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Article

Educators' Utilizing One-Stop Mobile Learning Approach amid Global Health Emergencies: Do Technology Acceptance Determinants Matter?

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Abstract: In July 2022, the World Health Organization (WHO) declared the rapidly spreading monkeypox outbreak a global health emergency; in the future, this may cause the closure of higher education institutions and a shift toward digital learning. As before, specifically in March 2020, the WHO expressed that COVID-19 is a worldwide pandemic. This transformation was accompanied by the widespread adoption of mobiles and their applications in learning with organised or non-organised forms. Although many articles have recorded the importance and effectiveness of mobile learning in higher education, other articles have indicated the weak utilisation of mobile learning amid the COVID-19 pandemic, especially by university educators (UEs). In addition, these articles often focus on the opportunities, challenges, and weaknesses of mobile learning amid COVID-19, but few studies have handled the acceptance of the UEs to adopt a mobile learning approach amid COVID-19 by the unified theory of acceptance and use of technology (UTAUT). This article's main contribution is extending the (UTAUT) model in context and reviewing the acceptance of the adoption of mobiles and their applications in education as an approach amid global health emergencies, i.e., COVID-19 and monkeypox. The data were gathered from university educators (N = 392) in Saudi Arabia. The hypotheses were evaluated with data that were analysed using structural equation modelling (SEM). The results demonstrated that six of the eight hypotheses had high and significant effects on behaviour intention (performance expectancy (PE), effort expectancy (EF), social influence (SI), facilitating conditions (FC), self-efficacy (SE), and users' awareness (UA)). Two of the eight factors have insignificant or negative impacts on behaviour intention (users' perceptions (UP) and technology challenges (TC)), which need an additional review by policymakers, practitioners, mobile learning providers, and investigators looking to develop efficient strategies concerning mobile learning.

Keywords: mobile learning; digital learning; the (UTAUT); global health emergencies; COVID-19; monkeypox; sustainability of teaching; Kingdom of Saudi Arabia

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1. Introduction

In 2014, UNESCO's "Global Education 2030 Framework" included the critical position of mobile devices and their applications in student learning, called mobile Learning/m-Learning; it also indicated students' adoption of almost all the information from the internet directly using tablets and mobile devices [1]. Likewise, the widespread use of mobile devices and applications allows educators to organise the educational process [2]. Additionally, UNESCO's Framework added that mobile learning would become more integrated with higher education in the next fifteen years and regular with formal and non-formal education [1]. Mobile learning (ML) is an improved association between technological and pedagogical innovations; mobile learning helps learners develop technical and digital skills, find answers to their inquiries, develop a mind of cooperation, authorise knowledge sharing, and exploit their learning outcomes [3]. Similarly, ML allows educators to personalise education and allow learners to self-regulate education [4]. Furthermore, educators can make available the teaching methods at any place, anytime, and anywhere; ML makes the learning process not limited to one place [5].

In March 2020, the World Health Organization (WHO) expressed that COVID-19 is a worldwide pandemic [6]. By maintaining social distancing to control the COVID-19 attacks, the nations pushed to shift many life practices, such as the education process, which has transformed from physical classrooms to virtual classrooms and remote teaching [7]. In the Kingdom of Saudi Arabia (KSA), higher education organisations have adopted diversity in providing digital education through technologies and online platforms that provide high-quality education, which is equal to that provided in physical classrooms [8]. Several universities have adopted diverse online platforms, e.g., Blackboard, D2L, Moodle, and other platforms [9]. Others adopted collaborative online platforms that were less pricey, e.g., Google Meet, Zoom, Teams, and others [10]. Likewise, universities have embraced social network applications, e.g., telegram, Kaizala, WhatsApp, and others, to support teaching and learning [11]. Most Saudi Arabia universities' have adopted mobile learning applications (e.g., IKFU app, ETC KSU app, myKAU app, KFUPM app, MyKKU app, and others), which work as complete learning tools to provide online lectures, alerts, quizzes, academic advising, and includes digital content storages [12]. Additionally, mobile platforms have been excellently integrated into smartphone store applications to be available anytime, anywhere. Hence, this transformation and all of these techniques have become an obligation for university educators (UE), who must choose the suitable tools for digital learning; these needs are assessed based on several criteria, such as protection, cost, efficiency, quality of service, data security, and others [4]. All of the above have kept the higher education organisations in KSA to achieve their first academic assignment, with continuous teaching/learning once a state of emergency is declared and COVID-19 spreads.

The mobile learning approach (MLA) has provided multiple benefits, such as sustainability, flexibility, applicability, and facilitating digital learning (DL) [13]. Furthermore, several studies have indicated the effectiveness of mobile learning within higher education [14]. However, several studies have shown the limited use of mobile learning within higher education in Saudi Arabia during COVID-19 [15]. According to Tamilmani, K., N.P. Rana and Y.K. Dwivedi [16], and Alvi, I. [17], university educators' pedagogical beliefs, behaviours, and intentions impact the adoption and use of technologies in education. Moreover, the practical and acceptable use of technologies, such as mobiles, in the learning environment depends mainly on the educators' readiness, comfort level, attitudes, beliefs, and previous experience [18]. Furthermore, investigating the educators' behavioural intentions and users' behaviour is essential because both are values of acceptance for utilising technologies in education, such as mobiles, and substantially affect sustainability [19]. Hence, this article is an endeavour to answer the following question: what are the acceptance determinants of university educators to adopt the mobile learning approach amid global health emergencies, i.e., COVID-19 and Monkeypox?

Therefore, this article investigates Saudi Arabia's university educators' acceptance of the sustainable utilisation of mobile technologies in the teaching environment amid global health emergencies. Additionally, this article's contribution is to study the university educators' behavioural intention (B.I.) and inspect their use behaviour (U.B.) of the mobile teaching approach (MLA); likewise, this article provides a discussion of the relevance of mobile learning as an approach from the perspective of digital learning sustainability. Additionally, it aims to gain feedback from users about utilising mobile learning amid emergencies to determine and experiment with the factors which have impacted utilising this approach in education. In addition, this article involved the (UTAUT) model by extending factors to examine the university educators' behavioural intention (B.I.) and their use behaviour (U.B.) to adopt the (MLA). The article focused on university educators in fourteen King Faisal University colleges. The university educators were chosen because they usually include various affiliates such as nationalities, gender, age, and technologies.

Finally, the current article is organised as follows: the first part is the intro, and the second part reviews the theoretical foundation and hypotheses building. The third part elucidates the research model. Then, the fourth part excuses the approaches used to execute the estimation. The fifth part is a discussion of the significant results. In the last part, the results are summarised, essences are marked, and future studies and limitations are explained

2. Theoretical Foundation and Hypotheses Building

2.1. Mobile Learning in Higher Education Amid the COVID-19 Pandemic

Many articles have been studied that handle higher education institutions' reactions to COVID-19 [15,20,21]. Additionally, several prior articles have reviewed the benefits and opportunities of mobile learning (ML) amid COVID-19 and emphasised the significance of embracing mobile learning to ensure the effectiveness of digital education [19]. Likewise, the studies conducted on the scale of developing countries' scopes, i.e., Nigerian, Indonesia, and Thailand, showed that despite limited educational resources and poor infrastructure, the mobile learning approach was the most helpful option for maintaining the quality of digital learning, ensuring a digitalisation shift, and enhancing learning outcomes in higher education amid COVID-19 [22]. Furthermore, the other articles showed that the mobile learning approach supports the success of digital learning and helps manage a shift process in the curriculum that reflects knowledge structure shifts and educational competencies amid and after COVID-19 [14]. In the same vein, several articles emphasised that higher education organisations should know the educators' needs to create positive digital learning experiences through mobile technology and adopt a mobile learning approach within the curricula amid and after COVID-19 [23]. Additionally, according to Alowayr, Ali [24], and Bacolod, DB, 2022 [25], the value of the mobile learning approach in the digital transformation launched in education amid COVID-19 could not be questioned. However, educators' acceptance degree of the mobile learning approach should be considered to develop their knowledge, competencies, and skills and achieve educational outcomes. In addition, the impressions of university educators (UEs) were diverse between acceptance and rejection of the adoption of the mobile learning approach amid COVID-19; multiple studies in Bangladesh and India agreed that the context indicated that the UEs rejected the mobile learning approach due to poor support services, applications, resources, training on usage, and digital issues [26]. Additionally, the same impression was documented by the UEs in Malaysia, indicating that mobile learning may not have the expected effects in an emerging country [27]. By comparison, Butt et al. [25], in Pakistan, stated that the UEs in some private colleges indicated an acceptance impression of the mobile learning approach [28]. So, the UEs perceive mobile learning as flexible due to mobile applications, activities, and resources that save effort, time, and money [29]. Female university educators in Indonesia have an extra impression of mobile learning than males, despite discovering that mobile learning encourages their attraction [30]; therefore, the UEs are ready to adopt mobile learning. Other studies on Nepal nursing educators indicated a positive attitude concerning mobile learning, although they faced some technical issues while implementing mobile learning [31]. The article documented that mobile learning may be a significant choice for digital learning resources if mobile learning evolves user familiarity via handling inflexible technological issues and their intent.

Similarly, in a study by Aziz M et al. [12], the acceptance levels among the UEs concerning mobile learning were high (96.2% vs. 13.8%), and the same article extrapolated that interpretation on an organisational, technological, and professional basis. Other barriers among the UEs are necessary for mobile learning success and the execution of any technology approach in higher education [14]. Alotaibi et al. [8] conducted a study on Saudi Arabia's higher education educators and reported some issues of mobile learning, such as communication, building skills and knowledge, and a better understanding of mobile learning; they concluded that mobile learning did not provide an effective method for all comparisons with others digital learning approaches during COVID-19 [9]. Moreover, this article experiments if the educators in Saudi Arabia's higher education institutions accept mobile learning adoption based on their different experiences amid COVID-19. Furthermore, the article highlights factors supporting the UEs' usage of mobile learning based on behavioural intention and user behaviour which could be created post-COVID-19.

2.2. The Extended UTAUT Model, Concepts, and Hypotheses

Multiple theories and models have focused on the acceptance and use of technologies, hence, explaining the users' acceptance, actions, and behaviours of technologies and applications, such as a model of technology acceptance (TAM), a model of motivational (MM), a theory of innovation diffusion (IDT), a theory of planned behaviour (TPB), a unified theory of acceptance and use of technology (UTAUT & UTAUT2), and more [32]. Moreover, multiple articles have compared and performed extended examinations of theories and models [33]. Furthermore, studies were conducted on the scale of developing the countries' scope, i.e., India., while numerous articles have approved the superiority of the UTAUT in the technology acceptance scenario, especially technology that was used in learning and education as mobile technology and applications [34]. The UTAUT can also explain 41% of the variances within the behavioural intention of technology users and 23% of the technology use behaviour [35]. The UTAUT setup estimates duo variables of dependent (DVs), such as behavioural intent (BI) and user behaviour (UB), via the assessment of influence and four main variables of independent IVs: the expectancy of performance (PE), the expectancy of effort (EE), the influence of socially (SI), and the conditions of facilitating (FC) [34].

Likewise, the current article used the extending (UTAUT) model that has been created based on analysing theories and models of technology acceptance following the (TAM), (MM), (IDT), (TPB), (TRA), PC utilization model (MPCU), the TAM and TPB combined model (CTAM-TPB), and theory of social cognitive (SCT) [36]. Furthermore, the extending UTAUT was designed as a suitable model to examine all affecting factors on the users' intention of using mobile learning approaches in higher educational institutions; the articles reveal the presence of additional elements, which are the users' perceptions (UP), self-efficacy (SE), technologies challenges (TC), and users' awareness (UA); these variables may have an impact on the behavioural intention of university educators to accept the mobile learning approach [3].

This article tried to extend the (UTAUT) with four variables that might exemplify mobile learning use in higher education. Additionally, it proposes that the intention of behavioural (BI) to use mobile learning is instructed by (UP), (SE), (PE), (EE), (SI), (TC), (UA), and (FC). (Figure 1 displays the extending (UTAUT) model).

Furthermore, research on the differences among university educators' behavioural intention and behaviour to understand their acceptance of the mobile learning approach in Saudi Arabia's higher education institutions amid COVID-19 remains very limited. So, the current article expects significant differences between the university educators' behavioural intention (BI) and user behaviour (UB) to understand their acceptance of the adoption of the mobile learning approach, especially in users' perceptions (UP), self-efficacy (SE), the performance expectancy (PE), the effort expectancy (EE), the social influence (SI), the technologies challenges (TC), the users' awareness (UA), and the conditions of facilitating (FC) amid COVID-19.

The users' perceptions (UP) of mobile education's quality, such as its safety, reliability, speed, user-friendliness, customization, and user interface [37], typically reflect the overall quality of mobile education for users. These perceptions can significantly impact the behavioural intention (BI) to adopt mobile education [38]. Self-efficacy (SE), or the level of competence that users have in adopting mobile education to complete a particular educational task [39], can also significantly affect the BI to adopt mobile education [40]. Performance expectancy (PE) is the belief that using mobile education will lead to progress in the educational process and significantly affect BI to the adoption of mobile education [37,41]. Effort expectancy (EE), or the belief that using mobile education will lead to achievement in the learning process in exchange for the effort put in, can both significantly impact the BI to adopt mobile education [41,42].

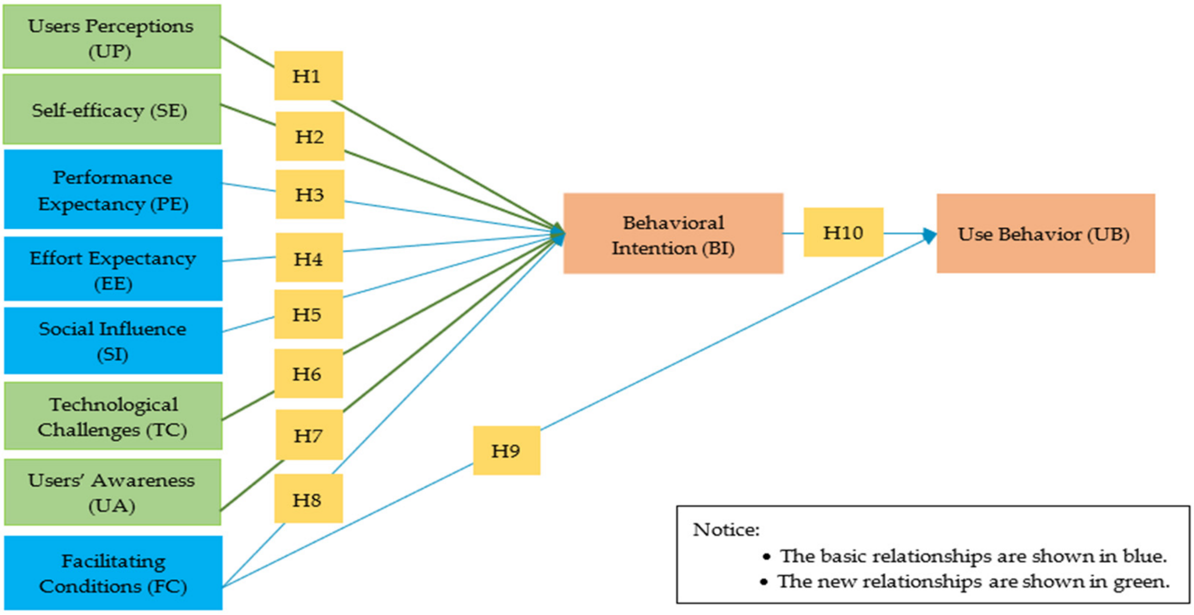

Figure 1. The extending (UTAUT) model.

Social influence (SI), or the perception that others believe mobile education is important, can also significantly impact the BI to adopt mobile education [17]. Technological challenges (TC), including technical infrastructure, management, and support for adopting mobile educational technology [43], can also significantly impact the BI to adopt mobile education [17]. The users' awareness (UA) of challenges and limitations in adopting mobile education, such as technology and internet access, can also significantly affect the BI to adopt mobile education [41]. Facilitating conditions (FC), or the understanding of the importance and role of mobile technology in education and the technical issues that may hinder its optimal use, could significantly impact the BI [44] and the user behaviour (UB) to adopt mobile education [45,46]. UB can also significantly impact the BI to adopt mobile education [8,44,47]. Hence, based upon the above debate, the article examines the following hypothesizes:

Hypothesis 1 (H1). *User perception (UP) has a positive impact on university educators' behavioural intentions (UEBI).*

Hypothesis 2 (H2). *Self-efficacy (SE) has a positive impact on UEBI.*

Hypothesis 3 (H3). *Performance expectancy (PE) has a positive impact on UEBI.*

Hypothesis 4 (H4). *Effort expectancy (EE) has a positive impact on UEBI.*

Hypothesis 5 (H5). *Social influence (SI) has a positive impact on UEBI.*

Hypothesis 6 (H6). *Technological challenges (TC) have a positive impact on UEBI.*

Hypothesis 7 (H7). *User awareness (UA) has a positive impact on UEBI.*

Hypothesis 8 (H8). *Facilitating conditions (FC) has a positive impact on UEBI.*

Hypothesis 9 (H9). *The impact of facilitating conditions (FC) has a positive impact on user behaviour (UB).*

Hypothesis 10 (H10). *The university educators' behavioural intention (UEBI) has a positive impact on user behaviour (UB).*

3. Research Methodology

3.1. Sampling

The population of the article included all university educators enlisted in King Faisal University (KFU) colleges in Al-Ahsaa (Eastern Region), Saudi Arabia. According to statistics, in 2021, over 1500 faculty members registered in fifteen colleges. The article investigates colleges in the KFU that considerably relied on Blackboard mobile applications in addition to online platforms to manage content, lectures, exams, and student communication amid the COVID-19 pandemic. Roscoe [48] indicated that the sample size calculation must be based on the total number of items. Muthén [49] added that a sample should be more than 150.

Additionally, the faculty members were selected who were well-versed in utilizing mobile phone technologies in learning who considerably relied on Blackboard mobile applications in addition to online platforms to manage content, lectures, exams, and student communication amid the COVID-19 pandemic. Likewise, five hundred (500) e-questionnaires were sent to college educators. The entirety of 392 surveys was received, with an overall response of over 78%. The investigators provided the surveys to faculty educators via their private networks, i.e., WhatsApp, e-mails, and more. There was no authority over faculty educators, so they were informed that the survey was just for scientific research and that their responses would be unidentified. Participations were voluntary and unnamed, and all the essential safeguards were on site to assure data confidentiality. All personally identifiable information about them was removed from the publicly available analysis to ensure that answers could not be recognized. Further, keen items such as name, age, etc., were optional.

3.2. Instrument Development

The questionnaire estimated the study factors utilizing a multi-item scale (Likert's 5-point scale). The questionnaire was constructed of eight formative factors and 24 derived items. Furthermore, all measurement factor items were selected from the documented literature to estimate the multiple elements [17]. The questionnaire measured the research factors employing a multi-item scale (Likert's 5-point scale), varying from strongly agree (5) to strongly disagree (1). The survey had 24 items and was organized to define the eight factors of the revised (UTAUT) model (See Table 1).

Table 1. Questionnaire factors items.

Factors	Code	Indicator
Users' Perceptions (UP)	UP1	I would not perceive the adoption of mobile education to gain good interaction between educators and students.
	UP2	I would not perceive the adoption of mobile education as helpful because others might hack my data at any time.
	UP3	I sense that mistakes have occurred when adopting the mobile education approach.
Self-efficacy (SE)	SE1	I can adapt the mobile education approach when the application assistance guide is available.
	SE2	I could adopt the mobile education approach if someone guides me to use it ideally, as in the (LMS).
	SE3	I will adopt the mobile education approach if I train well to achieve the highest performance with my students.

Table 1. *Cont.*

Factors	Code	Indicator
Performance Expectancy (PE)	PE1	I expect my teaching performance will be increased if I adopt the mobile teaching approach.
	PE2	I believe the mobile teaching approach is better than other methods in digital education.
	PE3	I consider adopting the mobile teaching approach more efficacious in driving learning and receiving knowledge.
Effort Expectancy (EE)	EE1	I expect the mobile education approach is uncomplicated.
	EE2	I anticipate that the mobile education approach can achieve interaction, navigation, and comprehensibility.
	EE3	Overall, I expect the mobile education approach to be effortless to utilize.
Social Influence (SI)	SI1	I utilize mobile education to ensure it is adopted and confirmed in college.
	SI2	I utilize mobile education because all faculty members in the college are using it.
	SI3	Overall, I found that all faculty members in the college, like me, have a good impression of adopting the mobile education approach.
Facilitating Conditions (FC)	FC1	Using the mobile education approach enhances students' independence.
	FC2	The mobile education approach enhances and supports students' individual learning.
	FC3	Using the mobile education approach facilitates students' access to knowledge and mastery of it.
Technological Challenges (TC)	TC1	The technical support team delivers help and service for adopting the mobile education approach.
	TC2	The content production team enables the resources and knowledge for adopting the mobile education approach.
	TC3	Adopting a mobile education approach is suited for my courses.
Users' Awareness (UA)	UA1	I can access teaching by mobile from anywhere.
	UA2	I am aware that mobile devices are suitable for education.
	UA3	Overall, I know utilizing the (MLA) is important.

As soon as the questionnaire was completed, the investigators started creating the online different faculty members who were verified before providing the URL to participants. An opening was created to describe the study goals and welcome participants. The participants were informed of their confidentiality and the survey objective. After the opening, contact information and demographical data were contained for any more queries. Pursuing the survey translation from the original language (English) into the respondents' native language (Arabic), twenty academics were asked to check the items for essential suitability, clearness, and simpleness. Throughout this process, no significant changes were created, whereas a few recommendations for boosting the clearness of the reader were included. The survey URL (in English and Arabic) was circulated via participants' private e-mails and social media in April 2022 and endured for four weeks (See the URL: https://forms.office.com/r/XdirhiUgXt) (accessed on 1 April 2020). Day to day, the investigators reviewed and observed the responses. By terms, gender was 78.57% female and 21.43% male, while the age range was 25–45.

3.3. The Demographical Characteristics of the Participants

Below is a summary of the demographical characteristics of the participants. By terms, the gender was 78.57% female and 21.43% male, while the age range was 25–45 (See Table 2).

Table 2. Participants' demographical characteristics.

The Demographical Items	Frequency	Percentage
Gender		
Male	84	21.43%
Female	308	78.57%
Age		100.00%
25–35	107	27.30%
36–40	215	54.85%
41–45	67	17.09%
46+	3	0.77%
Occupation		100.00%
Lecture	107	27.30%
Assistant Professor	215	54.85%
Associate Professor	67	17.09%
Full Professor	3	0.77%
Level of education		100.00%
Masters	107	27.30%
Ph.D.	215	54.85%
Others	70	17.86%
Ethnicity		100.00%
Agriculture and Food Sciences	28	7.14%
Veterinary Medicine	11	2.81%
Education	12	3.06%
Business Administration	31	7.91%
Medicine	7	1.79%
Science	37	9.44%
Computer Sciences and Information Technology	2	0.51%
Clinical Pharmacy	28	7.14%
Engineering	7	1.79%
Applied Medical Sciences	34	8.67%
Arts	139	35.46%
Applied	25	6.38%
Law	23	5.87%
Dentistry	8	2.04%

3.4. Measurement Model and Data Analysis Techniques

This article has used the modelling of structural equation (SEM) to analyse the questionnaire information in two stages: (1) the measurement model for confirmatory factor analysis and (2) the structural model for path analysis. The tests were utilised to validate the measurement model for confirmatory factor analysis: (1) goodness-of-fit indices, (2) discriminant validity, and (3) convergent validity. To thoroughly analyse the data, a gauged general model vigour using a mixture of statistical techniques was employed, (1) namely chi-square, (2) root mean square error of approximation (RMSEA), (3) good-ness-of-fit (GFI), (4) comparative fit index (CFI), (5) Tucker–Lewis's index (TLI), and (6) adjusted goodness-of-fit index (AGFI) [50]. As recommended by several scholars, the article's measurement model attained good goodness-of-fit indices (See Table 3) [50,51]. The software was employed throughout the data analysis ware SPSS version 25 (SPSS Inc., Chicago, IL, USA) and AMOS V25.

Table 3. Comparison of goodness-of-fit statistics of full measurement models.

Threshold Values	χ^2/d.f (<2)	CFI (>0.9)	AGFI (>0.8)	TLI (>0.9)	GFI (>0.9)	RMSEA (<0.08)
Total Measurement Structural Model Fit Indices	1.734	0.971	0.863	0.952	0.921	0.049

4. Results

4.1. Data Analysis

The reliability test uses Cronbach's alpha and compound reliability (CR). The lowest value of 0.7 was demanded. The construct of internal consistency, which reflects a suitable reserve of Cronbach's alpha, was delivered by (CR) [50,51]. All the stated criteria for reliability tests were satisfied in this article. The Cronbach's alpha values varied between 0.793 and 0.882, and CRs between 0.798 and 0.887 (See Table 4).

Table 4. Measurement model's convergent validity and reliability.

Constructs and Items	Factor Loading (>0.7)	SMC	CR	Cronbach's α	AVE
(UP)			0.798	0.793	0.580
UP1	0.742	0.521			
UP2	0.797	0.598			
UP3	0.720	0.621			
(SE)			0.887	0.882	0.768
SC1	0.873	0.849			
SC2	0.854	0.737			
SC3	0.798	0.719			
(PE)			0.875	0.870	0.739
PE1	0.879	0.810			
PE2	0.812	0.712			
PE3	0.798	0.694			
(EE)			0.859	0.854	0.730
EE1	0.839	0.761			
EE2	0.791	0.699			
EE3	0.813	0.731			
(SI)			0.847	0.842	0.768
SI1	0.743	0.713			
SI2	0.869	0.803			
SI3	0.794	0.787			
(TC)			0.840	0.835	0.753
TC1	0.839	0.763			
TC2	0.761	0.725			
TC3	0.785	0.772			
(UA)			0.865	0.860	0.775
UA1	0.792	0.713			
UA2	0.846	0.811			
UA3	0.823	0.802			
(FC)			0.872	0.867	0.770
FC1	0.821	0.701			
FC2	0.871	0.846			
FC3	0.789	0.764			
(BI)			0.856	0.851	0.799
BI1	0.906	0.895			
BI2	0.927	0.903			
(UB)			0.810	0.805	0.693
UB1	0.831	0.724			
UB2	0.864	0.756			

Notices: The convergent values and discriminant validity are superior. Likewise, interior consistency values are superior (Cronbach's alpha test of reliability); Users'_Perceptions, UP; Self_efficacy, SE; Performance_Expectancy, PE; Effort_Expectancy, EE; Social_Influence, SI; Technological_Challenges, TC; Users'_Awareness, UA; Facilitating_Conditions, FC; Behavioral_Intention, BI; Use_Behavior, UB. (To test discriminant validity, the investigators correspond to the square root of AVE of every construct and its correlation coefficient with other constructs. The square root of the AVE value for every single latent variable is more than its correlation evaluations with other constructs [50].

Likewise, we calculated the discriminant and convergent validity evaluation. All standardized factor loadings (SFL) should be ≥0.60 [50]. Similarly, every construct's (CR) value should indicate a minimum value of 0.7 or above [50,51], while a minimum value of 0.50 is essential for the extracted average variance value (AVE) [50]. All constructs and variables met the needed requirements for adequate convergent validity. The items' values of (SFL, CR, and AVE) range between 0.720 and 0.927, between 0.798 and0.887, and between 0.580 and 0.799, respectively, indicating satisfactory convergent validity; the items' values must be ≥0.4 for modest square multiple correlations (SMC) to express the extent to which an item measures a construct [51] (See Table 5).

Table 5. Discriminant validity assessment.

	AVE	UP	SC	PE	EE	SI	TC	UA	FC	BI	UB
UP	0.580	−0.698									
SC	0.768	0.231 **	0.901 *								
PE	0.739	0.305 †	0.013	0.769 *							
EE	0.730	0.298 ***	0.132 *	0.201	0.568						
SI	0.768	0.199 *	0.244	0.234 *	0.153 *	0.796					
TC	0.753	−0.257	0.041	0.101	−0.231 *	0.109	0.698				
UA	0.775	0.101	0.172	0.114	0.201	0.312 **	0.301 **	0.689 †			
FC	0.770	0.297 *	0.198 *	0.102	0.136	0.146	0.159	0.273	0.689 *		
BI	0.799	0.401 *	0.468 **	0.233 **	0.214 **	0.192	0.247	0.209 *	0.397 **	0.829	
UB	0.693	0.132 *	0.102	0.175	0.148	0.201 **	0.237 ***	0.183	0.249 *	0.237	0.865

Notices: Significance threshold values † $p < 0.100$, * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$; the diagonals are indicative of the square root of average variance extracted [8].

4.2. Path Analysis and Structural Model

The path analysis implicates experimentation with the structural model of dependence level between the set of control and independent variables (1) and dependent variables (2) [50]. The goodness-of-fit enabled the acquisition of the value of the cut-off threshold of χ^2/d.f, RMSEA, CFI, AGFI, GFI, and TLI (See Table 6).

Table 6. Measurement model.

Threshold Values	χ^2/d.f (<2)	RMSEA (<0.08)	CFI (>0.9)	AGFI (>0.8)	GFI (>0.9)	TLI (>0.9)
Structural Model Fit Indices	1.801	0.0491	0.968	0.872	0.903	0.928

In summary, the structural model analyses the results and checks the hypotheses of the study; Table 7 indicates that the (UP) had an insignificant impact on the (BI) (β = 0.068); thus, the (H1) was disconfirmed. Likewise, the (H6) was disconfirmed because the (TC) had a negative impact on the (BI) (β =−0.194). On the other hand, the (SC) impacted positively and significantly on the (BI) (β = 0.261, $p < 0.05$); hence, the (H2) was confirmed. In addition, the (H3) was confirmed because the (PE) impacted positively and significantly on the (BI) (β = 0.168, $p < 0.05$). Additionally, the (EE) impacted positively and significantly on the (BI) (β = 0.229, $p < 0.01$); so, the (H4) was also confirmed. As cited, the (H5) was confirmed because the (SI) impacted positively and significantly on the (BI) (β = 0.237, $p < 0.05$). Hence, the (H7) confirmed that the (UA) impacted positively and significantly on the (BI) (β = 0.182, $p < 0.05$). Alike, the (H8) asserted that the (FC) impacted positively and significantly on the (BI) (β = 0.287, $p < 0.01$), so it was confirmed. Further, the (FC) impacted positively and significantly on the (UB) (β = 0.201, $p < 0.05$)., so the (H9) was also confirmed. Finally, the (H10) was confirmed because there was a positive and significant association between the (BI) and the (UB) (β = 0.304, $p < 0.001$).

Table 7. An overview of the structural model analysis results.

Hypotheses	Relationship	C.R. (*t*-Value)	*p*	β	Result
H1	UP→BI	1.014	0.162	0.068	Disconfirmed
H2	SC→BI	2.714	0.018	0.261 **	Confirmed
H3	PE→BI	3.012	0.003	0.168 *	Confirmed
H4	EE→BI	3.121	0.002	0.229 *	Confirmed
H5	SI→BI	2.871	0.032	0.237 *	Confirmed
H6	TC→BI	−2.965	0.202	−0.194	Disconfirmed
H7	UA→BI	1.967	0.021	0.182 *	Confirmed
H8	FC→BI	2.761	0.009	0.287 **	Confirmed
H9	FC→UB	2.543	0.012	0.201 **	Confirmed
H10	BI→UB	3.429	0.0001	0.304 ***	Confirmed

Notices: the dependent variable (IAE); *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; *p*-value is two_tailed.

5. Discussion

The results indicate that the users' perceptions (UP) had an insignificant influence on the user's behavioural intention (BI) for adopting the mobile education approach during COVID-19; this agrees with the study of Khlaisang et al. [52]; Although the (UP) is low, several studies reported on its effect with the (BI) to the acceptance of utilizing technologies and that the (UP) is a factor that increases the (BI) [38]. Hence, universities in Saudi Arabia need to understand the faculty members' perceptions which are reflected in their behavioural intention to adopt the mobile education approach amid global health emergencies, i.e., COVID-19 and monkeypox.

Concerning the impact of self-efficacy (SE) on the behavioural intention to adopt mobile education amid emergencies, the results indicate that the (SE) indicated a significant positive impact on the (BI), which conforms with a study by Delia [39]; this study confirmed that users who have a high self-efficacy to utilize technologies also have a behavioural intention to adopt a mobile education approach [40]. Therefore, the designers and developers of mobile applications, and platforms should innovate more issues based on faculty members' self-efficacy to work efficiently at universities, such as web learning management systems platforms and ensure no problems [52]. Moreover, the article indicated that performance expectancy (PE) had a positive impact on the (BI) adoption of the MLA during COVID-19. It revealed that technology implementation is essential to increase the users' expectancy performance and achieve the desired goals, which positively impact use. As well, an increase in the (PE) of mobile education encourages the behavioural intention to use it; this finding agrees with other studies [53]. Additionally, the effort expectancy (EE) indicated a significantly positive impact on the BI to adopt the mobile education approach, which is in line with studies [54]. Likewise, the EE is a critical predictor for the BI guiding enriched mobile education adoption. So, the duty of designing and developing mobile applications and platforms must concentrate on developing comfortable and suitable elements and interfaces for the expectancy effort of staff and students in Saudi Arabia universities to achieve higher performance [55].

Alike, social influence (SI) indicated a significant positive impact on the BI for the adoption of mobile education during COVID-19, which echoes what other researchers have found [56]. Further, the SI drives users to specific behaviour patterns in response to surrounding people, groups, or societal norms. Therefore, decision-makers in Saudi Arabia Universities should focus on the SI to enhance the BI of university faculty members to adopt a mobile education approach amid global health emergencies, i.e., COVID-19 and monkeypox [57]. Correspondingly, the technological challenges (TC) did not emerge to deliver any issues regarding reliability and validity. The results indicated that the TC included a negative and insignificant impact on the BI to adopt mobile education during COVID-19; this agrees with many studies [4]; Hence, the TC limits the use of technology and may be one of the reasons for its rejection. Some educators are not convinced of the importance of using technological means in teaching. The lack of competencies is adequately qualified to use technological devices in education. Therefore, decision-makers should focus on unravelling the TC to ensure sustainable mobile education in Saudi Arabia Universities [58].

Another finding is that the users' awareness (UA) factor leaned a significant impact positive on the BI of adoption for the (MLA) amid COVID-19, which is consistent with the findings of many studies [41]. Accordingly, the results about the (UP), (SE), (PE), (EE), (SI), (TC), and the (UA) when displayed to university faculty members, made them perceive the mobile education approach as advantageous to their position; these should not pause to adopt it. Furthermore, the educators realize and understand that adopting their peers makes them also take the (MLA) up. Similarly, the facilitating conditions (FC) and the impact of (BI) agrees with other works [13]. On the other hand, different researchers reject this finding, such as Lee et al. [58]. The FC includes the technical infrastructure and support for using the systems and applications [19], such as support delivered by the university to educators when using mobiles in education, including providing remote access to learning resources, professional training, mobile learning applications, and unique platforms, and other issues to adopt mobile education [4]. Moreover, the FC significantly impacted user behaviour (UB) for adopting mobiles in education. This finding agrees with studies [19]. Likewise, the FS has a force inspired to utilize the technologies as the finding for the BU has positively impacted the UB of adopting the mobile education approach. This conforms with [59], who concluded a significant positive relationship between the BI and BU.

Additionally, the adoption of mobile learning has stressed that factors such as objectively measuring their effectiveness and how their actual adoption changes students' learning habits and capabilities need to be considered. In this respect, one of the critical features of neurodidactics is the proposal of optimizing learning effectiveness in a personalized or customized fashion, e.g., because humans learn differently and present structural and functional brain differences [60].

6. Conclusions

The current article is positioned to determine and examine the determinants that impact the adoption of the mobile learning education approach (MLA) during global health emergencies, i.e., the COVID-19 pandemic. The existing UTAUT was modified by inserting four additional factors: users' perceptions (UP), self-efficacy (SE), technological challenges (TC), and users' awareness (UA). Likewise, the research of the structural model was validated and developed using a questionnaire survey given to participants. The practical results indicated that self-efficacy (SE), performance expectancy (PE), effort expectancy (EE), social influence (SI), users' awareness (UA), and facilitating conditions (FC) are factors that significantly predict the behavioural intention (BI) for the adoption of the (MLA), while users' perceptions and technologically challenging conditions are not. They want more studies and research from investigators. Similarly, facilitating conditions (FC) significantly facilitated the adoption of the (MLA) during the COVID-19 pandemic. The conclusions documented currently participate in our understanding of the potency of the pandemic's influence, particularly on higher education. The article performs as a stepping stone to elevate studies on the digital learning approach generally, and mobile education especially, in Arab countries by additional elements; thus, behavioural intention and user behaviours towards adopting mobile technologies can become an approach in education.

Implications and Contributes

This article's results theoretically, methodologically, and practically contribute to digital learning studies, especially mobile education, and the comprehension of its practices. Theoretically, the results apply to the publications associated with mobile education and its correlating attributes. The previous studies adopted the (UTAUT) model or other versions to evaluate the richness and deepness of the MLA. For the investigators, this is the main article for extending and modifying the UTAUT model and applying it to the learning faculty members' acceptance of the adoption of the MLA amid COVID-19 in Saudi Arabia. Concerning the contribution methodologically, the article describes the four-measure factors: users' perceptions (UP), self-efficacy (SE), technological challenges (TC), and users' awareness (UA). Likewise, concerning the implications of this article, this is foremost to document the factors impacting the faculty member's acceptance of the adoption of the (MLA) in Saudi Arabia's higher education section.

Further, the article's results will help the officials, administrators, decision-makers, mobile app developers, and others comprehend what should be revised and significantly expand awareness of educationally effective, user-familiar, and easy-to-utilize apps on various mobile devices. Further, the chief of universities, colleges, and academic departments must develop elevated understanding drives among faculty members about digital learning and its potential threats if mobile education platforms and apps are not used appropriately. Additionally, the service providers must ensure the capability of mobile education to perform all the time correctly, whenever, and anywhere. Likewise, the article's outcomes will enhance user behaviour among the individuals who would adopt the mobile education approach in their courses. Furthermore, organizations adopting the mobile education approach can boost user behaviour by focusing on critical factors in the article. The article includes some limitations that require handling in future exertions. The data were assembled from solely a tiny sample of faculty members in King Faisal University colleges in Saudi Arabia; thus, the generalizability of the findings to elsewhere in the Gulf, middle eastern, or a more geographical location should minister with caution. Likewise, this article applied the quantitative analysis method, and future research could integrate qualitative and quantitative approaches to discover further reasons and associations between the suggested factors. Additionally, other mediating and moderating variables (age, experience, and gender) could be combined in future research. Finally, for a future research opportunity, it would be beneficial to discuss recent ideas on the use of neuroscience approaches for education and the prospect of using the principles of brain research to understand the effects of the use of technology for remote education [59].

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