electronics

Article

Factors That Influence Mobile Learning among University Students in Romania

Mirela-Catrinel Voicu * **and Mihaela Muntean**

East-European Center for Research in Economics and Business, Faculty of Economics and Business Administration, West University of Timisoara, 300223 Timisoara, Romania
* Correspondence: mirela.voicu@e-uvt.ro

Abstract: During the pandemic years, universities worldwide adopted online teaching on a large scale. Besides desktop systems or laptops, many students also use smartphones for online learning. In our paper, we propose a hybrid theoretical model to analyze the continuance intention to use mobile learning in higher education. The scientific demarche is carried out from different perspectives opened by the models and theories integrated in a unitary approach. In addition to the main constructs taken from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the research model was enriched with new capabilities by considering the Motivational Model (MM), Flow Theory (FT) and the Social Cognitive Theory (SCT). The research model was applied to the Romanian higher education environment and proved that perceived usefulness (PU), habit (HB), perceived skill (PS), and self-efficacy (SE) directly influence the continuance intention to use (CU) smartphones in higher education. Further, performance expectancy (PFE), intrinsic motivation (IM), perceived ease of use (PEOU), and perceived enjoyment (PE) indirectly influence the continuance intention to use (CU). We presented our results according to top studies on the critical challenges and factors influencing smart mobile learning success usage during the COVID-19 pandemic. Thus, we found that Romanian universities provide excellent IT infrastructure and top management support and that creating habits of using m-learning in the context of university classes will strengthen the university culture. The conclusions of the undertaken research represent a starting point in the diversification and flexibility of educational processes in Romanian universities.

Keywords: mobile learning; continuance intention to use; perceived usefulness; habit; perceived skill; self-efficacy

check for updates

Citation: Voicu, M.-C.; Muntean, M. Factors That Influence Mobile Learning among University Students in Romania. *Electronics* **2023**, *12*, 938. https://doi.org/10.3390/electronics12040938

Academic Editors: Mohammed Amin Almaiah, Ahmad Al-Khasawneh, Sébastien Jacques, Omar Almomani and Christos J. Bouras

Received: 1 December 2022
Revised: 28 January 2023
Accepted: 10 February 2023
Published: 13 February 2023

1. Introduction

Mobile learning (m-learning) is a broad term for defining e-learning processes achieved with the help of personal mobile devices such as smartphones, tablets, laptops, and digital notebooks. M-learning represents a natural evolution of e-learning and adds a missing component, such as the wireless feature [1]. Studies on the educational and institutional implications of students' choices to use mobile devices in the learning process are up to date considering the explosion of m-learning during and after the COVID-19 period [2,3]. "The convergence of the mobile devices with existing educational technologies provides learners with greater flexibility by making homogenous learning activities available and accessible by heterogeneous mobile/smart devices" [4]. The learning process involves reading ebooks and documents (e.g., word or pdf); watching educational videos with learning content; attending video conferences; or any learning activity using mobile devices. M-learning is accessible in formal and informal learning environments (see [5,6]). Mobile devices permit students to continue their studies irrespective of location or time zone, improving their learning intention and significance [7,8]. M-learning is flexible learning—"just enough, just in time, just for me" [9]. M-learning helps learners' self-organization, self-direction, and personalized learning and is a valuable technique for delivering lessons and acquiring knowledge [10]. M-learning is essential where teaching and learning methods support a mix of digital and face-to-face meetings [8]. The interactive dimension allows students to practice and share their knowledge instead of passively receiving it from big screens [11]. Research has shown that online learning combined with mobile technology has become an important educational practice for teachers and students [7]. Students rely on m-learning tools and applications for their daily academic tasks. Students use smartphones to obtain various information from the Internet. Higher education is a particularly appropriate medium for integrating student-centered m-learning because mobile devices have become ubiquitous on college campuses [12]. Smartphones are a teaching tool, method, and mechanism to spread information quickly [13]. Some authors consider mobile devices and technologies innovative and vital in higher education [5,14]. Teachers should thoroughly utilize computers and Internet resources to enhance teaching [15]. Using mobile devices in the classroom needs no special skills and makes learning more accessible than using desktop computers [11]. Mobile learning supports informal learning, this being achieved by using WhatsApp, messaging, or YouTube applications. The role of m-learning is to complete but not replace existing learning methods [16]. Smartphones have proven to be dominant IT&C tools in transforming the educational sector, followed by notebooks and other handheld devices [5].

By the chosen research theme, this paper aims to analyze the continuance intention to use mobile learning in higher education, and we have formulated the following two main research questions.

RQ1: What factors affect the continuance intention to use mobile learning systems?

RQ2: What are the relationships among the factors in question RQ1?

The adoption of new technologies in general and mobile learning technologies in particular is a complex developmental process with cognitive, contextual, and social concerns. The massive adoption of mobile technologies by all stakeholders determines the rethinking of the learning processes in universities to the strengthening of mobile learning alternatives. According to Sharma and Mishra (2014), theories and models are combined in order to describe and analyze the adoption process of technologies by individuals and organizations [17]. Using e-learning systems is evolving for many universities during the COVID-19 pandemic [18]. Our research initiative is based on a hybrid theoretical model to identify the factors that influence mobile learning among university students. We propose a general research model, incorporating constructs from the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), the motivational model (MM), flow theory (FT), and social cognitive theory (SCT). The research model takes into account the different factors that might influence the adoption of a technology/information system, such as the user's belief and attitude to technology, user intention to use a technology and its behavior on using it, and social and physiological factors. In all educational processes, including mobile learning, the achievement of optimal learning experiences is considered. Nevertheless, individual experiences, the actions of others, and environmental factors on individual health behaviors might determine the adoption of a technology. The research model regarding mobile learning allows the identification of the factors leading to the consolidation of new quality education processes.

In Section 2, we perform a literature review. In Section 3, we present the model's assumptions and consider the sources we used to formulate these assumptions. Additionally, in Section 3, we present the demographic data of the students who responded to our online survey. In Section 4, we present the statistical results of the model. In Section 5, we discuss the results obtained and conclude that PU, HB, PS, and SE directly influence CU. PFE, IM, PEOU, and PE indirectly influence CU. Additionally, in Section 5, using descriptive statistics, we observe that the students have the necessary skills to use m-learning and intend to continue m-learning and that m-learning usage habits, as well as the desire to learn (in general), can be improved within university activities. In Section 5, we report our results of some top works regarding the adoption of m-learning during the pandemic and conclude that in Romania, technological factors, e-learning systems, and ICT literacy were of high quality, that students trust e-learning systems, and that the students' self-efficacy can be improved. In Section 6, we discuss two tables with statistical data regarding the adoption of the Internet and the use of online video content for learning in different countries. On the one hand, these statistics reinforce the results of our model for Romania. However, on the other hand, they show us that the adoption of the Internet and the use of online video content for learning vary in percentages from country to country (an observation also reported by numerous scientific works, e.g., [18]). Those statistics show us that, although our study can lead to significant results in the case of some countries, it can still have different results (or inapplicable parts) in the case of other countries—something that also signals the limitations of our model. In the final section, we present the conclusions of our study.

2. Literature Review

According to [19], learning content quality and technological, social, and individual factors are the four factors influencing the continuance intention to use m-learning. Our research is focused on individual factors that influence the continuance intention to use mobile learning. The success of an e-learning system depends on students' readiness and acceptance to use this system [18]. In our research, we have analyzed m-learning usage behaviors from different perspectives. Our proposal is based on a hybrid theoretical approach. The considered constructs are taken over from the following theories: the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), the motivational model (MM), flow theory (FT), and the social cognitive theory (SCT). The target construct is CU, and the analysis is focused on the factors that influence CU. Once this objective was established, we designed the research model by including the following constructs: continuance intention to use (CU), perceived usefulness (PU), perceived ease of use (PEOU), perceived enjoyment (PE), computer self-efficacy (SE), habit (HB), performance expectancy (PFE), intrinsic motivation (IM), perceived skill (PS), and ergonomy (ERG).

Current research indicates the continuance intention of using mobile devices in future teaching practice [20]—research models based on TAM [21] or UTAUT [22].

Continuance intention to use, perceived ease of use, and perceived usefulness are three main factors of the technology acceptance model (proposed by [21]). TAM considers the user's perspective and allows for "measuring the effects of perceptions of interactivity, achievement, and satisfaction with m-learning applications. of perceptions of interactivity, achievement, and satisfaction with m-learning applications". In addition to TAM, its various extended versions are relevant to examine the main factors influencing m-learning acceptance (e.g., [18,23]).

Continuance intention to use m-learning indicates a person's readiness to use mobile devices for learning. This construct was an antecedent of user acceptance in various technology acceptance theories [7,14,24–33].

Perceived usefulness means "the degree to which a person believes that using a particular system would enhance his or her job performance" [21]. The perceived usefulness of m-learning is the extent to which a person believes that m-learning can be a driving force towards achieving learning goals. PU refers to how m-learning might improve one's learning experience to achieve one's educational goals.

Perceived ease of use is "the degree to which a person believes that using a particular system would be free of effort" [21]. In the m-learning context, it means a student's individual belief that mobile learning will be easy for them.

Perceived usefulness and perceived ease of use influence continuance intention to use m-learning [2,5,7–9,14,19,24–51].

TAM 3 [52] added constructs: perceived enjoyment and computer self-efficacy construct.

Perceived enjoyment means "the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated" [21]. Perceived enjoyment is the extent to which the activity of using m-learning is perceived to be enjoyable aside from the instrumental value of the technology. There is a positive causal relationship between perceived enjoyment and attitude when people use m-learning services [36].

Perceived enjoyment influences continuance intention to use m-learning [36–38,42,49,51,53]. Perceived enjoyment direct influences perceived usefulness [51,53].

In psychology, self-efficacy is an individual's belief in their capacity to act in the ways necessary to reach specific goals (https://en.wikipedia.org/wiki/Self-efficacy (accessed on 26 November 2022)). The psychologist Albert Bandura proposed the self-efficacy concept within the context of social cognitive theory [13]. Different authors incorporated self-efficacy into technology adoption models [18,54]. Self-efficacy is an individual's assessment of his or her ability to perform a behavior [10,55]. Self-efficacy is one of the most decisive predictors of mobile learning use and profoundly influences students' behavioral intention to use mobile learning [5]. Self-efficacy is essential for academic learning, critical thinking, performance, and motivation. Students with solid self-efficacy are more open to new learning approaches and experiences [13]. Self-efficacy direct influences perceived ease of use [19,29,34,42,47]; self-efficacy direct influences perceived usefulness [19,29,42,46]; self-efficacy influences continuance intention to use m-learning [5,8–10,16,42,46].

According to the UTAUT model [23], four key constructs, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions, are the main determinants of users' usage intention and behavior. UTAUT2 (see [56]) added constructs: habit and performance expectancy.

A habit is "something people do often and regularly, sometimes without knowing that they are doing it" (https://dictionary.cambridge.org/dictionary/english/habit (accessed on 26 November 2022)). Reference [56] considered habits as the extent to which people tend to perform behaviors automatically because of learning. Study habits are generally understood as repeated learning to become an automatic reaction to the ability to achieve certain specific goals [15]. In the literature, we can find research on the influence of habit on user behavior toward information systems. Some focus on its role in the continuance use of software apps, especially m-learning apps [7]. Users with more active habits are less glad to assess the use of new systems and thus continue using familiar approaches [7]. If students use smartphones as a habit, they will have a higher intention to utilize mobile learning than those with a lower level of smartphone use [14]. Habits influence continuance intention to use [5,7,14,15,56]. Habits directly influence self-efficacy, perceived usefulness, and perceived ease of use [5].

Performance expectancy is "the degree to which technology will benefit consumers in performing certain activities" [56]. Performance expectancy means the extent of advantages students have in completing tasks through mobile learning. Mobile learning improves work performance and productivity, allowing them to gain knowledge conveniently and rapidly [14]. Performance expectancy influences continuance intention to use m-learning [11,14,51,57–60].

Intrinsic motivation is the perception that users will want to perform an activity [22]. Intrinsic motivation is a positive force to influence self-regulated learning [40]. Intrinsic motivation refers to the motivation to learn. The authors attempted to understand how learners' intrinsic motivation for learning influences their intention of mobile technology adoption [40]. Intrinsic motivation directly influences perceived ease of use and usefulness [40].

Perceived skill means the users' perception of how challenging it is to use mobile devices for m-learning [36]. Users become bored when their skills exceed the challenge of an assignment and become anxious when the challenge of an assignment exceeds their skills. The higher the control and competency of users in meeting the challenge of m-learning apps, the more pleasant their experience will be [7]. Perceived skill indirectly influences continuance intention to use m-learning [7,36].

Ergonomy is the scientific discipline concerned with understanding interactions among humans and other system elements, and the profession that applies theory, principles, data, and methods to design to optimize human well-being and overall system performance (https://en.wikipedia.org/wiki/Human_factors_and_ergonomics (accessed on 26 November 2022)). The authors of [61] introduce this construct in the context of TAM 3.

3. Research Model and Hypothesis Development

3.1. Research Hypothesis

We built a questionnaire from previous literature research papers, including questions on CU, PU, HB, PS, SE, PEOU, PE, IM, PFE, and ERG. All the survey questions are in Appendix A. For CU, we used four items: two from [7] and two from [61] concerning m-learning applications, the learning process, college courses, and using a recommendation to friends. For PU, we used seven items: one from [7], one from [61], three from [42], and two from [39], concerning chances of gaining additional knowledge, productivity, helpfulness, faster learning, better grades, accessing learning services quickly, and saving time. For HB, we used five items: three from [7] and two from [40]—concerning m-learning frequency, natural use, reflex use, a good fit for learning, and a better way to learn. For PS, we used three items: one from [7] and two from [42]—concerning the knowledge and ability to use m-learning applications, trust in operating mobile devices for learning, and understanding how they can use mobile devices for learning. For SE, we used three items: two from [48], two from [7], and three from [42]—concerning the learning process, a personalized learning process, app quality, m-learning services, m-learning fun, enjoyment, and good feeling. For PEOU, we used three items from [40] on interactions with learning apps, tools, and devices and ease of use. For PE, we used three items from [61] on interactivity, attractivity, and satisfaction in using m-learning. For IM, we used four items from [40] on the students' pleasure of learning. In this construct, all items refer to learning in general, not m-learning. For PFE, we used seven items from [62] on attention to lessons, creativity, a better understanding of lessons, less boring learning, control to learn with devices, the attractivity of lessons, less stress in learning, and more exciting lessons. For ERG, we used three items from [61] on using apps and content in m-learning.

Starting from the literature review presented in Section 2, we formulate the following research hypotheses:

H1a. *PU has a direct positive influence on CU.*

H1b. *HB has a direct positive influence on CU.*

H1c. *PS has a direct positive influence on CU.*

H1d. *SE has a direct positive influence on CU.*

H1e. *PEE has an indirect positive influence on CU.*

H1f. *IM has an indirect positive influence on CU.*

H1g. *PEOU has an indirect positive influence on CU.*

H1h. *PE has an indirect positive influence on CU.*

H2a. *PEE has a direct positive influence on PU.*

H2b. *IM has a direct positive influence on PU.*

H3a. *PEE has a direct positive influence on HB.*

H3b. *IM has a direct positive influence on HB.*

H4a. *PEOU has a direct positive influence on PS.*

H4b. *PE has a direct positive influence on PS.*

H4c. *PFE has an indirect positive influence on PS.*

H5a. *PFE has a direct positive influence on PEOU.*

H5b. *IM has a direct positive influence on PEOU.*

H5c. *ERG has a direct positive influence on PEOU.*

In Figure 1, we present the research model.

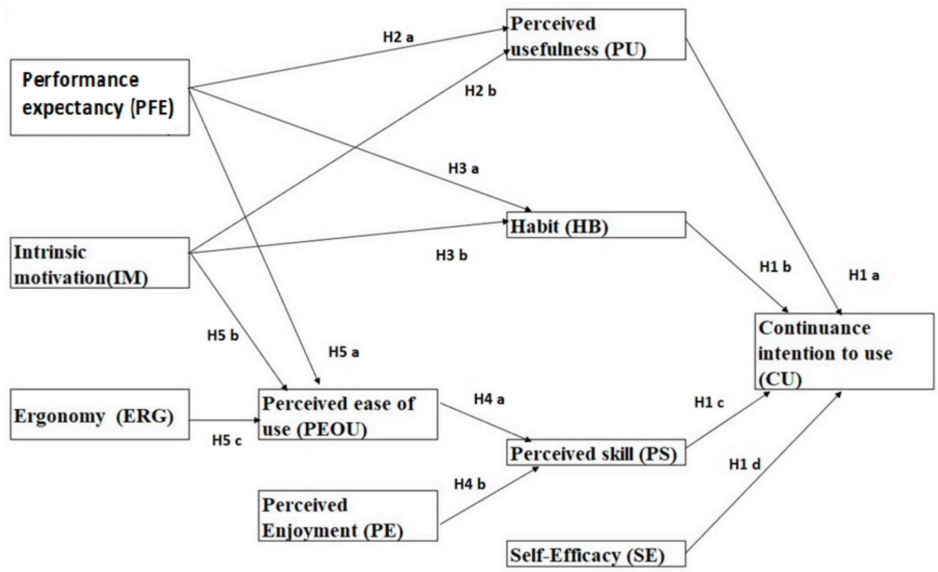

Figure 1. The research model and hypothesis.

3.2. Data Collection

To perform our analysis and test the research model (Figure 1), we applied an online survey for data collection in September–November 2022. Our study uses a Likert-type scale to scale answers in an online survey. In Appendix A, we showed the survey questions. The target group mainly comprised bachelor and master students and employees in postgraduate studies. The respondents, aged between 18 and 51 years, are natives of the following countries: Romania, the Republic of Moldova, the Republic of Serbia, and Hungary. Out of 509 answers, 474 were valid. Table 1 presents the demographic characteristics of the respondents.

Table 1. Respondents' information.

Characteristics	Category	Frequency	%
Gender	Female	310	65%
	Male	164	35%
Age	18–21	388	82%
	22–24	56	12%
	25–34	21	4.4%
	35–51	9	1.9%
Study level	Bachelor studies	278	59%
	Master studies	163	34%
	Postgraduates' studies	34	7%
Country	Romania	403	85%
	Republic of Serbia	37	7.8%
	Republic of Moldova	23	4.9%
	Hungary	11	2.3%

We use the PLS-SEM analysis that permits us to evaluate the model. We estimated validity, reliability, and correlations among factors and used the SmartPLS 3 Professional.

4. Statistical Results

4.1. Reliability and Validity

In Table 2 and Figure 2, we can see that the outer loading numbers are more significant than 0.7—the items' reliability. Composite Reliability (CR), rho_A, and Cronbach's Alpha values are between 0.7 and 0.95. The AVE (average variance extracted) numbers are more significant than 0.5—convergent validity (Table 2).

Table 2. Summary of the model results.

Constructs	Items	Outer Loadings	Cronbach's Alpha	Rho_A	Composite Reliability	Average Variance Extracted (AVE)
BUE			0.92	0.923	0.935	0.646
	PFE_1	0.868				
	PFE_2	0.786				
	PFE_3	0.756				
	PFE_4	0.736				
	PFE_5	0.712				
	PFE_6	0.867				
	PFE_7	0.793				
	PFE_8	0.893				
CU			0.85	0.851	0.899	0.691
	CU_1	0.851				
	CU_2	0.851				
	CU_3	0.845				
	CU_4	0.776				
ERG			0.733	0.739	0.851	0.657
	ERG1	0.855				
	ERG2	0.859				
	ERG3	0.708				
HB			0.868	0.869	0.904	0.653
	HB_1	0.788				
	HB_2	0.812				
	HB_3	0.836				
	HB_4	0.82				
	HB_5	0.783				
IM			0.829	0.834	0.886	0.661
	IM_1	0.858				
	IM_2	0.842				
	IM_3	0.787				
	IM_4	0.76				
PEOU			0.844	0.846	0.906	0.763
	PEOU_1	0.846				
	PEOU_2	0.899				
	PEOU_3	0.874				
PE			0.742	0.745	0.853	0.659
	PE_1	0.819				
	PE_2	0.803				
	PE_3	0.814				
PS			0.734	0.738	0.849	0.652
	PS_1	0.792				
	PS_2	0.795				
	PS_3	0.835				

Table 2. *Cont.*

Constructs	Items	Outer Loadings	Cronbach's Alpha	Rho_A	Composite Reliability	Average Variance Extracted (AVE)
PU			0.925	0.926	0.94	0.69
	PU_1	0.818				
	PU_2	0.811				
	PU_3	0.862				
	PU_4	0.827				
	PU_5	0.786				
	PU_6	0.869				
	PU_7	0.838				
SE			0.89	0.891	0.914	0.602
	SE_1	0.767				
	SE_2	0.779				
	SE_3	0.764				
	SE_4	0.766				
	SE_5	0.821				
	SE_6	0.772				
	SE_7	0.761				

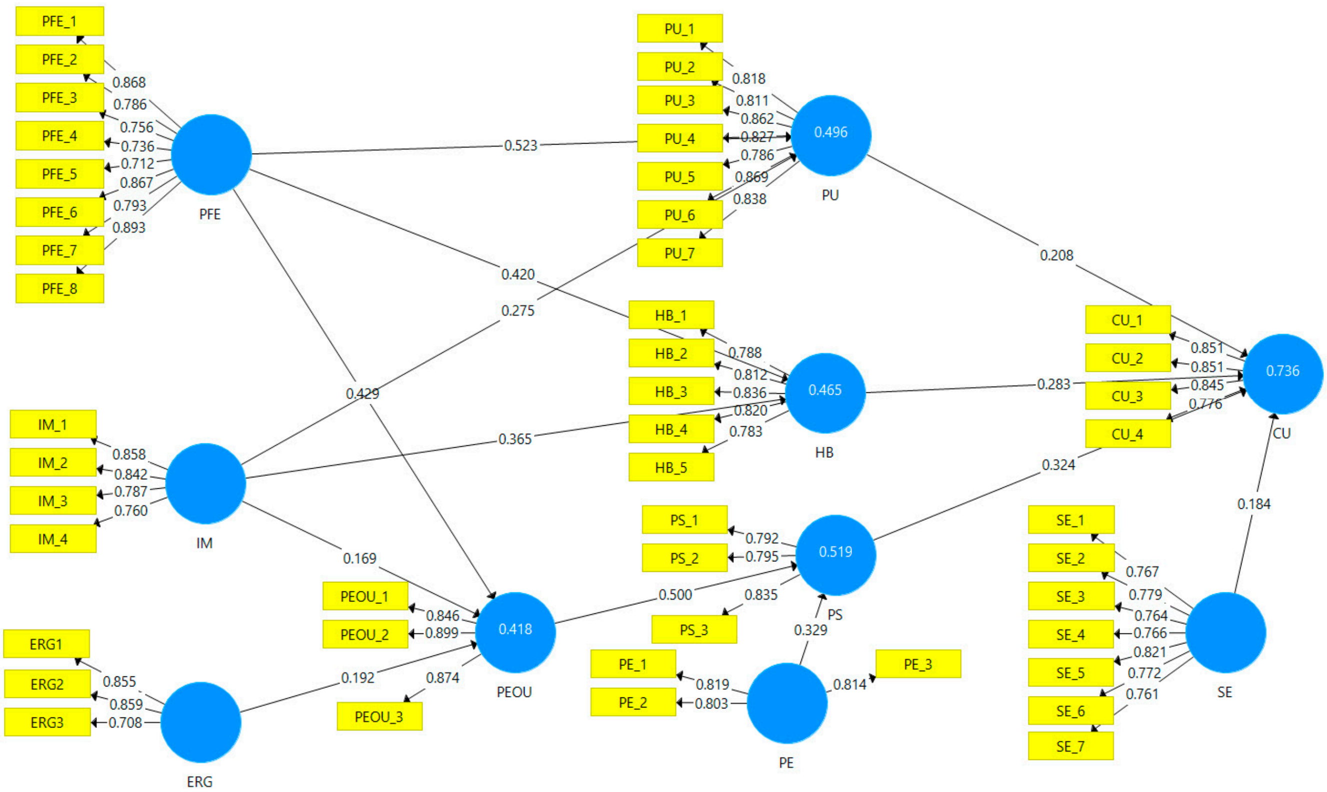

Figure 2. PLS-SEM results.

One manner to fit discriminant validity is to use the Fornell-Larcker standard. Each number on the diagonal is more significant than the values on its column and row, meaning that we set discriminant validity (Table 3).

Table 3. Fornell-Larcker standard study for investigating discriminant validity.

	CU	ERG	HB	IM	PE	PEOU	PFE	PS	PU	SE
CU	0.831									
ERG	0.475	0.811								
HB	0.753	0.424	0.808							
IM	0.447	0.343	0.579	0.813						
PE	0.673	0.604	0.657	0.429	0.812					
PEOU	0.61	0.437	0.542	0.454	0.485	0.873				
PFE	0.606	0.435	0.606	0.511	0.555	0.599	0.804			
PS	0.732	0.459	0.586	0.458	0.572	0.66	0.521	0.808		
PU	0.743	0.458	0.723	0.542	0.575	0.665	0.664	0.645	0.831	
SE	0.713	0.565	0.709	0.559	0.751	0.473	0.607	0.588	0.661	0.776

4.2. Model Evaluation

Usual check criteria contain R^2—the determination coefficient, variance inflation factor (VIF), the statistical significance and relevance of path coefficients, and the predictive relevance (Q2).

The VIF numbers are from 1.201 to 4.506—multicollinearity examination. The R^2 value is 0.736 for the CU construct, indicating that the four constructs (PU, HB, PS, and SE) define 73.6% of the weight in CU (see Table 4 and Figure 2). The values on the indicator are named the path coefficients and present how powerful one construct's impact is on another (see Figure 2). The model indicates that PS has the most considerable influence on CU (0.324), followed by HB (0.283), PU (0.208), and SE (0.184). The standardized path coefficient is more significant than 0.1 in each case presented in Table 4 and Figure 2—which means that hypothesized path association between constructs is significant. The coefficient R2 is 0.736 for the CU; it is 0.519 for PS; it is 0.465 for HB; it is 0.496 for PU; and it is 0.418 for PEOU.

Table 4. Path coefficient effects.

	Direct CU	Indirect CU	Direct HB	Direct PEOU	Direct PS	Indirect PS	Direct PU
PS	0.324						
HB	0.283						
PU	0.208						
SE	0.184						
PFE		0.297	0.420	0.429		0.215	0.523
IM		0.188	0.365	0.169		0.084	0.275
PEOU		0.162			0.500		
PE		0.107			0.329		
ERG		0.031		0.192		0.096	

SmartPLS produce t-statistics for meaning evaluation by operating a technique named bootstrapping. With 5000 iterations, we achieved a bootstrapping approach to examine the R^2 statistical significance. All hypotheses are supported—the numbers in Table 5 are statistically significant.

In Table 5, we presented path coefficients for direct and indirect effects. In Table 6, we can see the detailed information for indirect effects.

The value of f^2 (effect size) indicates how much a construct contributes to the value R^2 of another construct (see Table 7). The f^2 is low for values from 0.02 to 0.15; average for values from 0.15 to 0.35; and high for values more significant than 0.35, respectively.

Predictive relevance Q^2 is high for CU (0.502) and moderate for PU (0.337), PS (0.329), PEOU (0.312), and HB (0.297), illustrating the high predictive relevancy of the model.

We can quit the model in Figure 1's utility with the results in this section.

Descriptive statistics of the indicators are in Appendix B.

Table 5. Path coefficients.

	Effect	Path Coeff.	T Statistics	*p* Values	Remark
PU -> CU	direct	0.208	3.606	0.000	H1a is supported
HB -> CU	direct	0.283	5.168	0.000	H1b is supported
PS -> CU	direct	0.324	5.641	0.000	H1c is supported
SE -> CU	direct	0.184	3.854	0.000	H1d is supported
PFE -> CU	indirect	0.297	7.785	0.000	H1e is supported
IM -> CU	indirect	0.188	7.018	0.000	H1f is supported
PEOU -> CU	indirect	0.162	4.31	0.000	H1g is supported
PE -> CU	indirect	0.107	4.178	0.000	H1h is supported
PFE -> PU	direct	0.523	13.002	0.000	H2a is supported
IM -> PU	direct	0.275	6.769	0.000	H2b is supported
PFE -> HB	direct	0.420	11.054	0.000	H3a is supported
IM -> HB	direct	0.365	9.438	0.000	H3b is supported
PEOU -> PS	direct	0.500	8.125	0.000	H4a is supported
PE -> PS	direct	0.329	6.006	0.000	H4b is supported
PFE -> PS	indirect	0.215	5.649	0.000	H4c is supported
PFE -> PEOU	direct	0.429	8.533	0.000	H5a is supported
IM -> PEOU	direct	0.169	3.683	0.000	H5b is supported
ERG -> PEOU	direct	0.192	3.578	0.000	H5c is supported

Table 6. Path coefficients. Specific indirect effects.

	Effect	Path Coeff.	T Statistics	*p* Values
PFE -> PEOU -> PS	specific indirect	0.215	5.649	0.000
PEOU -> PS -> CU	specific indirect	0.162	4.310	0.000
PFE -> HB -> CU	specific indirect	0.119	4.865	0.000
PFE -> PU -> CU	specific indirect	0.109	3.336	0.001
PE -> PS -> CU	specific indirect	0.107	4.178	0.000
IM -> HB -> CU	specific indirect	0.103	5.009	0.000
PFE -> PEOU -> PS -> CU	specific indirect	0.070	3.582	0.000
IM -> PU -> CU	specific indirect	0.057	3.203	0.001
IM -> PEOU -> PS -> CU	specific indirect	0.027	2.734	0.006

Table 7. f^2 values.

	CU	HB	PEOU	PS	PU
PFE		0.243	0.210		0.401
ERG			0.050		
HB	0.114				
IM		0.184	0.035		0.111
PE				0.172	
PEOU				0.398	
PS	0.210				
PU	0.063				
SE	0.055				

5. Discussion

Mobile learning was an unavoidable alternative in higher education during the COVID-19 pandemic [63]. According to [63], the main factors that determine the adoption of m-learning were awareness, IT infrastructure, and top management support. Significant research analyzes students' perception of mobile learning, behavior in using mobile devices, and their satisfaction during the learning process [64]. Most analyses are based on the TAM or the UTAUT model in order to identify the factors that influence the adoption of a mobile device [23,65]. Beyond TAM and UTAUT, which focus on individuals' perceptions and intentions, there are other theoretical approaches that include social influence, human behavior, and psychological influence factors. We have identified mixed approaches based on two or three models. Commonly, TAM and FT are used to analyze users' acceptance behavior [66]. SCT theory is integrated with the TAM model for measuring students' satisfaction with the use of m-learning systems [67]. The relationships between motivation, the use of mobile devices, and satisfaction in the learning environment can be modeled by a hybrid approach of TAM or UTAUT and the motivation model [68].

Hybrid approaches give robustness to research models. Therefore, we propose a general research model, incorporating constructs from the TAM, UTAUT, MM, FT, and SCT models in order to study the factors that affect mobile learning. In our model, we have introduced ten constructs, namely, CU, PU, HB, PS, SE, PEOU, PE, BUE, IM, and ERG. PL is the theoretical framework being tested by using the PLS-SEM method in SmartPLS.

Factors that directly influence CU are PS, HB, PU, and SE. PS has the most influence on CU. Suppose some students are not too excited about m-learning; in that case, teachers should check to what extent they are used to using mobile devices, mobile applications in general, and mobile learning applications. Our study shows that the main problem that could generate animosity towards m-learning is when students interact too little with mobile devices and mobile applications; this generates real problems in m-learning.

As seen in the literature presented in Section 2, only two papers used the PS construct in the m-learning context [7,36]. There may be other references. However, we only found two. In the two references, the authors say that PS indirectly influences CU. The contribution of our study is that we found that PU directly influences CU on the one hand and is the factor with the most significant influence on CU on the other hand. Thus, we recommend that the authors consider the PS construct in the m-learning models.

The next factor influencing CU is HB. Our study shows that in the case of students for whom m-learning has become a habit, there is a high chance that they will want to continue this type of learning.

Teachers must introduce mobile use tasks to build habits in m-learning over time. Using these tasks should be moderate for beginners and introduced gradually; where there are problems, the teacher must fix them.

Some works introduced the HB construct into the models in the specialized literature [5,7,14,15,56]. In each case, HB influences CU, most of the time directly. Thus, we consider HB an essential factor influencing CU in m-learning models.

Another factor directly influencing CU is PU. In the case of students who perceived the usefulness of m-learning (increasing chances of gaining additional knowledge, productivity in learning, help in learning, fast learning, better grades at university, accessing quick learning services, saving time in learning), from Figure 1, these students will want to continue with mobile learning. The other students, who do not perceive the usefulness of m-learning, will not be so attracted to continue using it. As we saw in Section 2, almost all m-learning models included PU, concluding that PU directly influences CU.

In the model in Figure 1, SE is the last factor that directly influences CU. Students who think positively about mobile learning will be interested in continuing to use m-learning.

If it does not appear in all m-learning models, SE is a fairly common factor. The authors confirmed that this factor directly or indirectly influences CU [5,8–10,16,42,46].

One factor that indirectly influences CU is PFE. PFE influences direct PU and HB (two factors influencing direct CU). Such PFE has become an essential factor influencing CU. PFE also greatly influences PEOU. However, in the case of students who do not perceive the usefulness of m-learning or for which m-learning is not a habit, PFE does not influence CU. Even though PFE indirectly influences CU, we draw attention to PFE being the second most decisive factor in the model influencing CU (see Table 4). Most authors using PFE found that it directly influences CU [11,14,51,57–60].

IM is another factor that indirectly influences CU. In other words, whether we like to learn or not, in general, will also affect m-learning. Teachers must pay attention to students who are weaker in learning. They will be able to encounter real problems in m-learning.

Refs. [21,40] concluded that IM influences CU. IM is a rarely used factor in the specialized literature on m-learning.

Like PU, PEOU is the second TAM factor that influences CU. As we saw in Section 2, almost all m-learning models included PEOU, concluding that PEOU influences CU. Additionally, we obtained that PEOU direct influence PS.

The last factor in the model, ERG, directly influences PEOU but does not influence CU. The factor is not really found in the m-learning literature, but as it appears from our study, it is not important regarding CU.

Items regarding ERG, PS, PEOU, and the continuity of m-learning have a very high average value. These high values show that the students who answered our questionnaire have the necessary skills to use m-learning and intend to continue m-learning. The success of an m-learning system depends on students' desire and acceptance to use mobile devices [18]. Therefore, Romanian universities should continue to invest in extending m-learning systems, the feedback from students being excellent. Items regarding HAB, having fun learning, or using m-learning have the lowest average values in our survey (the lowest value is 3.827). This fact shows us that m-learning is already a habit for some students but is not fun for all of them (a result which is somewhat unsurprising). Romanian university teachers must create habits of using m-learning applications because, as we have seen, HB directly influences CU.

Some critical factors affected m-learning systems during the COVID-19 pandemic [18]. Referring to this work, we can conclude the following:

- PS and ERG scores (Appendix B) show that technological factors in Romanian universities were of high quality (from the authors' experience, we add here that before the pandemic, Romanian universities had in mind the creation of optimal technological conditions for students);
- PEOU, PU, ERG, SE, and PS scores indicate that e-learning systems were of high quality in Romanian universities;
- The general scores in Appendix B, supported by the percentages in [69], reflect very high ICT literacy among the population between 16 and 64 years old in Romania. University culture could recreate a vital function in how universities embrace m-learning systems [18,63];
- Self-efficacy scores are between 3.827 and 4.426 (Appendix B). According to our study, this concerns learning-related issues, not those related to the use of mobile devices—which nevertheless has consequences for m-learning. On the one hand, improvement can be brought about by involving weaker students in regular learning activities (including m-learning). On the other hand, regardless of the education system we refer to, we must expect students to be at a different level. Although we have noted this issue, it can continuously be improved but never fixed. Authors recommend regular awareness sessions [18,63] in order to let students feel confident and motivated in using the e-learning system;
- PS, CU, PE, and PEOU scores highlight that Romanian students trust e-learning systems.

In conclusion, our study shows (CU, PS, ERG, PE, and PEOU scores) that Romania is a country where universities deliver an excellent arsenal for continuing m-learning, providing IT infrastructure (see also [69]), and top management support—essential factors for smart mobile learning success [63]. The descriptive results from HAB show a university culture in Romania. University culture is one of the main factors influencing m-learning student acceptance [63]. Creating habits of using m-learning in the context of university classes will strengthen this university culture. The proposed research model allowed us to develop a proper research initiative with a focus on the two main research questions, RQ1 and RQ2.

6. Limitation and Future Research

Relevant statistics on Internet adoption in different countries ([69]—the slide 23) indicate various situations. Additionally, the interest in using online video content for learning differs from country to country ([69]—the slide 55). We identify four major challenges in adopting m-learning systems [18], namely: technological challenges, individual challenges, cultural challenges, and course challenges. The situation is different from country to country [18]. For Romania, we can see that 88% of people aged 16 to 64 are using the Internet ([69]—the slide 23), and of them, 45.10% use online videos as a source of learning ([69]—the slide 55).

Although in our study, the respondents are only students, the results we obtained are in accordance with the global values in [69], namely, that in Romania, there is an excellent potential for m-learning adoption.

Considering the global situation presented in [69] it is possible that, applying our research model to other countries, significant differences may appear compared to the situation in Romania. A limitation of our study would be that we focused only on Romanian students. Future work will consider respondents from different universities outside Romania, and we will compare the result with the statistical data presented in [69]. The issue of low use of m-learning systems still exists in different countries [54]. Indeed, the model in Figure 1 and the descriptive statistics will look different for those countries.

7. Conclusions

There are numerous studies on m-learning and on the factors that influence this phenomenon. The identified research initiatives use models such as TAM, UTAUT, MM, FT, and SCT in different approaches. Our proposal has been developed using a hybrid framework based on the models and theories mentioned above, and we obtained some new results that we hope will be beneficial for teachers in m-learning activities.

In our study, PS, PFE, and HB proved to be the most critical factors influencing CU. That is undoubtedly an important conclusion of our research. Besides these three constructs, in our research model, we have introduced the following factors PU, SE, IM, PEOU, and PE. Two of them, namely, SE and IM, are rarely treated in specialized literature.

Based on the consideration detailed in Section 5, the descriptive statistics results resumed in Appendix B, and the reference models regarding critical challenges and factors influencing the m-learning system usage during the COVID-19 pandemic [18], we were able to formulate meaningful conclusions about m-learning usage in Romanian universities. This demonstrates the robustness of the proposed research model.

According to those presented in Section 6 and other research papers (e.g., [18]), the statistics show that countries come with significantly different percentages regarding Internet adoption and online content as a source of learning. Therefore, the proposed model can have different results (or inapplicable parts) in cases of other countries. This observation outlines a limitation of our study.

Author Contributions: Conceptualization, M.-C.V. and M.M.; methodology, M.-C.V. and M.M.; validation, M.-C.V. and M.M.; formal analysis, M.-C.V. and M.M; writing—original draft preparation, M.-C.V. and M.M.; writing—review and editing, M.-C.V. and M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This article was supported by the UVT 1000 Develop Fund of the West University of Timisoara.

Data Availability Statement: Not Applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Survey Questions.

Construct	Item	Scale	Scale Reference
Continuance intention to use (CU)	CU_1	Assuming I have access to m-learning applications, I intend to use them again in the learning process.	[7]
	CU_2	I will continue to use m-learning applications.	[7]
	CU_3	I want to use m-learning apps to study for my college courses.	[61]
	CU_4	I recommend that friends use mobile when studying.	[61]
Perceived usefulness (PU)	PU_1	M-learning increased my chances of gaining additional knowledge.	[7]
	PU_2	M-learning helps me to be more productive.	[61]
	PU_3	M-learning is helpful in my learning.	[42]
	PU_4	Using m-learning allows me to learn faster.	[42]
	PU_5	If I use m-learning, I increase my chances of getting a better grade.	[42]
	PU_6	The m-learning apps facilitate me to use learning services more quickly	[39]
	PU_7	M-learning can save me time more efficiently.	[39]
Habit (HB)	HB_1	Learning with m-learning apps is something I frequently do.	[7]
	HB_2	Learning with m-learning applications comes naturally to me.	[7]
	HB_3	Learning with m-learning applications is a reflex for me.	[7]
	HB_4	Using mobile devices would be a good fit for how I learn.	[40]
	HB_5	Using mobile devices would be a better way to learn.	[40]
Perceived skill (PS)	PS_1	I have the knowledge and ability to use m-learning applications.	[7]
	PS_2	I have confidence in using a computer and mobile devices for m-learning	[42]
	PS_3	I understand the terms used for computer and mobile devices used for m-learning.	[42]
Self-Efficacy (SE)	SE_1	Mobile learning makes me more active in the learning process.	[48]
	SE_2	Mobile learning provides me with a personalized learning process (corresponding to my interests and learning style)	[48]
	SE_3	My experience using m-learning applications was better than I expected.	[7]
	SE_4	The level of service or features offered by the m-learning applications was better than I expected.	[7]
	SE_5	M-learning makes me feel good.	[42]
	SE_6	I have fun using m-learning.	[42]
	SE_7	Using m-learning is enjoyable.	[42]
Perceived ease of use (PEOU)	PEOU_1	I have no problem learning about the features of learning apps/tools on my mobile device(s).	[40]
	PEOU_2	My interaction with these tools/apps is clear and easy to understand.	[40]
	PEOU_3	Mobile learning apps/tools are easy to use.	[40]
Perceived Enjoyment (PE)	PE_1	I like interacting with mobile learning apps	[61]
	PE_2	Mobile applications make learning computer systems more attractive.	[61]
	PE_3	I am satisfied with m-learning applications.	[61]
Intrinsic motivation (IM)	IM_1	I like to learn.	[40]
	IM_2	Learning is fun.	[40]
	IM_3	The learning is fascinating.	[40]
	IM_4	I was pretty skilled to work on college projects.	[40]
Performance expectancy (PFE)	PFE_1	Mobile technology can stimulate students to pay more attention to lessons.	[62]
	PFE_2	Mobile learning boosts creativity.	[62]
	PFE_3	Mobile technology can help to understand the lesson better.	[62]
	PFE_4	Students may be less bored when using mobile technology compared to traditional learning methods.	[62]
	PFE_5	Students may feel in control to learn with their own mobile devices	[62]
	PFE_6	Students may find the lesson more attractive when using mobile devices	[62]
	PFE_7	Students are less stressed and learning is accepted as a game. when mobile technology is used.	[62]
	PFE_8	Students may find the lesson more interesting when mobile technology is used	[62]
Ergonomy (ERG)	ERG1	Mobile learning content can be read easily.	[61]
	ERG2	Mobile learning content is easy to use.	[61]
	ERG3	Interactivity components in mobile learning apps and tools work well.	[61]

Appendix B

Table A2. Descriptive Statistics.

	Mean	Median	Min	Max	St. dev.	Excess Kurtosis	Skewness
ERG1	4.641	5.000	1.000	5.000	0.868	4.381	−2.305
ERG2	4.671	5.000	1.000	5.000	0.817	4.578	−2.351
ERG3	4.582	5.000	2.000	5.000	0.866	1.243	−1.703
PE_1	4.443	5.000	2.000	5.000	0.897	−0.573	−1.097
PE_2	4.544	5.000	1.000	5.000	0.888	1.066	−1.586
PE_3	4.599	5.000	1.000	5.000	0.844	1.831	−1.791
SE_1	4.131	5.000	1.000	5.000	1.108	−0.717	−0.765
SE_2	4.350	5.000	1.000	5.000	0.989	−0.081	−1.114
SE_3	4.274	5.000	2.000	5.000	0.979	−1.201	−0.734
SE_4	4.262	5.000	1.000	5.000	1.018	−0.547	−0.902
SE_5	4.097	5.000	1.000	5.000	1.045	−1.364	−0.462
SE_6	3.827	3.000	1.000	5.000	1.121	−1.404	−0.160
SE_7	4.426	5.000	1.000	5.000	0.952	0.393	−1.294
HB_1	4.025	5.000	1.000	5.000	1.132	−1.251	−0.540
HB_2	3.962	5.000	1.000	5.000	1.115	−1.371	−0.383
HB_3	3.840	4.000	1.000	5.000	1.194	−1.115	−0.404
HB_4	4.152	5.000	1.000	5.000	1.107	−0.297	−0.902
HB_5	4.228	5.000	1.000	5.000	1.117	0.064	−1.114
PS_1	4.624	5.000	1.000	5.000	0.826	2.333	−1.913
PS_2	4.633	5.000	1.000	5.000	0.804	2.197	−1.882
PS_3	4.591	5.000	1.000	5.000	0.870	2.413	−1.882
CU_1	4.540	5.000	1.000	5.000	0.916	1.660	−1.705
CU_2	4.578	5.000	1.000	5.000	0.881	1.780	−1.782
CU_3	4.586	5.000	1.000	5.000	0.880	2.407	−1.887
CU_4	4.160	5.000	1.000	5.000	1.125	−0.284	−0.943
IM_1	4.093	5.000	1.000	5.000	1.098	−0.791	−0.683
IM_2	3.848	4.000	1.000	5.000	1.220	−1.021	−0.477
IM_3	4.118	5.000	1.000	5.000	1.111	−0.688	−0.771
IM_4	4.278	5.000	1.000	5.000	0.984	−0.764	−0.848
PEOU_1	4.414	5.000	1.000	5.000	0.971	0.581	−1.350
PEOU_2	4.578	5.000	1.000	5.000	0.866	1.580	−1.727
PEOU_3	4.608	5.000	1.000	5.000	0.873	2.923	−2.014
PU_1	4.253	5.000	1.000	5.000	1.016	−0.559	−0.886
PU_2	4.186	5.000	1.000	5.000	1.075	−0.548	−0.866
PU_3	4.439	5.000	1.000	5.000	0.942	1.056	−1.432
PU_4	4.321	5.000	1.000	5.000	1.001	0.327	−1.157
PU_5	4.169	5.000	1.000	5.000	1.038	−0.725	−0.729
PU_6	4.405	5.000	1.000	5.000	0.948	0.439	−1.274
PU_7	4.439	5.000	1.000	5.000	0.964	1.363	−1.511
PFE_1	4.249	5.000	1.000	5.000	1.122	0.262	−1.185
PFE_2	4.300	5.000	1.000	5.000	1.055	0.310	−1.184
PFE_3	4.540	5.000	1.000	5.000	0.934	2.121	−1.799
PFE_4	4.295	5.000	1.000	5.000	1.046	−0.062	−1.102
PFE_5	4.637	5.000	1.000	5.000	0.808	2.460	−1.942
PFE_6	4.405	5.000	1.000	5.000	0.988	0.979	−1.409
PFE_7	4.245	5.000	1.000	5.000	1.098	0.154	−1.129
PFE_8	4.329	5.000	1.000	5.000	1.028	0.337	−1.207

References

1. Al-Rahmi, A.M.; Al-Rahmi, W.M.; Alturki, U.; Aldraiweesh, A.; Almutairy, S.; Al-Adwan, A.S. Acceptance of mobile technologies and M-learning by university students: An empirical investigation in higher education. *Educ. Inf. Technol.* **2022**, *27*, 7805–7826. [CrossRef]
2. Almaiah, M.A.; Hajjej, F.; Lutfi, A.; Al-Khasawneh, A.; Alkhdour, T.; Almomani, O.; Shehab, R. A Conceptual Framework for Determining Quality Requirements for Mobile Learning Applications Using Delphi Method. *Electronics* **2022**, *11*, 788. [CrossRef]

3. Lisana, L. Factors affecting university students switching intention to mobile learning: A push-pull-mooring theory perspective. *Educ. Inf. Technol.* **2022**, *28*, 1–21. [CrossRef]
4. Sa'don, N.F.; Iahad, N.A. Collaborative Mobile Learning: A Systematic Literature Review. In *Critical Socio-Technical Issues Surrounding Mobile Computing*; ICI Global: Hershey, PA, USA, 2016. [CrossRef]
5. Kumar, J.A.; Bervell, B.; Annamalai, N.; Osman, S. Behavioral Intention to Use Mobile Learning: Evaluating the Role of Self-Efficacy, Subjective Norm, and WhatsApp Use Habit. *IEEE Access* **2020**, *8*, 208058–208074. [CrossRef]
6. Viberg, O.; Grönlund, Å. Understanding students' learning practices: Challenges for design and integration of mobile technology into distance education. *Learn. Media Technol.* **2017**, *42*, 357–377. [CrossRef]
7. Wang, Y.-T.; Lin, K.-Y. Understanding Continuance Usage of Mobile Learning Applications: The Moderating Role of Habit. *Front. Psychol.* **2021**, *12*, 736051. [CrossRef]
8. Gómez-Ramirez, I.; Valencia-Arias, A.; Duque, L. Approach to M-learning acceptance among university students: An integrated model of TPB and TAM. *Int. Rev. Res. Open Distance Learn.* **2019**, *20*, 141–164. [CrossRef]
9. Raza, S.A.; Umer, A.; Qazi, W.; Makhdoom, M. The Effects of Attitudinal, Normative, and Control Beliefs on M-Learning Adoption Among the Students of Higher Education in Pakistan. *J. Educ. Comput. Res.* **2018**, *56*, 563–588. [CrossRef]
10. Mohammadi, H. Social and individual antecedents of m-learning adoption in Iran. *Comput. Hum. Behav.* **2015**, *49*, 191–207. [CrossRef]
11. Badwelan, A.; Drew, S.; Bahaddad, A.A. Towards Acceptance M-Learning Approach in Higher Education in Saudi Arabia. *Int. J. Bus. Manag.* **2016**, *11*, 12. [CrossRef]
12. Cheon, J.; Lee, S.; Crooks, S.M.; Song, J. An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Comput. Educ.* **2012**, *59*, 1054–1064. [CrossRef]
13. Razzaq, A.; Samiha, Y.T.; Anshari, M. Smartphone Habits and Behaviors in Supporting Students Self-Efficacy. *Int. J. Emerg. Technol. Learn. IJET* **2018**, *13*, 94–109. [CrossRef]
14. Moorthy, K.; Yee, T.T.; T'Ing, L.C.; Kumaran, V.V. Habit and hedonic motivation are the strongest influences in mobile learning behaviours among higher education students in Malaysia. *Australas. J. Educ. Technol.* **2019**, *35*, 174–191. [CrossRef]
15. Wu, W.-C.; Perng, Y.-H. Research on the Correlations Among Mobile Learning Perception, Study Habits, and Continuous Learning. *Eurasia J. Math. Sci. Technol. Educ.* **2016**, *12*, 1665–1673. [CrossRef]
16. Kumar, J.A.; Osman, S.; Sanmugam, M.; Rasappan, R. Mobile Learning Acceptance Post Pandemic: A Behavioural Shift among Engineering Undergraduates. *Sustainability* **2022**, *14*, 3197. [CrossRef]
17. Sharma, R.; Mishra, R. A Review of Evolution of Theories and Models of Technology Adoption. *Indian Inst. Manag. Indore* **2014**, *6*, 17–29. Available online: https://www.iimidr.ac.in/wp-content/uploads/Vol6-2RETMTA.pdf (accessed on 1 December 2022).
18. Almaiah, M.A.; Al-Khasawneh, A.; Althunibat, A. Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic. *Educ. Inf. Technol.* **2020**, *25*, 5261–5280. [CrossRef]
19. Chavoshi, A.; Hamidi, H. Social, individual, technological and pedagogical factors influencing mobile learning acceptance in higher education: A case from Iran. *Telemat. Inform.* **2019**, *38*, 133–165. [CrossRef]
20. Mutambara, D.; Bayaga, A. Rural-based Science, Technology, Engineering and Mathematics teachers' and learners' acceptance of mobile learning. *SA J. Inf. Manag.* **2020**, *22*, 10. [CrossRef]
21. Davis, F.D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q.* **1989**, 319–339. [CrossRef]
22. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F. User acceptance of information technology: Toward a unified view. *Manag. Inf. Syst. Q.* **2003**, *27*, 425–478. [CrossRef]
23. Almaiah, M.A.; Al-Otaibi, S.; Lutfi, A.; Almomani, O.; Awajan, A.; Alsaaidah, A.; Alrawad, M.; Awad, A.B. Employing the TAM Model to Investigate the Readiness of M-Learning System Usage Using SEM Technique. *Electronics* **2022**, *11*, 1259. [CrossRef]
24. Wu, B.; Chen, X. Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Comput. Hum. Behav.* **2017**, *67*, 221–232. [CrossRef]
25. Khlaif, Z.N.; Sanmugam, M.; Ayyoub, A. Impact of Technostress on Continuance Intentions to Use Mobile Technology. *Asia-Pacific Educ. Res.* **2022**, *32*, 1–12. [CrossRef]
26. Joo, Y.J.; Kim, N.; Kim, N.H. Factors predicting online university students' use of a mobile learning management system (m-LMS). *Educ. Technol. Res. Dev.* **2016**, *64*, 611–630. [CrossRef]
27. Sprenger, D.A.; Schwaninger, A. Technology acceptance of four digital learning technologies (classroom response system, classroom chat, e-lectures, and mobile virtual reality) after three months' usage. *Int. J. Educ. Technol. High. Educ.* **2021**, *18*, 8. [CrossRef]
28. Baranova, T.; Kobicheva, A.; Tokareva, E. Factors Influencing Students' Continuance Intention to Learn in Blended Environments at University. *Electronics* **2022**, *11*, 2069. [CrossRef]
29. Al-Bashayreh, M.; Almajali, D.; Altamimi, A.; Masa'Deh, R.; Al-Okaily, M. An Empirical Investigation of Reasons Influencing Student Acceptance and Rejection of Mobile Learning Apps Usage. *Sustainability* **2022**, *14*, 4325. [CrossRef]
30. Al-Dokhny, A.; Drwish, A.; Alyoussef, I.; Al-Abdullatif, A. Students' Intentions to Use Distance Education Platforms: An Investigation into Expanding the Technology Acceptance Model through Social Cognitive Theory. *Electronics* **2020**, *10*, 2992. [CrossRef]

31. Almaiah, M.A.; Hajjej, F.; Lutfi, A.; Al-Khasawneh, A.; Shehab, R.; Al-Otaibi, S.; Alrawad, M. Explaining the Factors Affecting Students' Attitudes to Using Online Learning (Madrasati Platform) during COVID-19. *Electronics* **2022**, *11*, 973. [CrossRef]
32. Almaiah, M.A.; Alfaisal, R.; Salloum, S.A.; Al-otaibi, S.; Said, O.; Sawafi, A.; Al-maroof, R.S.; Lutfi, A.; Alrawad, M.; Mulhem, A.A.l.; et al. Determinants Influencing the Continuous Intention to Use Digital Technologies in Higher Education. *Electronics* **2022**, *11*, 2827. [CrossRef]
33. Almaiah, M.A.; Hajjej, F.; Shishakly, R.; Lutfi, A.; Amin, A.; Awad, A.B. The Role of Quality Measurements in Enhancing the Usability of Mobile Learning Applications during COVID-19. *Electronics* **2022**, *11*, 1951. [CrossRef]
34. Sánchez-Prieto, J.C.; Olmos-Migueláñez, S.; García-Peñalvo, F.J. MLearning and pre-service teachers: An assessment of the behavioral intention using an expanded TAM model. *Comput. Hum. Behav.* **2017**, *72*, 644–654. [CrossRef]
35. Khanh, N.T.V.; Gim, G. Factors Influencing Mobile-Learning Adoption Intention: An Empirical Investigation in High Education. *J. Soc. Sci.* **2014**, *10*, 51–62. [CrossRef]
36. Park, E.; Baek, S.; Ohm, J.; Chang, H.J. Determinants of player acceptance of mobile social network games: An application of extended technology acceptance model. *Telemat. Inform.* **2014**, *31*, 3–15. [CrossRef]
37. Abu-Taieh, E.M.; AlHadid, I.; Kaabneh, K.; Alkhawaldeh, R.S.; Khwaldeh, S.; Masa'Deh, R.; Alrowwad, A. Predictors of Smartphone Addiction and Social Isolation among Jordanian Children and Adolescents Using SEM and ML. *Big Data Cogn. Comput.* **2022**, *6*, 92. [CrossRef]
38. Akgül, Y.; Uymaz, A.O. Facebook/Meta usage in higher education: A deep learning-based dual-stage SEM-ANN analysis. *Educ. Inf. Technol.* **2022**, *27*, 9821–9855. [CrossRef]
39. Ismiyati, I.; Kartowagiran, B.; Muhyadi, M.; Sholikah, M.; Suparno, S.; Tusyanah, T. Understanding Students' Intention to Use Mobile Learning at Universitas Negeri Semarang: An Alternative Learning from Home During Covid-19 Pandemic. *J. Educ. Cult. Psychol. Stud.* **2021**, *2021*, 181–199. [CrossRef]
40. Sun, Y.; Gao, F. An investigation of the influence of intrinsic motivation on students' intention to use mobile devices in language learning. *Educ. Technol. Res. Dev.* **2020**, *68*, 1181–1198. [CrossRef]
41. Park, S.Y.; Nam, M.-W.; Cha, S.-B. University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *Br. J. Educ. Technol.* **2012**, *43*, 592–605. [CrossRef]
42. Pramana, E. Determinants of the Adoption of Mobile Learning Systems among University Students in Indonesia. *J. Inf. Technol. Educ. Res.* **2018**, *17*, 365–398. [CrossRef]
43. Xu, Q.; Hou, X.; Xiao, T.; Zhao, W. Factors Affecting Medical Students' Continuance Intention to Use Mobile Health Applications. *J. Multidiscip. Health* **2022**, *15*, 471–484. [CrossRef] [PubMed]
44. Saroia, A.I.; Gao, S. Investigating university students' intention to use mobile learning management systems in Sweden. *Innov. Educ. Teach. Int.* **2019**, *56*, 569–580. [CrossRef]
45. Naveed, Q.; Alam, M.; Tairan, N. Structural Equation Modeling for Mobile Learning Acceptance by University Students: An Empirical Study. *Sustainability* **2020**, *12*, 8618. [CrossRef]
46. Azizi, S.M.; Khatony, A. Investigating factors affecting on medical sciences students' intention to adopt mobile learning. *BMC Med. Educ.* **2019**, *19*, 381. [CrossRef] [PubMed]
47. Venkatesh, V. Determinants of perceived ease of use: Integrating perceived behavioral control, computer anxiety and enjoyment into the technology acceptance model. *Inf. Syst. Res.* **2000**, *11*, 3–11. [CrossRef]
48. Seta, H.B.; Theresiawati; Afrizal, S.; Hidayanto, A.N. Analysis of a Mobile Learning Adoption Model for Learning Improvement Based on Students' Perception. *J. Inf. Technol. Educ. Res.* **2022**, *21*, 169–196. [CrossRef]
49. Camilleri, M.A.; Camilleri, A.C. The students' readiness to engage with mobile learning apps. *Interact. Technol. Smart Educ.* **2020**, *17*, 28–38. [CrossRef]
50. Baghcheghi, N.; Koohestani, H.R.; Karimy, M.; Alizadeh, S. Factors affecting mobile learning adoption in healthcare professional students based on technology acceptance model. *Acta Fac. Med. Naissensis* **2020**, *37*, 191–200. [CrossRef]
51. Alyoussef, I.Y. Factors Influencing Students' Acceptance of M-Learning in Higher Education: An Application and Extension of the UTAUT Model. *Electronics* **2021**, *10*, 3171. [CrossRef]
52. Venkatesh, V.; Bala, H. Technology Acceptance Model 3 and a Research Agenda on Interventions. *Decis. Sci.* **2008**, *39*, 273–315. [CrossRef]
53. Sabah, N.M. Exploring students' awareness and perceptions: Influencing factors and individual differences driving m-learning adoption. *Comput. Hum. Behav.* **2016**, *65*, 522–533. [CrossRef]
54. Almaiah, M.A.; Al Mulhem, A. Thematic Analysis for Classifying the Main Challenges and Factors Influencing the Successful Implementation of E-Learning System Using NVivo. *Int. J. Adv. Trends Comput. Sci. Eng.* **2020**, *9*, 142–152. [CrossRef]
55. Kim, C.; Mirusmonov, M.; Lee, I. An empirical examination of factors influencing the intention to use mobile payment. *Comput. Hum. Behav.* **2010**, *26*, 310–322. [CrossRef]
56. Venkatesh, V.; Thong, J.Y.L.; Xu, X. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Q.* **2012**, *36*, 157–178. [CrossRef]
57. Sung, H.-N.; Jeong, D.-Y.; Jeong, Y.-S.; Shin, J.-I. The Relationship among Self-Efficacy, Social Influence, Performance Expectancy, Effort Expectancy, and Behavioral Intention in Mobile Learning Service. *Int. J. u- e- Serv. Sci. Technol.* **2015**, *8*, 197–206. [CrossRef]
58. Alasmari, T.; Zhang, K. Mobile learning technology acceptance in Saudi Arabian higher education: An extended framework and A mixed-method study. *Educ. Inf. Technol.* **2019**, *24*, 2127–2144. [CrossRef]

59. Nikolopoulou, K. Mobile learning usage and acceptance: Perceptions of secondary school students. *J. Comput. Educ.* **2018**, *5*, 499–519. [CrossRef]
60. Botero, G.G.; Questier, F.; Cincinnato, S.; He, T.; Zhu, C. Acceptance and usage of mobile assisted language learning by higher education students. *J. Comput. High. Educ.* **2018**, *30*, 426–451. [CrossRef]
61. Wibawa, S.C.; Sulistiyo, E.; Martiningsih, N.G.A.G.E.; Handoyo, E.; Johan, A. Moodle mobile development in enjoyable learning in computer system subjects. *IOP Conf. Series: Mater. Sci. Eng.* **2020**, *830*, 032017. [CrossRef]
62. Gorghiu, G.; Pribeanu, C.; Lamanauskas, V.; Slekiene, V. Usefulness of Mobile Teaching and Learning as Perceived by Romanian and Lithuanian Science Teachers. *Probl. Educ. 21st Century* **2020**, *78*, 719–733. [CrossRef]
63. Almaiah, M.A.; Ayouni, S.; Hajjej, F.; Lutfi, A.; Almomani, O.; Awad, A.B. Smart Mobile Learning Success Model for Higher Educational Institutions in the Context of the COVID-19 Pandemic. *Electronics* **2022**, *11*, 1278. [CrossRef]
64. Queirós-Reis, L.; Gomes da Silva, P.; Gonçalves, J.; Brancale, A.; Bassetto, M.; Mesquita, J.R. SARS-CoV-2 Virus−Host Interaction: Currently Available Structures and Implications of Variant Emergence on Infectivity and Immune Response. *Int. J. Mol. Sci.* **2021**, *22*, 10836. [CrossRef] [PubMed]
65. Alghazi, S.S.; Kamsin, A.; Almaiah, M.A.; Wong, S.Y.; Shuib, L. For Sustainable Application of Mobile Learning: An Extended UTAUT Model to Examine the Effect of Technical Factors on the Usage of Mobile Devices as a Learning Tool. *Sustainability* **2021**, *13*, 1856. [CrossRef]
66. Liu, S.H.; Liao, H.L.; Peng, D.J. Applying the technology acceptance model and flow theory to online e-learning users' acceptance behavior. *E-Learning* **2005**, *4*, 2.
67. Almogren, A.S.; Aljammaz, N.A. The integrated social cognitive theory with the TAM model: The impact of M-learning in King Saud University art education. *Front. Psychol.* **2022**, *13*, 1050532. [CrossRef]
68. Lu, Y.-T.; Chang, Y.-H.; Sung, T.-W. The Relationship between Motivation, the Use of Mobile Devices and Satisfaction with Life for Older Farmers. *Eurasia J. Math. Sci. Technol. Educ.* **2017**, *13*, 4009–4020. [CrossRef]
69. Digital 2022 Global Overview, Slides 23 and 55. Available online: https://www.slideshare.net/DataReportal/digital-2022-global-overview-report-january-2022-v05 (accessed on 24 November 2022).