 2021). Student Satisfaction (SS) reflects the desire for an information system and its related facilities (Petter *et al*., 2008). Previous literature indicated that user satisfaction positively relates to electronic-learning (Almarashdeh *et al*., 2010; Lutfi *et al*., 2022). M-learning is rapidly being used, but there is a need to be more understanding of the aspects that affect its acceptance, predominantly in developing countries (Alturki and Aldraiweesh, 2022) like Pakistan.

In developing countries, advanced tools are novel methodologies for institutions and faculty, including higher education institutions (Lara *et al*., 2020).

The motives for the satisfaction of mobile learning still need to be explored, as it is the most fundamental and enduring issue in the information system of academics (Almaiah *et al*., 2016; Mohammadi, 2015).

The actual execution of M-learning is in a primary phase due to the deficiency of considered dynamics that affect the acceptance of M-learning (Alowayr, 2022). Hence, little attention is paid to exploring the factors responsible for the Actual use of mobile learning (Almaiah *et al*., 2019; Granić and Marangunić, 2019) in the higher educational institutions of developing countries during COVID-19 specifically in Pakistan (Mumtaz *et al*., 2021). The earlier research studies are deficient in determining all the aspects that can play an essential part in determining the students' opinions on the Actual use of mobile learning.

The theoretical model of this research work is based on the 'Technology Acceptance Model' (TAM), underpinned by the notion that the practice of the TAM model is less focused on e-learning studies (Venkatesh *et al*., 2012; Venkatesh and Zhang, 2010). Here, the authors bridge the gap by incorporating the TAM model with two predictors (PEOU and SI) and two mediating variables (SS and TTF) to regulate the Actual use of mobile learning among the students of higher education institutions. The research objectives of the current research work are:

1. To explore the direct association between PEOU, SS, TTF, and SI on AUOML.
2. To identify the mediation role of SS between PEOU and AUOML.
3. To examine the mediating role of TTF between SI and AUOML.

Literature Review and Hypotheses Development

The research framework is grounded on the Technology Acceptance Model (TAM). TAM is responsible for providing the base for research as a refined view in this study. It depicted the behavior-related factors over time (Venkatesh *et al*., 2003). It elaborates on the aspects impacting users' satisfaction with the new technologies. The model is used to explain the phenomenon of the present study since it has explanatory power, completeness, and acceptance for information systems research (Lawson-Body *et al*., 2020). Earlier literature witnessed that TAM is rare in the studies of e-learning (Venkatesh *et al*., 2012; Venkatesh and Zhang, 2010) and is a reliable theoretical model for envisaging the students' usage of M-Learning (Al-Rahmi *et al*., 2022). Past literature witnessed that the user's enthusiasm to adopt innovative technology included the TAM, Theory of Planned Behavior, and Unified theory of acceptance and use of technology (Al-Mamary *et al* ., 2023; Gupta *et al*., 2021), and researchers opted for the TAM in this current

study because the TAM model is critical as it provides the foundation for study as an advanced vision (Golbabaei, 2023).

Perceived Ease of Use, Social Influence, and Actual use of Mobile Learning

In the learning process, mobile devices are beneficial and valuable to facilitate students (Almaiah, 2018). M-learning has developed a facilitating instrument in the knowledge process in higher education institutions. It significantly affects student learning and modifies their behavior for easy and quick access to learning activities (Bannon and Thomas, 2014). Using mobile learning (AUOML) or M-Learning facilitates teaching. It assists in accessing educational materials through the internet through mobile devices such as smartphones and tablets (Almaiah *et al*., 2019). Students' usage of M-learning for educational purposes is affected by their perception of device compatibility (Zaidi *et al*., 2023). When pupils use M-learning on mobile devices for learning motives and PEOU, it is linked to the degree to which they involve fewer thought-provoking or complex conditions in the academic setting (Alturki and Aldraiweesh, 2022). Therefore, PEOU is a person's opinion of a definite system or device that will be unrestricted of exertion (Davis *et al*., 1989).

Social influence (SI) represents the level of users since other individuals must consider practicing a specific technology (Venkatesh *et al*., 2012). Lutfi (2022) and Venkatesh *et al*. (2003) claimed that the SI depicts the convincing power of some noteworthy individuals in life to practice an innovative system. Other people influence students to make conclusive decisions regarding the use of a definite technology, and these other people are essential in the life circles of students (Lutfi, 2022). Therefore, students are influenced by these significant people to use M-learning services (Arain *et al*., 2019). Brown and Venkatesh (2005) and Venkatesh *et al*. (2003) clarified that the SI is the precision of the consumers or users about the importance of others as the users use the technology due to the influence of others. The impact of SI, effort, and performance expectancy on behavioral intention (BI) was also moderated by the characteristics of a person. These characteristics include experience, age groupings, and gender (Venkatesh *et al*., 2012).

Alfalah (2023), Mohammadi (2015), Prieto *et al*. (2014), and Sánchez-Prieto *et al*. (2016) asserted that PEOU is effective in empathetic individual opinion regarding the acceptance of the mobile knowledge system. In addition, Social influence has a profound impact on the recognition and practice of mobile devices for learning purposes (Abu-Al-Aish and Love, 2013; Jiajing and Honglei,2023), and it has also been elaborated that peers, academics, and others inclined the intention to usage M-learning (Liu *et al*., 2010). Further, it has been found that SI exhibited a noteworthy role in the acceptance of M-learning (Kaliisa

et al., 2019). Therefore, associating SI and PEOU with M-learning would be rational. Therefore, researchers postulate that:

H1. PEOU is positively linked to AUOML.
H2. SI is positively related to AUOML.

Mediation of Student Satisfaction

M-learning is the scholarship supported by mobile devices, smartphones, or tablets for educational purposes through internet services or network facilities through personal collaboration technology and various applications. (Almaiah and Alismaiel, 2019; Pedro *et al*., 2018). According to the research work of Abu-Al-Aish and Love (2013), M-learning refers to knowledge through wireless mobile procedures such as personal digital assistants (PDA), tablets, and smartphones. These wireless mobile gadgets or devices can quickly move with the users by permitting knowledge everywhere and anytime. The TAM model empirically investigated factors such as interactivity, user-interface scheme, functionality, accessibility, personalization, and receptiveness to explore the acceptance of students in the direction of M-learning (Almaiah *et al*., 2016). The model demonstrations that students use new technology enthusiastically when they realize it is beneficial to accomplish their goalmouths and stress-free to use. Sánchez-Prieto *et al*. (2019) recommended that integrating the TAM model is essential to study the features that boost the practice of M-learning in students.

In the previous literature, it has been observed that the achievement of online learning is crucial based on numerous factors (Ye *et al*., 2023), and Student satisfaction and persistence are among the critical aspects of online learning success (Joo *et al*., 2011). Petter *et al*. (2008) clarified that the user's satisfaction depicts the pleasure of exhausting the information system and related services. In the opinion of Almarashdeh *et al*. (2010) and Lutfi *et al*. (2022), it has been witnessed that user satisfaction is considerably positively connected to the use of e-learning. Almaiah and Alismaiel (2019) and Alshurideh *et al*. (2019) claimed that it had a constructive impact on users' intentions towards the services of e-learning. The extant literature presented that the students' satisfaction increased with e-learning phases as they became stress-free and valuable (Rajeh *et al*., 2021). Based on the explanation, PEOU is directly related to the satisfaction and attitudes of the individuals (Hong *et al*., 2009), and the satisfaction of users is positively influenced by trust (Lavuri, 2023), perceived usefulness, and PEOU with mobile devices positively (Amin *et al*., 2014). However, Student satisfaction is linked with practice (Alkfaween *et al*., 2023) and intention to use mobile learning (Rajeh *et al*., 2021; Ramírez-Correa *et al*., 2015; Weng *et al*., 2015). *The utility of M-learning is a decisive p*redecessor of satisfaction and affects the intentions to continue (Cheng, 2021) due to the perceived use of ease. Thus, the PEOU of M-learning is a crucial

antecedent of satisfaction and influences the intentions to continue (Shaya *et al*., 2022). The literature review has proposed that SS and PEOU play substantial roles in using mobile learning. Therefore, research scholars posit that:

H3. PEOU is directly related to SS.
H4. SS is positively linked with AUOML.
H5. SS mediates the relationship between PEOU and AUOML.

The mediation of Task-Technology Fit (TTF)

In today's era, the development of smartphones and electronic devices has facilitated the various uses of applications (Kreps and Kimppa, 2015). M-learning skill is generated to provide comfort to the users regularly and by performing numerous education accomplishments competently. Thus, M-learning technology is imperative to produce personalized tasks by merging numerous technology-related tactics. The Task-technology fit (TTF) level can measure the individual's satisfaction (Al-Rahmi *et al*., 2021; Goodhue and Thompson, 1995; Qashou, 2021). TTF denotes the level of technology that supports the person in performing a range of assignments or tasks. TTF is the most used aspect when evaluating how information technology influences performance and practice and assessing the fit between task and technology features. TTF is the most used aspect to measure the effect of IT on performance and, therefore, assess the fit between task and technology (Mustafa *et al*., 2022). Most researchers used TTF with the TAM model to measure the adoption of e-learning among students; for example, Bhimasta & Suprapto (2016) extended this model to explore students' adoption of mobile e-textbooks (Or, 2023).

The task and technology features directly connect to the TTF and impact the students. The job and technological elements are closely related to the TTF and influence the pupils (Al-Rahmi *et al*., 2023). The moderating impact of gender and experience is also noteworthy between TTF and behavioral intentions (Gan *et al*., 2017). Scholars have vigorously researched TTF's usefulness to various information systems (Aljukhadar *et al*., 2014).

Social influence (SI) comprises encouragement and support (Alasmari, 2017). Information system academics scholars reported that people espouse a specific technology not due to personal encouragement but due to the opinions and influence of other persons (Princely Ifinedo, 2016). The SI consequence of the intention to use M-learning in developing states is emerging compared to the advanced countries (Arpaci, 2015; Iqbal and Qureshi, 2012). Social influence has been investigated in several models to assess the user's acceptance of information technology and proves to be a strong driver of user behavior (Al-Qaysi *et al*., 2023;

Hsu and Lu, 2004). Mobile learning is A fast-growing learning technology (Alrasheedi *et al*., 2015). The TTF elaborates that individual performance is influenced by new technology and holds that the user performs the task if the new technology matches the tasks being performed. Based on this literature review, Social influence and task technology have been recognized as critical constructs that predict the AUOML.
Thus, in light of the above discussion, the following hypotheses are established:

H6. SI is positively related to TTF.

H7. TTF is positively connected with AUOML.

H8. TTF mediates the association between SI and AUOML.

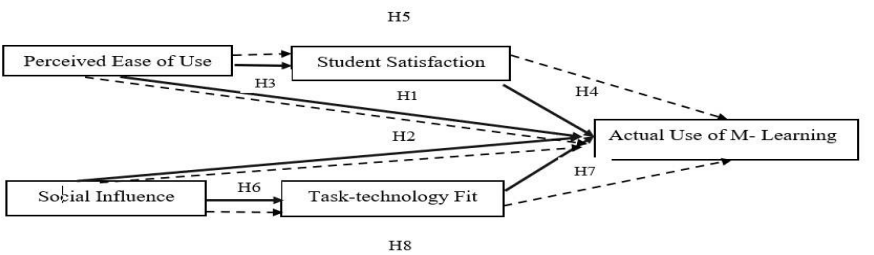

Fig.1. Research Framework

Note: The straight line ⟶ shows direct relationship between the variables and dotted line shows the mediating relationship between the variables.

Methodology

Sample and Procedures

The data comprises students from higher education institutions in Pakistan's public and private sectors. The authors elucidated the purpose of the research and obtained prior consent from the registrars of the universities for data collection. University students with at least a bachelor's degree were the study sample. The questionnaires were in English since this language is the learning medium in all Higher Education Institutions. These questionnaires were distributed using convenience sampling through a cross-sectional study design in line with the prior research study (Gull, Parveen, *et al*., 2023). The quantitative and survey methods are affirmed trustworthy by previous research studies to test the hypotheses (Davis and Venkatesh, 2004; Gull *et al*., 2023; Hadadgar *et al*., 2016). Therefore, 620 self-

administered questionnaires were distributed personally and through social media among the students, ensuring the anonymity of the participants' responses. Of 620 questionnaires, 440 were received with a response rate of 71%, and the sample size follows the threshold value of 200-400 responses, representing 35 responses per construct (Kline, 2016). Data collection was completed between February 2023 and April 2023.

Measures

The renowned scales of previous studies (PEOU, SI, TTF, SS, and AUOML) were used to measure the constructs of this study. All study variables were measured using a ‘5-point' Likert scale. The Likert scale ranged from "strongly disagree" (1) to "strongly agree" (5).

Actual Use of Mobile Learning

AUOML was measured with the two-item scale, adapted from the research study of Almaiah *et al*. (2019) and Sung *et al*. (2015). An example item includes "I like to use the M-learning system."

Perceived Ease of Use

The three items scale of Davis (1985) was used for the PEOU. An illustration item includes, "Overall, using online learning platforms will be easy even after the start of the face-to-face classes."

Social Influence

SI was measured with a scale adapted from Alasmari's (2017) and Venkatesh *et al*. (2003) work. The scale included four items: "People who influence my behavior think I should use the system."

Student Satisfaction

SS was measured with a scale from the prior research work of Rajeh *et al*. (2021). The scale included two items, "I am satisfied with the performance of M-learning."

Task-Technology Fit

The 4-item scale was adapted from the research study of Wu and Chen (2017) and Kim *et al*. (2010) to measure TTF. A specimen item includes "Technology like Google Classrooms and Zoom fit my learning requirements."

Study Instrument

The six hypotheses have been measured with a survey tool (Questionnaire) in the present research. The questionnaire comprised Segments A and B. Segment A comprised the demographic characteristics, and Segment B comprised the items to measure the study variables: PEOU, TTF, SS, SI, and AUOML. Five constructs were measured in the questionnaire with a total of 15 items. The items are adapted from the reputed scales of previous researchers. The reliability of the questionnaire is 0.918, consisting of 15 items.

Analysis

Data were analyzed through SPSS 24.0 and Smart PLS 3.0. Statistical procedures, descriptive demographical analysis, and CMB (Common Method Bias) were performed with the help of SPSS. The measurement and structural models were determined through Smart PLS. According to Hair *et al*. (2019) and Henseler *et al*. (2016), Smart PLS can be employed for small sample sizes and is better for regression analysis, especially in mediation analysis. The research methodology of this study has three objectives. Firstly, to analyze the direct relationship of PEOU and SI with AUOML. Secondly, to explore the mediation analyses of SS between PEOU and AUOML. Finally, to determine the mediation of TTF between SI and AUOML.

Results and Data Analysis

Descriptive Statistics

Most respondents were females, comprised of 286 (65.0%), and 154 (35.0%) were males. Most students are in the age bracket of 20–30 years (97.7%) and have a bachelor's degree (82.5%). The students having at least bachelor degree are the current sample of the study because at bachelor level the students have comprehensive understanding of study variables and can provide truly and trustworthy responses. 414 (94.1%) participants were single, and 26 were married. The details of the statistics of Demographical Attributes are listed in Table 1.

Table 1. Descriptive Statistics of Demographical Attributes

Attributes	Items	Responses	Percentages
Gender	Male	154	35.0
	Female	286	65.0
Age (Years)	20-30	430	97.7
	31-40	8	1.8

	41-50	2	0.5
	Above 50	0	------
Qualifications	Bachelor	363	82.5
	Master	30	6.8
	MS/MPhil	12	2.7
	Ph.D. Scholar	4	0.9
	Ph.D.	1	0.2
	Any other	30	6.9
Marital Status	Married	26	5.9
	Individual	414	94.1

Measurement Model

The theoretical framework of this study was analyzed by adopting the two-step guidelines (Measurement and Structural model) of Anderson and Gerbing (1988). According to the point of view of Hair *et al*. (2019) and Ramayah *et al*. (2018), the validity and reliability were assessed in the measurement model (see Fig. 2). The hypothesis was analyzed in the structural model (see Fig. 3). The average variance extracted (AVE), Alpha, R square, and the composite reliability (CR) are evaluated (see Table 2) in the measurement model. The alpha values of all the study variables are above the threshold value of 0.70 (Table 3), hence showing acceptable reliability (Peterson, 1994). Values of AVE are beyond 0.5. The values of CR are beyond 0.7 for all the constructs depicting the acceptable criteria (Hair *et al*., 2019). The discriminant validity is evaluated with the help of the Heterotrait-Monotrait Ratio (HTMT). Franke and Sarstedt (2019) and Henseler *et al.* (2015) asserted that the values of HTMT are satisfactory if there are fewer than or equal to 0.85 according to the sticker criteria or less than or equal to 0.90 according to the lenient criteria. Therefore, all the values of HTMT (see Table 3) lie in acceptable criteria, representing that all five constructs are distinctive. The R square for AUOML is 0.602, SS is 0.312, and TTF is 0.307. The values of R square greater than 0.26 represented a significant influence (Hair *et al*., 2019). The R square for AUOML was 0.602, indicating that 60.2% of the total variation is enlightened by PEOU, SI, SS, and TTF, thus proving the model's fitness.

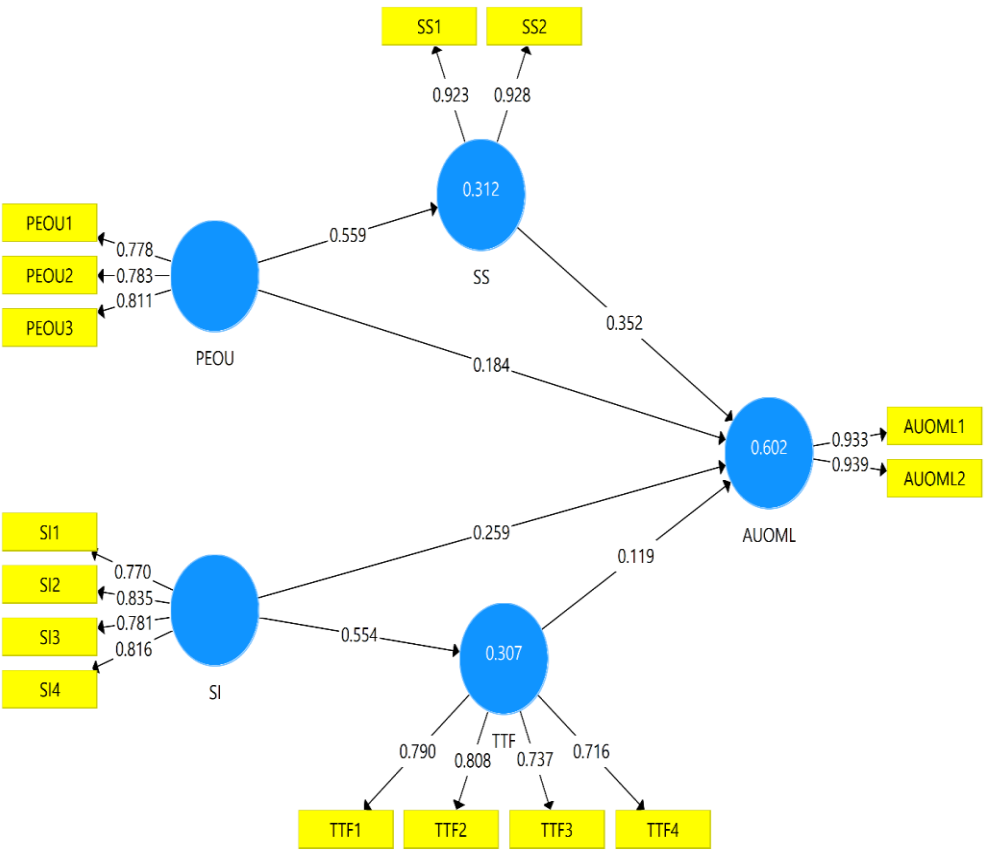

Fig 2. Measurement model

Table 2. Reliability, Validity, and R Square

Constructs	Alpha	R Square	CR	AVE
AUOML	0.859	0.602	0.934	0.877
PEOU	0.701	-------	0.833	0.625
SI	0.813	-------	0.877	0.641
SS	0.833	0.312	0.923	0.857
TTF	0.761	0.307	0.848	0.583

Table 3. HTMT

	AUOML	PEOU	SI	SS	TTF
AUOML					
PEOU	0.779				
SI	0.811	0.777			
SS	0.826	0.729	0.844		
TTF	0.702	0.866	0.704	0.672	

Structural Model

The bootstrapping process evaluated the structural model by selecting 5000 subsamples (95% confidence interval). The variance inflation factor (VIF) was used to measure multicollinearity (See Table 4) and having less than 3 values as per acceptable criteria (Hair *et al*., 2019). The Common method bias (CMB) issue is tackled with the guidelines of Podsakoff *et al*. (2012). Harman's single factor was used to measure the CMB. It is a statistical test showing the covariance value explained as 47.100 (See Table 5). The value of covariance explained is fewer than 50% (Harman, 1976). Hence, the results are not anticipated to be inflated by the researcher or the respondent of the research study.

Table 4. Variance Inflation Factor (VIF)

	VIF
AUOML1	2.312
AUOML2	2.312
PEOU1	1.276
PEOU2	1.436

PEOU3	1.442
SI1	1.620
SI2	1.916
SI3	1.707
SI4	1.827
SS1	2.039
SS2	2.039
TTF1	1.675
TTF2	1.742
TTF3	1.429
TTF4	1.363

Table 5. Common Methods of Bias Analysis (CMB)

Total Variance Explained						
Compo	Initial Eigenvalues			Extraction Sums of Squared Loadings		
nent	Total	% of variance	Cumulative %	Total	% of variance	Cumula tive %
1	7.065	47.100	47.100	7.065	47.100	47.100
2	1.264	8.428	55.528			
3	.912	6.081	61.609			
4	.811	5.410	67.019			
5	.710	4.732	71.752			
6	.655	4.364	76.115			
7	.585	3.898	80.013			
8	.495	3.302	83.316			
9	.479	3.192	86.508			
10	.431	2.871	89.379			
11	.396	2.643	92.022			
12	.368	2.453	94.474			
13	.335	2.231	96.706			
14	.268	1.787	98.492			
15	.226	1.508	100.000			
Extraction Method: Principal Component Analysis.						

The path coefficients, t-values, and confidence intervals bias-corrected 95%, of direct and mediation relationships were depicted as statistically significant (see Table 6). The p-value of all the direct relationships (Hypothesis 1, 2, 3, 4, 6, and 7) are $p < 0.05$, and the t-value is greater than 1.96, which supports the significant direct relationships between study variables, as suggested by Hair *et al*. (2019) and Gull, Parveen, *et al*., (2023). The confidence intervals bias-corrected (BCI-LL and BCI-UL) did not indicate the '0' value. Therefore, the findings of the current framework support the partial mediation for two hypotheses, i.e., H5 and H8, as suggested by Gull, Rashid, *et al*., (2023); Preacher and Hayes, (2004).

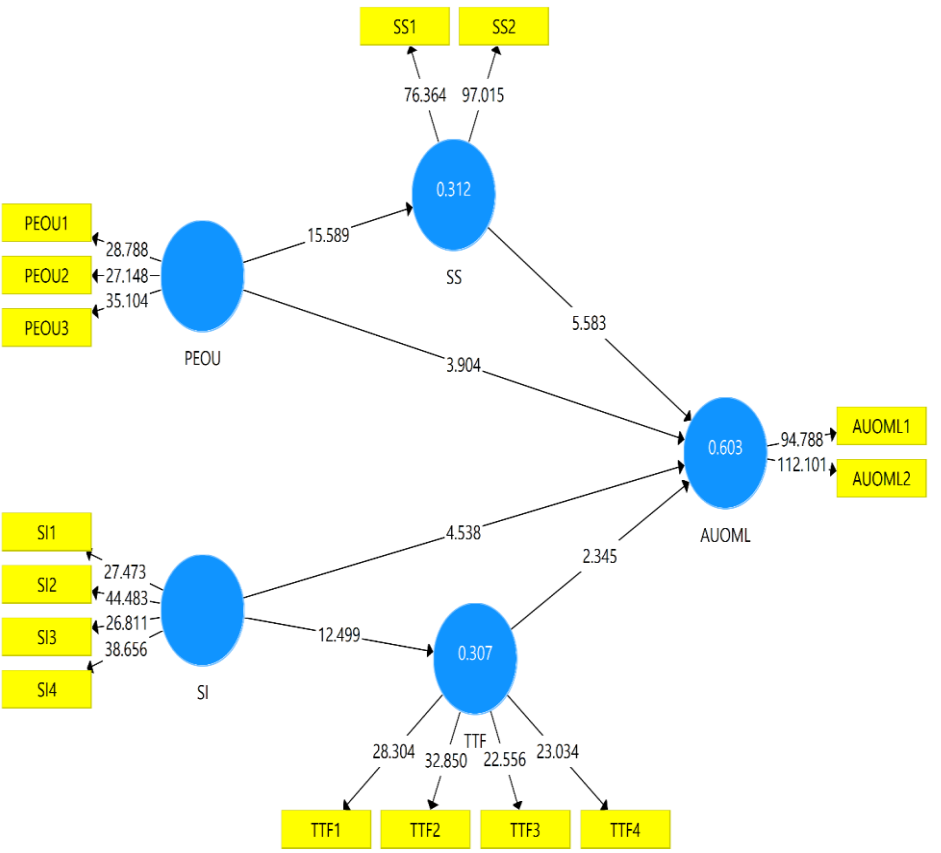

Fig 3. Structural model

Table 6. Hypotheses Testing and Decision

Paths	t-values	BCI LL 2.5%	BCI UL 97.5%	p-values
PEOU → AUOML	6.990	0.273	0.489	0.000
SI → AUOML	5.473	0.208	0.440	0.000
PEOU → SS	15.589	0.480	0.624	0.000
SS → AUOML	5.583	0.228	0.480	0.000

PEOU → SS → AUOML	12.052	0.125	0.277	0.000
SI → TTF	12.499	0.458	0.631	0.000
TTF → AUOML	2.345	0.018	0.219	0.019
SI → TTF → AUOML	8.897	0.011	0.126	0.000

Discussions

With the application of the TAM, this study attempts to determine if there is an association among Student satisfaction, Perceived ease of use, Social influence, Task-technology fit, and Actual use of mobile learning. Eight hypotheses have been generated to explore the relationship between the constructs proposed.

Our first hypothesis depicts that PEOU is positively linked with the AUOML in students of higher education institutions (H1). In higher education institutions, mobile learning has developed as an essential tool for the learning system because it positively influences students' assertiveness and increases their perception of the easy right to use for learning activities (Abachi and Muhammad, 2014). Since the introduction of M-learning, mobile technology turned mobile devices into an M-learning tool for students (Lee *et al*., 2005), and students perceive it as easy to use. PEOU is imperative and excessively used for online or e-learning (Wu and Zhang, 2014). It refers to the belief that students would be more enthusiastic to adopt mobile learning if the technology were accessible, and ease of use improves the intention to adopt mobile learning (Tan *et al*., 2012). The findings of our study are in line with the studies of Almaiah *et al*., (2021); Almaiah and Alismaiel, (2019); Shodipe and Ohanu, (2021), supporting our hypothesis 1, that Perceived ease of use has a substantial influence on students' recognition of mobile learning. Hypothesis 2 is also supported as Social Influence (SI) positively connected with AUOML in the current study. The results depicted a strong association between SI and AUOML, which is allied with the earlier studies (Arain *et al*., 2019; Sung *et al*., 2015). Lin and Lu (2015) argue that many empirical studies expect that Social influence substantially impacts individuals' information technology practice. When the number of peers increases through IT, its utility increases and it becomes a Social influence for others in the group to adopt it (Lin and Bhattacherjee, 2008). It is also true for mobile, which enhances mobile learning under Social influence.

Perceived ease of use projected students' satisfaction with e-learning programs (Roca *et al*., 2006). It was also reported in the study conducted at Taiwan

University that PEOU is significantly related to the satisfaction level of students (Chiu *et al*., 2005). Students reported high satisfaction with e-learning applications due to their fit with the learning requirements (Islam, 2013). In the studyof Heafner (2004) states that technology will positively affect students' learning results because technologies make their work more accessible and more enjoyable. Satisfaction towards an information system indicates a high willingness to use it (Liaw and Huang, 2013).

Moreover, extant literature depicts that PEOU predicts Student satisfaction among higher education institutions in online learning, which is consistent with our H3 that PEOU is directly related to SS. Assisted mobile learning with different online applications (Skype, Blogs, Zoom, and Teams) improves Student satisfaction and positive attitude toward mobile learning (Gikas and Grant, 2013). Al-Emran *et al*. (2016) asserted that Student satisfaction plays a vital role in the usefulness and recognition of mobile learning. It would help to embed learning into mobile technologies, which leads to the effectiveness of mobile learning, in compliance with our H4 that SS is positively linked with AUOML. Almaiah and Alismaiel (2019) in their study elaborated on the amalgamation of the TAM with the revised model of DeLone and McLean (DL&ML) to identify the relationship between Student satisfaction with Perceived ease of use and Actual use of mobile learning in compliance with our H5 that SS mediates the relationship between PEOU and AUOML supported by the studies of Lutfi *et al*., (2022) and Almarashdeh *et al*., (2010).

Social influence is a topic of debate in information systems technology for using and accepting various information technology models. Individuals opt for a specific technology based on the options of others, not because of their personal choices (Princely Ifinedo, 2016). The reasoning behind this is the person's motive to adapt to other beliefs to strengthen their association (Hernandez *et al*., 2011). TTF theory describes the best fit between task and technology (Liang and Wei, 2004), and high-task technology results in better performance. TTF denotes the aptitude of the information supplier to match the technology to the task's loads (Klaus *et al*., 2003). New technology is more likely to impact better performance if it matches the demand of the task. Therefore, the hypothesis (H6) that Social influence positively impacts TTF is accepted in this study.

E-learning and remote knowledge are compulsions in lockdowns and distancing due to the pandemic (Ali, 2020) in developed and underdeveloped countries. Without opting for online learning with mobiles, continuing education is questionable. M-learning is easily approachable, wireless, inexpensive, user-friendly, and, most meaningfully, the best approach for sharing educational material by saving energy and time. Task-technology Fit (TTF) mediates the association between SI and AUOML (H8), and the findings are in line with the past

study of Yu and Yu (2010), describing that TTF has a positive influence on PEOU in the e-commerce field. The SI further impacts the aim to use M-learning in developing countries (Arpaci, 2015; Iqbal and Qureshi, 2012). SI is positively linked to using a particular technology in Pakistan (Nandwani and Khan, 2016). The research findings of Abdelwahed and Soomro (2022) depicted that TTF, perceived usefulness, and PEOU are significantly related to mobile usage attitudes. Therefore, this study provides practical implications that PEOU, SI, SS, and TTF influence the implementation process of mobile learning throughout and after COVID-19.

Theoretical Contributions

Theoretically, this study adds numerous ways to the existing research on M-learning services. Firstly, this research contributed to including Student satisfaction (SS) as a mediator in the association between PEOU and AUOML. The execution of M-learning is in a preliminary stage owing to the shortage of several factors that encourage the recognition of M-learning (Alowayr, 2022). Therefore, more consideration is required to explore the factors that are liable for the AUOML (Almaiah *et al*., 2019; Granić and Marangunić, 2019) in the higher educational institutions of developing countries during COVID-19 specifically in Pakistan (Mumtaz *et al*., 2021). Secondly, it incorporates TTF to mediate the association between SI and AUOML. Moreover, integrating the two mediating variables (Student satisfaction and Task-technology fit) in a framework is a gigantic theoretical contribution.

The following contribution implies that the research study supported that PEOU and SI are positively related to the AUOML among students of higher education institutions in Pakistan as the use of technology was swiftly implemented due to epidemic situations in higher educational institutions for ground-breaking educational approaches (Alismaiel, 2021; Cifuentes-Faura *et al*., 2021). Furthermore, the influence of TTF on M-learning has rarely been explored in the past literature in South Asian settings. Then TAM was used to determine the noteworthy effect of SI and PEOU on AUOML with underlying mechanisms of Student satisfaction and Task-technology fit, thus contributing theoretically. It has been observed that user satisfaction is positively associated with using e-learning (Lutfi *et al*., 2022), and it has a practical impact on the users towards e-learning (Alshurideh *et al*., 2019).

In addition, the current study extends the existing literature related to the TAM model that postulates that technology is accepted by users' behavioral targets that are affected by the utility and ease of use of technology in the execution of tasks. However, the current study postulates that Student satisfaction, Social influence, and Task technology fit also play an essential starring role in the

AUOML, the most flexible and effective technology among students nowadays (Jurayev, 2023). Therefore, this study offers insights to education policymakers, the government, and educational institutions to focus on the usage of M-learning not only during the pandemic but also after the pandemic since students are satisfied with the usage of M-learning.

Practical implications

The findings of the current research study encourage education policymakers, government, and educational institutions to implement M-learning policy in institutions with different evaluation criteria. In this regard, the support of family, friends, institutions, and the state is desirable and mandatory. Higher education institutions should have IT infrastructure to promote online learning, providing faculty members access to e-learning platforms (Ali, 2020). Therefore, educational institutions should espouse easy-to-use e-learning services to enhance students' confidence to find opportunities with less hustle because satisfied students will be more interested in using e-learning services (Rajeh *et al*., 2021).

Further, this study inspires students to use M-learning services to be knowledgeable in society and direct policymakers to devise strategies for developing e-education or learning after post-COVID-19 pandemic conditions (Al-Rahmi *et al*., 2022). The current study's findings provide educational institutions, the government, and mobile phone manufacturers with an essential guiding principle on the design and implementation of the Actual use of mobile learning, as well as to facilitate those students who do not have access to traditional classroom learning.

Moreover, PEOU, SI, TTF, and SS towards M-learning services encourage educational policymakers, government, and higher education institutions to continue education in a blended mode. In the blended mode, theoretical knowledge of the subject can be delivered to students with M-learning services, and practical or numerical subjects can be taught on campus. This blended mode with M-learning services will enhance the chances of a high literacy rate, especially in underdeveloped countries. It can promote knowledge among the students with low cost, energy, and time.

Limitations and Future Suggestions

It is a rigorous and wide-ranging study; however, a few limitations are related to this research, which can serve as future suggestions. At first, this study is based on a single model, TAM. Future researchers should integrate other leading models with TAM to determine the more rigorous relationships of different constructs. Secondly, this research study explores the variables simultaneously (cross-sectional study). Future researchers should consider longitudinal studies to determine the

AUOML of students after fully controlling for the circumstances of the COVID-19 pandemic.

Further, the convenience sampling technique is used here. However, future researchers can select the sample from probability sampling with stratified or cluster sampling techniques for more generalizable results. In this research, two mediating variables, student satisfaction, and TTF, were used with the PEOU and the SI. Likewise, more mediating variables, such as facilitating conditions or perceived usefulness, can also be explored. The future researcher should conduct systematic review of Actual use of mobile learning or M-learning to unexplored the antecedents, moderators and mediators as prior research by Gull *et al*., (2022), conducting the systematic review. Finally, this research study is limited to Pakistani students from higher education institutions. Future scholars are encouraged to extend the study model to various cultural settings and contexts to learn more about the post-pandemic approach of students toward AUOML.

References

Abachi, H. R., & Muhammad, G. (2014). The impact of m-learning technology on students and educators. Computers in Human Behavior, 30, 491–496. https://doi.org/10.1016/j.chb.2013.06.018

Abdelwahed, N. A. A., & Soomro, B. A. (2022). Attitudes and intentions towards the adoption of mobile learning during COVID-19: building an exciting career through vocational education. Education and Training. https://doi.org/10.1108/ET-02-2022-0048

Abdullah, F. M., Maatuk, A. M., Mohammed, A. A., & Elberkawi, E. K. (2019). Application of electronic management system in governmental institutions: An empirical study on the Libyan civil registration. ACM International Conference Proceeding Series. https://doi.org/10.1145/3368691.3368710

Abu-Al-Aish, A., & Love, S. (2013). Factors influencing students' acceptance of m-learning: An investigation in higher education. International Review of Research in Open and Distance Learning, 14(5), 82–107. https://doi.org/10.19173/irrodl.v14i5.1631

Al-Emran, M., Elsherif, H. M., & Shaalan, K. (2016). Investigating attitudes towards the use of mobile learning in higher education. Computers in Human Behavior, 56, 93–102. https://doi.org/10.1016/j.chb.2015.11.033

Al-Qaysi, N., Granić, A., Al-Emran, M., Ramayah, T., Garces, E., & Daim, T. U. (2023). Social media adoption in education: A systematic review of disciplines, applications, and influential factors. Technology in Society, 73. https://doi.org/10.1016/j.techsoc.2023.102249

Al-Rahmi, A. M., Al-Rahmi, W. M., Alturki, U., Aldraiweesh, A., Almutairy, S., & Al-Adwan, A. S. (2022). Acceptance of mobile technologies and M-learning by university students: An empirical investigation in

higher education. Education and Information Technologies, 27(6), 7805–7826. https://doi.org/10.1007/s10639-022-10934-8

Al-Rahmi, A. M., Shamsuddin, A., Alturki, U., Aldraiweesh, A., Yusof, F. M., Al-Rahmi, W. M., & Aljeraiwi, A. A. (2021). The influence of information system success and technology acceptance model on social media factors in education. Sustainability (Switzerland), 13(14). https://doi.org/10.3390/su13147770

Al-Rahmi, W. M., Al-Adwan, A. S., Al-Maatouk, Q., Othman, M. S., Alsaud, A. R., Almogren, A. S., & Al-Rahmi, A. M. (2023). Integrating Communication and Task–Technology Fit Theories: The Adoption of Digital Media in Learning. Sustainability (Switzerland), 15(10). https://doi.org/10.3390/su15108144

Alasmari, T. M. (2017). Mobile learning technology acceptance among Saudi higher education students. In ProQuest Dissertations and Theses. https://search.proquest.com/docview/1885003244?accountid=14645

Alfalah, A. A. (2023). Factors influencing students' adoption and use of mobile learning management systems (m-LMSs): A quantitative study of Saudi Arabia. International Journal of Information Management Data Insights, 3(1). https://doi.org/10.1016/j.jjimei.2022.100143

Ali, W. (2020). Online and Remote Learning in Higher Education Institutes: A Necessity in light of COVID-19 Pandemic. Higher Education Studies, 10(3), 16. https://doi.org/10.5539/hes.v10n3p16

Alismaiel, O. A. (2021). Using structural equation modeling to assess online learning systems' educational sustainability for university students. Sustainability (Switzerland), 13(24). https://doi.org/10.3390/su132413565

Aljawarneh, S. A. (2020). Reviewing and exploring innovative ubiquitous learning tools in higher education. Journal of Computing in Higher Education, 32(1), 57–73. https://doi.org/10.1007/s12528-019-09207-0

Aljukhadar, M., Senecal, S., & Nantel, J. (2014). Is more always better? Investigating the task-technology fit theory in an online user context. Information and Management, 51(4), 391–397. https://doi.org/10.1016/j.im.2013.10.003

Alkfaween, O. J., El-Ebiary, Y. A., & Mohamad, M. B. (2023). A Comparison Between The Existing Unisza's Mobile Learning And The Proposed Design According To A New Conceptual Framework. Journal of Pharmaceutical Negative Results, 14, 1247–1264. https://doi.org/10.47750/pnr.2023.14.S02.153

Almaiah, M. A. (2018). Acceptance and usage of a mobile information system services in University of Jordan. Education and Information Technologies, 23(5), 1873–1895. https://doi.org/10.1007/s10639-018-9694-6

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT Model to Explain the Students' Acceptance of Mobile Learning System in Higher Education. IEEE Access, 7, 174673–174686. https://doi.org/10.1109/ACCESS.2019.2957206

Almaiah, M. A., & Alismaiel, O. A. (2019). Examination of factors influencing the use of mobile learning system: An empirical study. Education and Information Technologies, 24(1), 885–909. https://doi.org/10.1007/s10639-018-9810-7

Almaiah, M. A., Almomani, O., Al-Khasawneh, A., & Althunibat, A. (2021). Predicting the Acceptance of Mobile Learning Applications During COVID-19 Using Machine Learning Prediction Algorithms. Studies in Systems, Decision and Control, 348, 319–332. https://doi.org/10.1007/978-3-030-67716-9_20

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

Almarashdeh, I., Sahari, N., Zin, N. A. M., & Alsmadi, M. (2010). The success of learning management system among distance learners in Malaysian Universities. Journal of Theoretical & Applied Information Technology, 21(2). https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Almarashdeh%2C+I.A.%3B+Sahari%2C+N.%3B+Zin%2C+N.A.M.%3B+Alsmadi%2C+M.+The+success+of+learning+management+system+among+distance+learners+in+Malasian+universities.+J.+Theor.+Appl.+Inf.+Technol.+2010%2C

Alowayr, A. (2022). Determinants of mobile learning adoption: extending the unified theory of acceptance and use of technology (UTAUT). International Journal of Information and Learning Technology, 39(1), 1–12. https://doi.org/10.1108/IJILT-05-2021-0070

Alrasheedi, M., Capretz, L. F., & Raza, A. (2015). A systematic review of the critical factors for success of mobile learning in higher education (university students' perspective). Journal of Educational Computing Research, 52(2), 257–276. https://doi.org/10.1177/0735633115571928

Alshurideh, M., Salloum, S. A., Al Kurdi, B., Monem, A. A., & Shaalan, K. (2019). Understanding the quality determinants that influence the intention to use the mobile learning platforms: A practical study. International Journal of Interactive Mobile Technologies, 13(11), 157–183. https://doi.org/10.3991/ijim.v13i11.10300

Alturki, U., & Aldraiweesh, A. (2022). Students' Perceptions of the Actual Use of Mobile Learning during COVID-19 Pandemic in Higher Education. Sustainability (Switzerland), 14(3). https://doi.org/10.3390/su14031125

Amin, M., Rezaei, S., & Abolghasemi, M. (2014). User satisfaction with mobile websites: the impact of perceived usefulness (PU), perceived ease of use (PEOU) and trust. Nankai Business Review International, 5(3), 258–274. https://doi.org/10.1108/NBRI-01-2014-0005

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. Psychological Bulletin, 103(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Arain, A. A., Hussain, Z., Rizvi, W. H., & Vighio, M. S. (2019). Extending UTAUT2 toward acceptance of mobile learning in the context of higher education. Universal Access in the Information Society, 18(3), 659–673. https://doi.org/10.1007/s10209-019-00685-8

Arpaci, I. (2015). A comparative study of the effects of cultural differences on the adoption of mobile learning. British Journal of Educational Technology, 46(4), 699–712. https://doi.org/10.1111/bjet.12160

Bhimasta, R. A., & Suprapto, B. (2016). An empirical investigation of student adoption model toward mobile e-textbook: Utaut2 and ttf model. ACM International Conference Proceeding Series, 167–173. https://doi.org/10.1145/3018009.3018046

Bibi, A., Bukhari, S., Sami, A., Irfan, A., Liaqaut, H. (2018). Effect of Latest Technology and Social Media on Interpersonal Communication on Youth of Balochistan. Journal of Managerial Sciences, XI (3), 475-490

Brown, S. A., & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. MIS Quarterly: Management Information Systems, 29(3), 399–426. https://doi.org/10.2307/25148690

Cheng, Y. M. (2021). Investigating medical professionals' continuance intention of the cloud-based e-learning system: an extension of expectation–confirmation model with flow theory. Journal of Enterprise Information Management, 34(4), 1169–1202. https://doi.org/10.1108/JEIM-12-2019-0401

Chiu, C. M., Hsu, M. H., Sun, S. Y., Lin, T. C., & Sun, P. C. (2005). Usability, quality, value and e-learning continuance decisions. Computers and Education, 45(4), 399–416. https://doi.org/10.1016/j.compedu.2004.06.001

Cifuentes-Faura, J., Obor, D. O., To, L., & Al-Naabi, I. (2021). Cross-cultural impacts of covid-19 on higher education learning and teaching practices in Spain, Oman, Nigeria and Cambodia: A cross-cultural study. Journal of University Teaching and Learning Practice, 18(5). https://doi.org/10.53761/1.18.5.8

Davis, F D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results. Management, Ph.D., 291. https://doi.org/oclc/56932490

Davis, Fred 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

Davis, Fred D., & Venkatesh, V. (2004). Toward preprototype user acceptance testing of new information systems: Implications for software project management. IEEE Transactions on Engineering Management, 51(1), 31–46. https://doi.org/10.1109/TEM.2003.822468

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. Internet Research, 29(3), 430–447. https://doi.org/10.1108/IntR-12-2017-0515

Gan, C., Li, H., & Liu, Y. (2017). Understanding mobile learning adoption in higher education An empirical investigation in the context of the mobile library. Electronic Library, 35(5), 846–860. https://doi.org/10.1108/EL-04-2016-0093

Gikas, J., & Grant, M. M. (2013). Mobile computing devices in higher education: Student perspectives on learning with cellphones, smartphones & social media. Internet and Higher Education, 19, 18–26. https://doi.org/10.1016/j.iheduc.2013.06.002

Golbabaei, F. (2023). Challenges and opportunities in the adoption of autonomous demand responsive transit (ADRT) by adult residents of South East Queensland (Doctoral dissertation, Queensland University of Technology).

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. MIS Quarterly: Management Information Systems, 19(2), 213–233. https://doi.org/10.2307/249689

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

Gull, M., Ahmed, A., & Warraich, I. A. (2022). Conducting a Bibliometric Study through a Systematic Literature Review regarding Job Characteristics and Work Engagement. Journal of Management and Research, 9(2). https://doi.org/10.29145/jmr.92.02

Gull, M., Parveen, S., & Sridadi, A. R. (2023). Resilient higher educational institutions in a world of digital transformation. Foresight. https://doi.org/10.1108/FS-12-2022-0186

Gull, M., Rashid, M., Hassan, S., & Rehman, S. (2023). Role of top management green commitment, adaptability culture and green product innovation in boosting organizational green performance in Pakistan. Research Journal of Textile and Apparel, ahead-of-p(ahead-of-print). https://doi.org/10.1108/RJTA-12-2022-0159

Gupta, Y., Khan, F. M., & Agarwal, S. (2021). Exploring Factors Influencing Mobile Learning in Higher Education - A Systematic Review. International Journal of Interactive Mobile Technologies, 15(12), 140–157. https://doi.org/10.3991/ijim.v15i12.22503

Hadadgar, A., Changiz, T., Dehghani, Z., Backheden, M., Mirshahzadeh, N., Zary, N., & Masiello, I. (2016). A theory-based study of factors explaining general practitioners' intention to use and participation in electronic continuing medical education. Journal of Continuing Education in the Health Professions, 36(4), 290–294. https://doi.org/10.1097/CEH.0000000000000123

Hair, J F, Anderson, R. E., Tatham, R. L., & Black, W. C. (2019). Multivariate Data Analysis, Multivariate Data Analysis. Book, 87(4), 611–628. https://digitalcommons.kennesaw.edu/facpubs/2925/

Hair, Joseph F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Harman, H. (1976). Modern factor analysis (3rd ed). Chicago, IL: University of Chicago Press. https://books.google.com/books?hl=en&lr=&id=e-vMN68C3M4C&oi=fnd&pg=PR15&dq=Harman,+H.+H.+(1976).+Modern+factor+analysis+(3rd+ed).+Chicago,+IL:+University+of+Chicago+Press.&ots=t6OkOwgO_z&sig=G5_bv6oiiVBci1JiNvXwTy_3zDg

Heafner, T. (2004). Using technology to motivate students to learn social studies. Contemporary Issues in Technology and Teacher, 4(1), 42–53. http://www.citejournal.org/vol4/iss1/socialstudies/article1.cfm

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. Industrial Management and Data Systems, 116(1), 2–20. https://doi.org/10.1108/IMDS-09-2015-0382

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hernandez, B., Montaner, T., Sese, F. J., & Urquizu, P. (2011). The role of social motivations in e-learning: How do they affect usage and success of ICT interactive tools? Computers in Human Behavior, 27(6), 2224–2232. https://doi.org/10.1016/j.chb.2011.07.001

Hong, J. yi, Suh, E. ho, & Kim, S. J. (2009). Context-aware systems: A literature review and classification. Expert Systems with Applications, 36(4), 8509–8522. https://doi.org/10.1016/j.eswa.2008.10.071

Hsu, C. L., & Lu, H. P. (2004). Why do people play on-line games? An extended TAM with social influences and flow experience. Information and Management, 41(7), 853–868. https://doi.org/10.1016/j.im.2003.08.014

Ifinedo, P, & Usoro, A. (2016). Students' Intentions To Continue Using Blogs To Learn: a Socio-Cognitive Perspective. Computing & Information Systems, 20(3), 14–24. http://search.ebscohost.com/login.aspx?direct=true&db=iih&AN=119342780&amp%0Alang=ko&site=ehost-live

Ifinedo, Princely. (2016). Applying uses and gratifications theory and social influence processes to understand students' pervasive adoption of social networking sites: Perspectives from the Americas. International Journal of Information Management, 36(2), 192–206. https://doi.org/10.1016/j.ijinfomgt.2015.11.007

Iqbal, S., & Qureshi, I. A. (2012). M-learning adoption: A perspective from a developing country. International Review of Research in Open and Distance Learning, 13(3), 147–164. https://doi.org/10.19173/irrodl.v13i3.1152

Irfan, A., Rasli, A., Sulaiman, Z., Sami, A., & Qureshi, M. I. (2018). Use of Social Media Sites by Malaysian Universities and its Impact on

University Ranking. International Journal of Engineering and Technology, 7(4.28), 67-71

Irfan, A., Rasli, A., Sulaiman, Z., Sami, A., Liaquat, H., & Qureshi, M. I. (2020). Student's Perceived University Image is an Antecedent of University Reputation. International Journal of Psychosocial Rehabilitation, 24(01). 650-663

Islam, A. K. M. N. (2013). Conceptualizing perceived usefulness in elearning context and investigating its role in improving students' academic performance. ECIS 2013 - Proceedings of the 21st European Conference on Information Systems. https://scholar.archive.org/work/c5kx4xiuljeute6egu5vvv6s3e/access/wayback/https://aisel.aisnet.org/cgi/viewcontent.cgi?article=1231&context=ecis2013_cr

Joo, Y. J., Lim, K. Y., & Kim, E. K. (2011). Online university students' satisfaction and persistence: Examining perceived level of presence, usefulness and ease of use as predictors in a structural model. Computers and Education, 57(2), 1654–1664. https://doi.org/10.1016/j.compedu.2011.02.008

Jurayev, T. N. (2023). The use of mobile learning applications in higher education institutes. Advances in Mobile Learning Educational Research, 3(1), 610–620. https://doi.org/10.25082/amler.2023.01.010

Kaliisa, R., Palmer, E., & Miller, J. (2019). Mobile learning in higher education: A comparative analysis of developed and developing country contexts. British Journal of Educational Technology, 50(2), 546–561. https://doi.org/10.1111/bjet.12583

Kim, T. T., Suh, Y. K., Lee, G., & Choi, B. G. (2010). Modelling roles of task-technology fit and self-efficacy in hotel employees' usage behaviours of hotel information systems. International Journal of Tourism Research, 12(6), 709–725. https://doi.org/10.1002/jtr.787

Klaus, T., Gyires, T., & Wen, H. J. (2003). The use of Web-based information systems for non-work activities: An empirical study. Human Systems Management, 22(3), 105–114. https://doi.org/10.3233/hsm-2003-22302

Laraib, Sami, A., & Irfan, A. (2020). Academic Achievement of college students based on Co- curricular Activities. Journal of Management Info, 7(1), 16-23

Kline, R. B. (2016). Principles and practice of structural equation modeling (fourth ed). Guilford Press. https://scholar.google.com/scholar_lookup?title=Principals and practice of structural equation modeling&author=R.B. Kline&publication_year=2011

Kreps, D., & Kimppa, K. (2015). Theorising Web 3.0: ICTs in a changing society. Information Technology and People, 28(4), 726–741. https://doi.org/10.1108/ITP-09-2015-0223

Lara, J. A., Aljawarneh, S., & Pamplona, S. (2020). Special issue on the current trends in E-learning Assessment. Journal of Computing in

Higher Education, 32(1), 1–8. https://doi.org/10.1007/s12528-019-09235-w

Larsen, T. J., Sørebø, A. M., & Sørebø, Ø. (2009). The role of task-technology fit as users' motivation to continue information system use. Computers in Human Behavior, 25(3), 778–784. https://doi.org/10.1016/j.chb.2009.02.006

Lavuri, R. (2023). Intrinsic factors affecting online impulsive shopping during the COVID-19 in emerging markets. International Journal of Emerging Markets, 18(4), 958–977. https://doi.org/10.1108/IJOEM-12-2020-1530

Lawson-Body, A., Willoughby, L., Lawson-Body, L., & Tamandja, E. M. (2020). Students' acceptance of E-books: An application of UTAUT. Journal of Computer Information Systems, 60(3), 256–267. https://doi.org/10.1080/08874417.2018.1463577

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 and Management, 42(8), 1095–1104. https://doi.org/10.1016/j.im.2003.10.007

Liang, T. P., & Wei, C. P. (2004). Introduction to the special issue: Mobile commerce applications. International Journal of Electronic Commerce, 8(3), 7–17. https://doi.org/10.1080/10864415.2004.11044303

Liaw, S. S., & Huang, H. M. (2013). Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self-regulation in e-learning environments. Computers and Education, 60(1), 14–24. https://doi.org/10.1016/j.compedu.2012.07.015

Lin, C. P., & Bhattacherjee, A. (2008). Elucidating individual intention to use interactive information technologies: The role of network externalities. International Journal of Electronic Commerce, 13(1), 85–108. https://doi.org/10.2753/JEC1086-4415130103

Lin, K. Y., & Lu, H. P. (2015). Predicting mobile social network acceptance based on mobile value and social influence. Internet Research, 25(1), 107–130. https://doi.org/10.1108/IntR-01-2014-0018

Liu, Y., Li, H., & Carlsson, C. (2010). Factors driving the adoption of m-learning: An empirical study. Computers and Education, 55(3), 1211–1219. https://doi.org/10.1016/j.compedu.2010.05.018

Lu, H. P., & Yang, Y. W. (2014). Toward an understanding of the behavioral intention to use a social networking site: An extension of task-technology fit to social-technology fit. Computers in Human Behavior, 34, 323–332. https://doi.org/10.1016/j.chb.2013.10.020

Lutfi, A. (2022). Factors Influencing the Continuance Intention to Use Accounting Information System in Jordanian SMEs from the Perspectives of UTAUT: Top Management Support and Self-Efficacy as Predictor Factors. Economies, 10(4), 75. https://doi.org/10.3390/economies10040075

Lutfi, A., Saad, M., Almaiah, M. A., Alsaad, A., Al-Khasawneh, A., Alrawad, M., Alsyouf, A., & Al-Khasawneh, A. L. (2022). Actual Use

of Mobile Learning Technologies during Social Distancing Circumstances: Case Study of King Faisal University Students. Sustainability (Switzerland), 14(12). https://doi.org/10.3390/su14127323

Maatuk, A. M., Elberkawi, E. K., Aljawarneh, S., Rashaideh, H., & Alharbi, H. (2022). The COVID-19 pandemic and E-learning: challenges and opportunities from the perspective of students and instructors. Journal of Computing in Higher Education, 34(1), 21–38. https://doi.org/10.1007/s12528-021-09274-2

Mohammadi, H. (2015a). Social and individual antecedents of m-learning adoption in Iran. Computers in Human Behavior, 49, 191–207. https://doi.org/10.1016/j.chb.2015.03.006

Mohammadi, H. (2015b). Social and individual antecedents of m-learning adoption in Iran. Computers in Human Behavior, 49, 191–207. https://doi.org/10.1016/j.chb.2015.03.006

Mumtaz, N., Saqulain, G., & Mumtaz, N. (2021). Online academics in Pakistan: COVID-19 and beyond. Pakistan Journal of Medical Sciences, 37(1), 1–5. https://doi.org/10.12669/pjms.37.1.2894

Mustafa, A. S., Alkawsi, G. A., Ofosu-Ampong, K., & Vanduhe, V. Z., Garcia, M. B., Baashar, Y. (2022). Gamification of E-learning in African universities: Identifying adoption factors through task-technology fit and technology acceptance model. In Next-Generation Applications and Implementations of Gamification Systems, 73–96. https://doi.org/10.4018/978-1-7998-8089-9.ch005

Mutambara, D., & Bayaga, A. (2020). Understanding Rural Parents' Behavioral Intention to Allow Their Children to Use Mobile Learning. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12066 LNCS, 520–531. https://doi.org/10.1007/978-3-030-44999-5_43

Nandwani, S., & Khan, S. (2016). Teachers' Intention towards the Usage of Technology: An Investigation Using UTAUT Model. Journal of Education & Social Sciences, 4(2), 95–111. https://doi.org/10.20547/jess0421604202

O'Bannon, B., & Thomas, K. (2014). New technology–old barrier: Relationship of teachers' perceptions of mobile phone use and age. Society for Information Technology & Teacher Education International Conference, 2014(1), 936–946. https://lucee.learntechlib.org/p/130885/

Or, C. C. P. (2023). Towards an integrated model: Task-Technology fit in Unified Theory of Acceptance and Use of Technology 2 in education contexts. Journal of Applied Learning & Teaching, 6(1). https://doi.org/10.37074/jalt.2023.6.1.8

Pakistan Telecommunication Authority. Annual Report 2021. (2021). https://www.pta.gov.pk/en/annual-reports

Pedro, L. F. M. G., Barbosa, C. M. M. de O., & Santos, C. M. das N. (2018). A critical review of mobile learning integration in formal educational

contexts. International Journal of Educational Technology in Higher Education, 15(1). https://doi.org/10.1186/s41239-018-0091-4

Peterson, R. A. (1994). A meta-analysis of Cronbach's coefficient alpha. Journal of Consumer Research, 21(2), 381-391. https://academic.oup.com/jcr/article-abstract/21/2/381/1799516

Petter, S., DeLone, W., & McLean, E. (2008). Measuring information systems success: Models, dimensions, measures, and interrelationships. European Journal of Information Systems, 17(3), 236–263. https://doi.org/10.1057/ejis.2008.15

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. Annual Review of Psychology, 63, 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. Behavior Research Methods, Instruments, and Computers, 36(4), 717–731. https://doi.org/10.3758/BF03206553

Prieto, J. C. S., Miguelánez, S. O., & García-Peñalvo, F. J. (2014). Mobile learning adoption from informal into formal: An extended TAM model to measure mobile acceptance among teachers. ACM International Conference Proceeding Series, 595–602. https://doi.org/10.1145/2669711.2669961

Qashou, A. (2021). Influencing factors in M-learning adoption in higher education. Education and Information Technologies, 26(2), 1755–1785. https://doi.org/10.1007/s10639-020-10323-z

Rajeh, M. T., Abduljabbar, F. H., Alqahtani, S. M., Waly, F. J., Alnaami, I., Aljurayyan, A., & Alzaman, N. (2021). Students' satisfaction and continued intention toward e-learning: a theory-based study. Medical Education Online, 26(1). https://doi.org/10.1080/10872981.2021.1961348

Ramayah, T. J. F. H., Cheah, J., Chuah, F., Ting, H., & Memon, M. A. (2018). Partial least squares structural equation modeling (PLS-SEM) using smartPLS 3.0. An updated guide and practical guide to statistical analysis. (2nd ed.). Pearson. https://www.researchgate.net/profile/Hiram-Ting/publication/341357609_PLS-SEM_using_SmartPLS_30_Chapter_13_Assessment_of_Moderation_Analysis/links/5ebc2be6a6fdcc90d674eb9c/PLS-SEM-using-SmartPLS-30-Chapter-13-Assessment-of-Moderation-Analysis.pdf

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).

Roca, J. C., Chiu, C. M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. International Journal of Human-Computer Studies, 64(8), 683–696.

https://www.sciencedirect.com/science/article/pii/S107158190600005X?casa_token=eDa7ZTNa0XQAAAAA:U-2CT7KvBKvhn6LkZ7b34batS_QIButxAMoGdiRzIIwFuayrY1oOOoRBs_DEVPVZdrLyjf5SCf8e

Sánchez-Prieto, J. C., Huang, F., Olmos-Migueláñez, S., García-Peñalvo, F. J., & Teo, T. (2019). Exploring the unknown: The effect of resistance to change and attachment on mobile adoption among secondary pre-service teachers. British Journal of Educational Technology, 50(5), 2433–2449. https://doi.org/10.1111/bjet.12822

Sánchez-Prieto, J. C., Olmos-Migueláñez, S., & García-Peñalvo, F. J. (2016). Informal tools in formal contexts: Development of a model to assess the acceptance of mobile technologies among teachers. Computers in Human Behavior, 55, 519–528. https://doi.org/10.1016/j.chb.2015.07.002

Shaya, N., Abukhait, R., Madani, R., & Khattak, M. N. (2022). Correction: Organizational Resilience of Higher Education Institutions: An Empirical Study during Covid-19 Pandemic (Higher Education Policy, (2022), 10.1057/s41307-022-00272-2). Higher Education Policy, 1–27. https://doi.org/10.1057/s41307-022-00287-9

Shodipe, T. O., & Ohanu, I. B. (2021). Electrical/electronics technology education teachers attitude, engagement, and disposition towards actual usage of Mobile learning in higher institutions. Education and Information Technologies, 26(1), 1023–1042. https://doi.org/10.1007/s10639-020-10297-y

Sun, P. C., Tsai, R. J., Finger, G., Chen, Y. Y., & Yeh, D. (2008). What drives a successful e-Learning? An empirical investigation of the critical factors influencing learner satisfaction. Computers and Education, 50(4), 1183–1202. https://doi.org/10.1016/j.compedu.2006.11.007

Sung, H.-N., Jeong, D.-Y., Jeong, Y.-S., & Shin, J.-I. (2015). The Relationship among Self-Efficacy, Social Influence,Performance Expectancy, Effort Expectancy, and Behavioral Intention in Mobile Learning Service. International Journal of U- and e- Service, Science and Technology, 8(9), 197–206. https://doi.org/10.14257/ijunesst.2015.8.9.21

Tan, G. W. H., Ooi, K. B., Sim, J. J., & Phusavat, K. (2012). Determinants of mobile learning adoption: An empirical analysis. Journal of Computer Information Systems, 52(3), 82–91. https://www.tandfonline.com/doi/abs/10.1080/08874417.2012.11645561?casa_token=GXqp66W0h6wAAAAA:PZiqKYQ7BJdVZQQZgXrROYgTTUbQN2GCTsjInr64yHXXXAwxMLEgv-W67nnbHUy1rH_Cn5A7VoKFmFF7

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly: Management Information Systems, 27(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly: Management Information Systems, 36(1), 157–178. https://doi.org/10.2307/41410412

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. Journal of Global Information Technology Management, 13(1), 5–27. https://doi.org/10.1080/1097198X.2010.10856507

Weng, C., Tsai, C. C., & Weng, A. (2015). Social support as a neglected e-learning motivator affecting trainee's decisions of continuous intentions of usage. Australasian Journal of Educational Technology, 31(2), 177–192. https://doi.org/10.14742/ajet.1311

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. Computers in Human Behavior, 67, 221–232. https://doi.org/10.1016/j.chb.2016.10.028

Wu, B., & Zhang, C. (2014). Empirical study on continuance intentions towards E-Learning 2.0 systems. Behaviour and Information Technology, 33(10), 1027–1038. https://doi.org/10.1080/0144929X.2014.934291

Ye, J. H., Lee, Y. S., Wang, C. L., Nong, W., Ye, J. N., & Sun, Y. (2023). The Continuous Use Intention for the Online Learning of Chinese Vocational Students in the Post-Epidemic Era: The Extended Technology Acceptance Model and Expectation Confirmation Theory. Sustainability (Switzerland), 15(3). https://doi.org/10.3390/su15031819

Yu, T. K., & Yu, T. Y. (2010). Modelling the factors that affect individuals-utilisation of online learning systems: An empirical study combining the task technology fit model with the theory of planned behaviour. British Journal of Educational Technology, 41(6), 1003–1017. https://doi.org/10.1111/j.1467-8535.2010.01054.x

Zaidi, S. F. H., Kulakli, A., Osmanaj, V., & Zaidi, S. A. H. (2023). Students' Perceived M-Learning Quality: An Evaluation and Directions to Improve the Quality for H-Learning. Education Sciences, 13(6), 578. https://www.mdpi.com/2227-7102/13/6/578