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Antecedents of Satisfaction and Use of Mobile Learning in Higher Education

Os Antecedentes da Satisfação e Uso da Aprendizagem Móvel no Ensino Superior

Los Antecedentes de la Satisfacción y Uso del Aprendizaje Móvil en la Enseñanza Superior

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Abstract

The migration to emergency remote teaching has forced universities to adapt their teaching methodologies with the help of tools such as remote teaching, which has become a significant component of higher education technology. Additionally, higher education has enabled students to study, collaborate, and exchange ideas using the internet, technology, and mobile devices. Thus, this study analyzed which factors positively impacted satisfaction with mobile learning during the COVID-19 pandemic and which factors positively impacted the intention to use such devices in the future. Using research based on the Unified Theory of Acceptance and Use of Technology, data were collected from 498 undergraduate students at the State University of Campinas, Brazil, and analyzed using partial least squares structural equation modeling. In terms of intention to use, the results reveal that the most influential constructs are performance expectation, price, and hedonic motivations, while effort expectation, social influence, and facilitating conditions did not present a significant impact. Concerning the level of satisfaction, the constructs that have the most influence are hedonic motivations, performance expectation, effort expectation, price, and social influence. Only facilitating conditions did not show a significant impact on satisfaction. The results provided important information for improving the learning environment, teaching methods, curriculum formulation, and educational policy development. Furthermore, they contribute to Sustainable Development Goal 4 – Quality Education, by promoting new learning opportunities.

Keywords: higher education, mobile learning, the COVID-19 pandemic, remote teaching, information and communication technologies.

Resumo

A migração para o ensino remoto emergencial fez com que as universidades adaptassem suas metodologias de ensino com o auxílio de ferramentas, como o ensino remoto, que se tornou um componente significativo da tecnologia do ensino superior. Além disso, o ensino superior permitiu que os alunos estudassem, colaborassem e trocassem ideias enquanto usavam a internet, tecnologia e dispositivos móveis. Assim, este estudo analisou quais fatores impactaram positivamente a satisfação com o ensino móvel durante a pandemia da Covid-19, bem como quais fatores impactaram positivamente na intenção de usar tais dispositivos no futuro. Com uma pesquisa baseada na Teoria Unificada de Aceitação e Uso de Tecnologia, os dados foram coletados de 498 alunos de graduação da Universidade Estadual de Campinas, Brasil, e analisados com a aplicação da modelagem de equações estruturais por mínimos quadrados parciais. Os resultados, em termos de intenção de uso, revelam que os construtos mais influentes são: expectativa de desempenho, preço e motivações hedônicas; enquanto expectativa de esforço, influência social e condições facilitadoras não apresentaram influência significativa. Quanto ao nível da satisfação, os construtos que mais influenciam são: motivações hedônicas, expectativa de desempenho, expectativa de esforço, preço e influência social. Apenas as condições facilitadoras não apresentaram influência significativa na satisfação. Os resultados forneceram informações importantes para melhorar o ambiente de aprendizagem, métodos de ensino, formulação de currículo e desenvolvimento de políticas educacionais. Além disso, contribuem para o Objetivo de Desenvolvimento Sustentável 4 – Educação de Qualidade, ao promover novas oportunidades de aprendizagem.

Palavras-chave: ensino superior, aprendizagem móvel, pandemia da Covid-19, ensino remoto, tecnologias de informação e comunicação.

Resumen

La migración para la enseñanza remota de emergencia hizo con que las universidades adataran sus metodologías de enseñanza con la ayuda de herramientas, como la enseñanza remota, que se volvió un componente significativo de la tecnología de la enseñanza superior. Además de eso, la enseñanza superior permitió que los alumnos estudiasen, colaborasen e intercambiasen ideas mientras usaban la internet, tecnología y dispositivos móviles. Así, este estudio analizó cuáles factores impactan positivamente la satisfacción con la enseñanza móvil durante la pandemia de Covid-19, como también cuáles factores impactaron positivamente en la intención de usar tales dispositivos en el futuro. Con una investigación basada en la Teoría Unificada de Aceptación y Uso de Tecnologías, los datos fueron colectados de 498 alumnos de grado de la Universidad Estadual de Campinas, Brasil, y analizados con la aplicación del modelaje de ecuaciones estructurales por mínimos cuadrados parciales. Los resultados, en términos de intención de uso, revelan que los constructos más influyentes son: expectativa de rendimiento, precio y motivaciones hedónicas; mientras expectativa de esfuerzo, influencia social y condiciones facilitadoras no presentan influencia significativa. Con relación al nivel de satisfacción, los constructos que más influencian son: motivaciones hedónicas, expectativa de rendimiento, expectativa de esfuerzo, precio e influencia social. Solamente las condiciones facilitadoras no presentan influencia significativa en la satisfacción. Los resultados ofrecieron informaciones importantes para mejorar el ambiente de aprendizaje, métodos de enseñanza, formulación de currículo y desarrollo de políticas educacionales. Además de eso, contribuyen para el Objetivo de Desarrollo Sostenible 4 – Educación de Calidad, al promover nuevas oportunidades de aprendizaje.

Palabras llave: *enseñanza superior, aprendizaje móvil, pandemia de Covid-19, enseñanza remota, tecnologías de información y comunicación.*

Due to the global health crisis caused by the COVID-19 pandemic, more than 1.2 billion students from 186 countries were obligated to engage in remote learning from their homes (Khan et al., 2022; Sigahi et al., 2022), changing the traditional teaching methods that relied on in-person and face-to-face. However, the advent of the COVID-19 pandemic has significantly shifted the global perception of online education, as learners and educators worldwide have increasingly turned to online platforms on a large scale (Saikat et al., 2021).

To ensure continuity in the teaching process, numerous educational institutions implemented policies and regulations that facilitated the shift from traditional offline classroom instruction to online teaching. They adopted electronic learning (e-learning) environments and explored various solutions for a smooth transition (Zaidi et al., 2021). Remote teaching makes learning more flexible, and mobile, and ubiquitous, enabling students to access it anytime and anywhere. Therefore, some teachers use mobile learning, often called m-learning, whose definition implies using mobile and wireless Information and Communication Technologies (ICTs) as a learning aid and, mainly, focused on student mobility (Kim, 2020).

Previous research has empirically proven m-learning offers benefits in education, like collaboration between instructors and learners, immediate feedback, participation and engagement, authentic learning, and evaluation, in addition to providing flexibility and accessibility, serving as a valuable tool to improve digital literacy, student learning outcomes, and independent learning skills (Garzón & Lampropoulos, 2023; Klimova, 2019). However, especially in higher education, it is still an emerging resource. To have a positive impact on education, m-learning needs good practices, ranging from a concise explanation of how the application works to methods of self-assessment and student motivation (Kim, 2020; Romero-Rodríguez et al., 2020). Nevertheless, it allowed students to study using the technology (Alturki & Aldraiweesh, 2022; Pebriantika et al., 2021).

As also stated in several studies, m-learning applications are various. It is possible to find m-learning in courses, through WhatsApp (Braga & Martins, 2020), and in business English learning (Alanya-Beltran & Panduro-Ramirez, 2021). Meantime, researchers also highlight negative aspects and challenges related to the implementation of m-learning in teaching, like unequal access since all students would need a good connection, good equipment, and technological mastery (Dias & Ramalho, 2021; Pires, 2021), and resistance to the paradigm shift in traditionally expositive classes, requiring an adaptation in the didactic-pedagogical training of teachers (Gunter & Braga, 2018; Lima et al., 2018).

It is also important to highlight that m-learning faces socio-economic, cultural, and technological challenges in its adoption, which indeed vary across different geographic and educational contexts. Compared to developed countries, for example, in low-income areas, the cost of a mobile device (m-device) can be prohibitive, as social inequalities and marginalized groups create barriers. In the same way, in regions where digital skills are less developed, users might struggle with technology and develop a resistance to change. Furthermore, particularly in rural areas, reliable and high-speed internet access is limited, which impedes the use of m-learning platforms (Alsswey & Al-Samarraie, 2019; Wairiya et al., 2022). These barriers became more evident during COVID-19 pandemic (Singha & Mohapatra, 2023; Thanh et al., 2024).

Based on these arguments, the emerging trend of implementing learning on mobile and embedded devices, such as the importance of studies on this subject, has increased to understand the most effective practices and experiences in the use of m-learning (Chen et al., 2020; Romero-Rodríguez et al., 2020). In such a background, scholars have extensively examined the subject of m-learning, with a majority focusing on the emerging issues and trends within specific domains and timeframes (Al-Qora'n et al., 2023). Indeed, mainly driven by the COVID-19 context, various studies have been investigating the interactions between different factors of students m-learning acceptance and intention of use (Voicu & Muntean, 2023).

While there is a growing body of research on m-learning during the COVID-19 crisis, more research is needed, especially in developing countries (Alsswey & Al-Samarraie, 2019; Alzaidi & Shehawy, 2022). Assessing students satisfaction, the impact of m-learning usage on their performance during the COVID-19 pandemic, and their behavioural intentions regarding m-learning are crucial aspects to consider: first, to improve student performance; second, to help design effective online learning strategies for future challenges; and third, to comprehend predictors that impact students' satisfaction (Qamar et al., 2023; Singha & Mohapatra, 2023; Thanh et al., 2024). Alzaidi & Shehawy (2022) also highlight the importance of exploring the factors that contribute to the adoption of m-learning by students in higher education. Understanding these factors is crucial, as universities' return on investment could be limited if students reject the current mode of study (Alturki & Aldraiweesh, 2022; Alzaidi & Shehawy, 2022).

In this context, this research aims to understand the antecedents of satisfaction and the intention of future use of m-learning in the education process of undergraduate students, considering its use during the pandemic period. More specifically, we analysed what factors positively impacted satisfaction with m-learning during COVID-19 and what factors positively impacted the intention to use m-learning in the future, considering performance and effort expectancy, social influence, facilitating conditions, hedonic motivations, and price.

We adopted the Unified Technology Acceptance and Use Theory (UTAU) model using a quantitative methodology and applied multivariate statistics for data analysis to achieve our objective. Our investigation involved Brazilian undergraduate students, once especially in Brazil, universities suspended face-to-face activities and began replanning undergraduate courses, including an adaptation of academic and discipline standards in addition to the scope in the use of technology (Pires, 2021).

Our research offers valuable practical and theoretical contributions. Firstly, it identifies the key factors that influenced the adoption of m-learning during the COVID-19 pandemic. Secondly, by integrating the Unified Technology Acceptance and Use Theory (UTAUT) framework, our study enhances the understanding of the intention to use and satisfaction with m-learning. Lastly, it investigates the adoption of m-learning in higher education within a developing country context. The findings will help teach methods, curriculum formulation, and educational policy development to evolve strategies that enhance m-learning efficiency.

Theoretical Framework

Mobile Learning in Higher Education

Conceptually, m-learning encompasses a wide range of e-learning processes facilitated through personal m-devices like smartphones, tablets, and laptops (Voicu & Muntean, 2023). Yuan et al. (2021) suggest that m-learning emerged from the concepts of distance learning and electronic learning, representing a learning approach conducted through the use of mobile devices. As m-devices have advanced, the paradigm of m-learning has transitioned from enabling learning anytime and anywhere through a seamless and personalized learning paradigm. M-learning has emerged as a product of ICT (Yuan et al., 2021).

The COVID-19 pandemic has witnessed a surge in the popularity of m-learning in higher education (Li et al., 2023). The widespread impact of COVID-19 has significantly transformed the education industry's paradigm and has influenced user behaviour (Yuan et al., 2021). Previous studies on m-learning have primarily been conducted under ordinary circumstances, with limited exposure to the prolonged and extensive use of m-learning as observed in the year 2020 (Alzaidi & Shehawy, 2022).

In such a way, researchers affirm COVID-19 pandemic has exposed the significance of online learning and may transform learning in the future (Abdelwahed & Soomro, 2023; Alzaidi & Shehawy, 2022; Santos et al., 2022). For Almaiah et al. (2022), during the COVID-19 pandemic, ICT has helped universities on a global scale to ensure the continuity of learning processes. On the other hand, this transformation could be considered part of a 'natural process', since universities have passed by academic revolutions along the years and new forms of learning have been created (Buarque et al., 2021). According to a study conducted by Al-Qora'n et al. (2023), m-devices have emerged as indispensable tools in higher education, providing students and lecturers with convenient access to impactful instructional resources and facilitating effective interaction among them (Al-Qora'n et al., 2023).

Previous studies have pointed out advantages related to m-learning, like to access information quickly and learn anywhere and at any time (Yalcinkaya & Yucel, 2023); reachability, comfort, mobility, portability, and flexibility; interaction among participants; and ease of sharing information (Alzaidi & Shehawy, 2022). In addition, m-learning supports the collaborative learning by facilitating interactions in the learning community (Alismaiel et al., 2022; Yuan et al., 2021).

While numerous empirical studies have validated the advantages of m-learning, it is not devoid of certain obstacles, including cost considerations and negative attitudes displayed by healthcare professionals (Yalcinkaya & Yucel, 2023). In line with Yuan et al. (2021), even though mechanisms such as remote check-ins and online question-and-answer sessions ensure student attendance and participation in daily classes, learners' positive feedback on the learning experience is not guaranteed. The authors also emphasize that m-learning entails pedagogical designs grounded in theory to address learning needs, in addition to technological aspects related to IT infrastructure support, mobile hardware, and mobile applications, all of which significantly influence the quality of m-learning (Yuan et al., 2021).

Hypotheses Development

Various theoretical models have been utilized in research to identify the factors influencing individuals' intention to use technologies and their satisfaction with them. For instance, Marinković et al. (2020) mention the Technology Acceptance Model (TAM) developed by Davis (1989) and the UTAUT proposed by Venkatesh et al. (2003) as examples of such models. These frameworks provide valuable insights into the understanding of user behaviour and technology acceptance.

The UTAUT framework encompasses four fundamental constructs, namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Condition (FC). These constructs, as proposed by Venkatesh et al. (2003), are intended to elucidate users' intentions regarding the adoption and utilization of information systems or technologies (Alzaidi & Shehawy, 2022) or usage satisfaction (Marinković & Kalinic, 2017). For Yuan et al. (2021), UTAU constructs have the same meaning as some constructs from TAM.

Performance expectancy can be defined as how much the individual believes the use of technology can contribute to improving their performance on the task, being considered as an important predictor of the intention to use technology in the future (Li et al., 2023; Venkatesh et al., 2003), as well as a predictor of satisfaction with its use (Al-Rahmi et al., 2022; Marinković & Kalinic, 2017). Regarding the higher education context, we believe performance expectancy can influence the student's intention of using and satisfaction with m-learning. Thus, we present our first research hypotheses:

H1: Performance Expectancy positively influences the Intention of Use.
H2: Performance Expectancy positively influences Satisfaction.

Effort expectancy is associated with the ease and difficulty of using technology, that is, it is proportional to the complexity of the usage (Li et al., 2023; Venkatesh et al., 2003). For Al-Rahmi et al. (2022), the degree of adoption of m-learning is directly associated with the expectation of the complexity of its use. In this way, we expect that the effort expectancy of an undergraduate student can influence the intention of use and satisfaction with m-learning. Thus, our hypotheses 3 and 4 range as follows:

H3: Effort Expectancy positively influences the Intention of Use.
H4: Effort Expectancy positively influences Satisfaction.

Social influence is linked to the perception of the significance attributed by others to the individual, regardless of whether they themselves use the technology or not. It encompasses how the individual is perceived based on their utilization of the technology (Venkatesh et al., 2003, 2012). In the context of technology use such as m-learning, peer influence is also expected to have an effect both in terms of future use intention and satisfaction (Al-Rahmi et al., 2022; Marinkovic & Kalinic, 2017). In this context, we present hypotheses 5 and 6:

H5: Social Influence positively influences the Intention of Use.
H6: Social Influence positively influences Satisfaction.

Facilitating conditions encompass the environment and organizational infrastructure that foster the adoption and use of technology. In essence, the technological and organizational environment is structured to eliminate obstacles and facilitate the seamless integration of technology. According to Venkatesh et al. (2003), facilitating conditions play a pivotal role in influencing individuals' intention to use new technology and their satisfaction with its usage. Thus:

H7: Facilitating Conditions positively influence the Intention of Use.
H8: Facilitating Conditions positively influence Satisfaction.

After a few years of the presentation of UTAUT, Venkatesh et al. (2012) extended the model, incorporating some new latent variables. The model was named UTAUT 2, and it was widely accepted by the academic community due to the increase in the explanatory power of the phenomena. Among these constructs, two of them are important for this research, namely: hedonic motivations and price.

Hedonic motivations can be understood as how much the individual has fun or takes pleasure in using a certain technology (Venkatesh et al., 2012). Thus, hedonic motivations can have a positive influence on the intention to use and satisfaction of m-learning (Alalwan, 2020), even considering a situation like the COVID-19 pandemic. In this manner, we present hypotheses 9 and 10:

H9: Hedonic Motivations positively influence the Intention of Use.
H10: Hedonic Motivations positively influence Satisfaction.

Price is a significant construct that plays a crucial role in the decision-making process and satisfaction related to technology adoption. The financial aspect serves as a critical analytical factor in assessing the feasibility of adopting a technology. Additionally, it draws upon the marketing concept wherein the cost of the service is associated with the quality of the user experience. As a result, the cost structure of the technology and the promised benefits of its implementation exert a tangible influence on the decision to utilize it (Venkatesh et al., 2012).

H11: Price positively influences the Intention of Use.
H12: Price positively influences Satisfaction.

The role of satisfaction is pivotal in shaping individuals' behaviour when it comes to adopting information technology. Extensive research has highlighted satisfaction as a critical factor influencing the intention to adopt and utilize information technology (DeLone & McLean, 2016). Academics have placed additional emphasis on the importance of educators' preparedness, abilities, self-assurance, and proficiency, encompassing their online technological, communication, and teaching aptitudes, in influencing students' satisfaction and their inclination to persist with m-learning (Alzaidi & Shehawy, 2022; Zaidi et al., 2021). It is generally observed that students' satisfaction with electronic learning is influenced by the quality of the online learning medium (Aldholay et al., 2018).

Importantly, if individuals experience low levels of satisfaction while using technology, the likelihood of continued technology use diminishes (Yalcinkaya & Yucel, 2023). Therefore, it is suggested that students' satisfaction with mobile learning significantly impacts their behavioural intentions to continue using mobile learning in the future.

H13: Satisfaction positively influences the Intention of Use.

Research Methodology

This study employed a quantitative methodology and utilized multivariate statistics for data analysis. Following the approach suggested by Hair et al. (2019), which aims to predict and explain the constructs under investigation while providing a common ground between path modelling and confirmatory factor analysis, Partial Least Squares Structural Equation Modelling (PLS-SEM) was chosen as the analytical technique.

PLS-SEM is a robust statistical method used for analysing complex relationships between variables. Due to its characteristics, it is usually applied to examine behavioural intentions, including regarding the usage of m-learning, like in Ahmed et al. (2024), and Ali et al. (2023). Furthermore, PLS-SEM was adopted by scholars who aimed to understand m-learning adoption during COVID-19 pandemic in emerging countries (Thanh et al., 2024; Wairiya et al., 2022).

Prior to commencing the research, various research protocols were prepared, including the project description, preliminary questionnaire, authorization from the university management, and researchers' commitment statements. These documents were then submitted to the research ethics committee via *Plataforma Brasil* for evaluation and approval. Once approved by the ethics committee, a pre-test was conducted with experts and potential survey respondents. The expert validation confirmed the face validity and appropriateness of the questionnaire for the intended research objective. The validation with potential respondents aimed to assess their comprehension of the questions and did not require any modifications.

As study objects, the participants involved undergraduate students from the Faculty of Applied Sciences at Campinas State University (UNICAMP), located in the State of São Paulo, Brazil. These students were chosen because the campus contains six courses in different areas, which increases the relevance of the results, namely: Administration, Public Administration, Sports Science, Manufacturing Engineering, Production Engineering, and Nutrition.

Regarding the empirical model, indicators of Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence were based on Venkatesh et al. (2003), while the indicators of Hedonic Motivations, and Price were based on Venkatesh et al. (2012). Finally, the Satisfaction was based on research conducted by Maiden (2008).

Results

The final sample consisted of 498 valid responses. Respondents from the Administration course totalled 40% of the sample; Public Administration, 18%; Sports Science 7%; Manufacturing Engineering 8%; Production Engineering 14%; and Nutrition, 12%. Regarding gender, 54% declared themselves to be male; 45% female and 1% other gender.

On average, respondents attended 20 disciplines and four semesters in a remote format. The most used devices were smartphones (52%), notebooks (43%), and tablets (5%).

The first step of the empirical analysis in this research involved evaluating the measures included in the conceptual model. Given that some indicators were adapted while others were originally developed, it became necessary to employ Confirmatory Factor Analysis (CFA) to determine whether the selected indicators (items) provided an adequate measurement for the constructs that comprise the model (Hair et al., 2009). The CFA was conducted using the SmartPLS 3 software.

According to Hair et al. (2019), factor loadings of 0.7 or higher are recommended for retaining indicators in the model. However, it is acceptable to retain factor loadings between 0.4 and 0.7 as long as they do not significantly affect the Average Variance Extracted (AVE) and Composite Reliability (CR) values. Based on this criterion, no indicators were excluded from the model. The results of the CFA are presented in Table 1.

Table 1

Confirmatory factor analysis

Questions	Factor Loadings	Mean	Std. Dev.	T-value	P-value
Performance Expectancy					
PE1. Using mobile learning has improved my academic performance.	0.794	3.243	1.205	32.925	0.000
PE2. Using mobile learning increased my chances of achieving a knowledge considered important to me.	0.798	3.106	1.180	32.734	0.000
PE3. Using mobile learning allowed me to accomplish learning tasks more quickly.	0.581	3.984	0.971	14.016	0.000
Effort Expectancy					
EE1. Learning how to use mobile learning was easy for me.	0.775	4.221	0.925	24.976	0.000
EE2. My interaction with mobile learning was clear and understandable.	0.838	3.962	0.936	50.667	0.000
EE3. I found it easy to use mobile learning.	0.862	4.203	0.870	43.812	0.000
EE4. It was easy for me to use mobile learning to do what I wanted to do.	0.837	4.102	0.882	43.978	0.000
Social Influence					
SI1. People who are important to me think I should use mobile learning.	0.903	2.940	1.083	66.608	0.000
SI2. People who influence my behavior think I should use mobile learning.	0.902	2.972	1.051	66.269	0.000
SI3. People whose opinion I value preferred students to use mobile learning.	0.833	2.793	1.058	39.262	0.000
Facilitating Conditions					
FC1. I had the necessary resources to use mobile learning.	0.726	4.319	0.961	16.825	0.000
FC2. I had the necessary knowledge to use mobile learning.	0.814	4.317	0.821	21.495	0.000
FC3. Using mobile learning is similar to other technologies I use.	0.828	4.219	0.844	30.998	0.000
FC4. I got help from others when I had difficulty using mobile learning.	0.582	3.827	1.037	8.006	0.000

Hedonic Motivations					
HM1. Using mobile learning is enjoyable.	0.866	3.526	1.089	67.104	0.000
HM2. The process of using mobile learning was pleasant.	0.912	2.910	1.149	105.963	0.000
HM3. I had fun using mobile learning.	0.857	2.849	1.144	47.742	0.000
Price					
PR1. Mobile learning devices are reasonably priced.	0.426	2.263	0.984	4.897	0.000
PR2. I consider mobile learning devices a good investment for studying.	0.904	3.829	0.964	39.709	0.000
PR3. At current prices, mobile learning devices provide good value.	0.709	3.189	1.030	13.573	0.000
Intention of Use					
IU1. Assuming I have access to mobile learning in the future, I plan to use it.	0.889	3.829	1.030	67.028	0.000
IU2. Given that I have access to mobile learning, I predict that I would use it.	0.917	3.878	0.959	95.715	0.000
IU3. I plan to use mobile learning in the future for my educational activities.	0.916	3.753	1.038	92.121	0.000
IU4. I plan to use mobile learning in my future courses.	0.879	3.691	1.068	63.395	0.000
Satisfaction					
SAT1. I am very satisfied with the use of mobile learning.	0.899	3.297	1.072	97.508	0.000
SAT2. I am satisfied with the efficiency of mobile learning.	0.834	3.454	1.019	44.572	0.000
SAT3. Mobile learning satisfies my educational needs.	0.821	3.227	1.145	46.748	0.000
SAT4. Mobile learning is enjoyable to use.	0.815	3.418	1.065	38.168	0.000
SAT5. Overall, I am satisfied with mobile learning.	0.894	3.556	1.009	88.681	0.000

Note: PE: Performance Expectancy; EE: Effort Expectancy; SI: Social Influence; CF: Facilitating Conditions; HM: Hedonic Motivations; PR: Price; IU: Intention of Use; SAT: Satisfaction.

The next step following CFA is the analysis of the empirical model. This analysis generally involves comparing the measurements provided between the indicators and the constructs (measurement model) and among the constructs (structural model) to determine how well the theory fits the collected data (Hair et al., 2009). The analysis of the measurement model should also be divided into formative and reflective indicators, according to the recommendations of Hair et al. (2009).

The SEM used in this research was developed through Partial Least Squares (PLS). This method interactively and multivariately analyses both the measurement model and the structural model to enhance the accuracy and validity of the results, thereby minimizing potential measurement errors (Hair et al., 2019).

In this study, all indicators are reflective, meaning that the items used in the field research represent the theoretical constructs (Hair et al., 2009). Thus, when assessing the measurement model, the focus was on examining the convergent validity, discriminant validity, and reliability of the indicators, considering that all constructs in the study were reflexive (Hair et al., 2018). Table 2 presents the necessary indicators for these evaluations, all of which fulfil the predetermined criteria (Fornell & Larcker, 1981; Hair et al., 2019). Consequently, no indicators needed to be excluded at this stage of the analysis.

Table 2

Assessment of the measurement model

Constructs	PE	EE	SI	FC	HM	PR	IU	SAT
Performance Expectancy (PE)	0.788							
Effort Expectancy (EE)	0.302	0.829						
Social Influence (SI)	0.460	0.232	0.880					
Facilitating Conditions (FC)	0.263	0.538	0.206	0.744				
Hedonic Motivations (HM)	0.627	0.384	0.423	0.300	0.879			
Price (PR)	0.417	0.212	0.313	0.249	0.522	0.707		
Intention of Use (IU)	0.642	0.356	0.422	0.313	0.658	0.523	0.900	
Satisfaction (SAT)	0.651	0.416	0.453	0.314	0.773	0.508	0.721	0.853
Cronbach's Alpha	0.842	0.849	0.854	0.728	0.852	0.574	0.922	0.906
rho_A	0.858	0.863	0.856	0.771	0.856	0.799	0.922	0.911
Composite Reliability	0.890	0.898	0.912	0.830	0.910	0.735	0.945	0.930
Average Variance Extracted (AVE)	0.621	0.687	0.775	0.553	0.772	0.500	0.811	0.728

To validate the structural model, the initial step entailed scrutinizing the variance inflation factor (VIF), and it was observed that all values fell within the acceptable range determined by Hair et al. (2019). The coefficients between the constructs and their corresponding Student's t-test values are presented in Table 3. According to the findings presented in Table 3, all hypotheses of the study were supported, except for H3, H5, H7, and H8.

Table 3

Assessment of the structural model

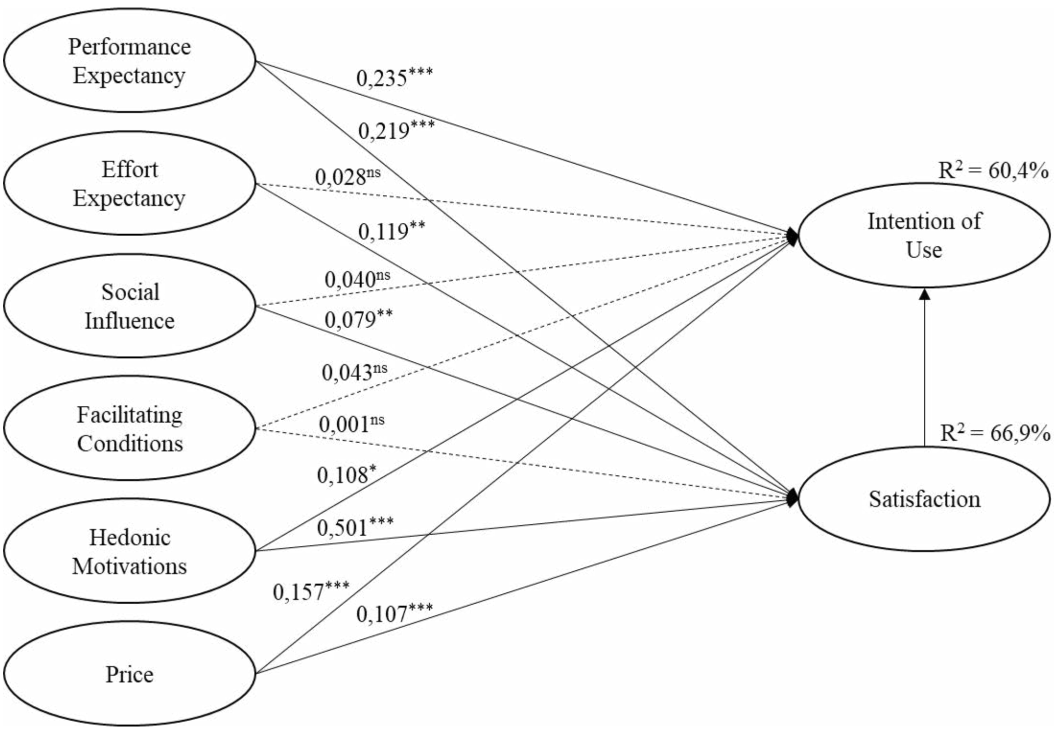
Path	Mean	Std. Dev.	T-value	P-value
Performance Expectancy → Intention of Use	0.233	0.047	5.043	0.000
Performance Expectancy → Satisfaction	0.225	0.037	5.912	0.000
Effort Expectancy → Intention of Use	0.030	0.037	0.729	0.467
Effort Expectancy → Satisfaction	0.119	0.042	2.727	0.007
Social Influence → Intention of Use	0.040	0.037	1.088	0.277
Social Influence → Satisfaction	0.079	0.031	2.618	0.009
Facilitating Conditions → Intention of Use	0.043	0.040	1.096	0.274
Facilitating Conditions → Satisfaction	0.001	0.042	0.016	0.987
Hedonic Motivations → Intention of Use	0.108	0.053	2.102	0.036
Hedonic Motivations → Satisfaction	0.496	0.044	11.442	0.000
Price → Intention of Use	0.156	0.047	3.264	0.001
Price → Satisfaction	0.104	0.040	2.601	0.010
Satisfaction → Intention of Use	0.362	0.071	5.098	0.000

The results point to a coefficient of determination considered high, with R^2 of 60.4% for Intention of Use and 66.9% for Satisfaction. Furthermore, the Q^2 was 0.480 for Intention of Use and 0.482 for Satisfaction, with values considered adequate (Cohen, 2013; Faul et al., 2009; Hair et al., 2019).

The PLS-SEM results are illustrated in Figure 1.

Figure 1

Complete empirical model



Note: ns: not significant; * = significant at 5%; ** = significant at 1%; *** = significant at 0.1%.

Discussions

Scholars have recently indicated that m-learning is still an active research area, mainly with the advent of the COVID-19 epidemic. This research sought to understand the antecedents of satisfaction and the intention of future use of m-learning in the process education of undergraduate students, considering its use during the pandemic period.

Our results, in terms of intention of use, reveal the most influential constructs are: performance expectancy, price, and hedonic motivations, in this order of importance. The results indicate that increasing academic performance and learning is the main impact factor regarding intention of use. Next, price is the second factor with the most impact, indicating that students consider that the current price of m-devices is reasonable, considering it a good investment. Hedonic motivations appear in third place, indicating that students consider the use of m-learning for educational purposes to be pleasant.

Our findings are in line with previous studies, like Alzaidi & Shehawy (2022) and Li et al. (2023). Li et al. (2023), for example, aimed to extend UTAUT by incorporating three sub-dimensions of self-efficacy for measuring students' acceptance of m-learning in 900 students from Chinese higher vocational education. They found performance expectancy was directly affected by students' self-efficacy in using m-learning.

They did not show any significant influence on intention of use, effort expectancy, social influence, and facilitating conditions. Therefore, factors related to prior knowledge, resources, or referrals from acquaintances have no impact on future m-learning usage. The coronavirus pandemic probably reduced this influence since these respondents had to use m-learning to continue their studies in Brazilian higher education.

The insignificant influence of effort expectancy and facilitating conditions is similar to the results from Alzaidi & Shehawy (2022). In a study conducted in Saudi Arabia, Egypt and the UK, the authors applied UTAU and did not validate this hypothesis related to students' continued intentions to use m-learning. On the other hand, the rejection of social influence on intention of use contradicts many authors.

In accordance with Li et al. (2023), social influence is similar to social control. However, in our study, it does not appear to influence students' intentions of using m-learning. Maybe undergraduate students are at an age where influences do not strongly impact certain behaviours (Alismaiel et al., 2022).

In terms of satisfaction, the constructs that most influence it are: hedonic motivations, performance expectancy, effort expectation, price, and social influence. These results demonstrate that, in general, students were highly satisfied with the use of m-learning, with almost all tested backgrounds having a positive influence. Thus, in the first place, appeared the hedonic motivations, indicating that the more fun to use, the greater the satisfaction. In second place came performance expectations, showing that facilitating learning leads to satisfaction. In third place appeared the effort expectancy, indicating that the clear and understandable interaction leaves the student satisfied. Fourthly, price, demonstrating that as the investment provides a good return, they are satisfied. Lastly, social influence, demonstrating that the recommendation of acquaintances has an impact, to a lesser extent, on satisfaction.

This finding is consistent with prior findings. In a survey conducted by Hong et al. (2011), 477 users of agile information systems found satisfaction was affected by performance and effort expectancy, which they named perceived usefulness and perceived ease of use, respectively. For Hong et al. (2011), performance and effort expectancy are key cognitive variables. In other words, performance and effort are directly related to learning and academic performance. As a consequence, this construct, aligned with hedonic motivations, price and social influence, is highly related to students m-learning satisfaction.

Still, regarding satisfaction, only facilitating conditions showed no significant influence. Facilitating conditions is equivalent to perceived behavioural control in TPB (Li et al., 2023). In the context of m-learning, it is defined as the extent to which a student believes that the university or hardware environment supports his or her use of m-devices Venkatesh et al. (2003). Prior m-learning studies highlighted that the effect of facilitating conditions on students' is expected to influence students' decision to continue to use m-learning (Alzaidi & Shehawy, 2022). However, in accordance with Alzaidi & Shehawy (2022), the feeling of social isolation and loneliness will negatively influence students' continuous use of m-learning. On the contrary, our results show that satisfaction positively influences the intention to use m-learning in Brazilian higher education universities.

Conclusion

This paper examined antecedents of satisfaction and the intention of future use of m-learning in the process education of undergraduate students using an extended UTAUT model. We investigated a sample of 498 undergraduate students from Brazil. Our findings showed that intention to use m-learning is significantly affected by performance expectation, price, hedonic motivations, and students' satisfaction. Furthermore, satisfaction with m-learning is influenced by hedonic motivations, performance and effort expectations, price, and social influence. Additionally, our research presented a robust model with a high coefficient of determination (R^2) for Intention of Use and Satisfaction.

The results presented important insights for improving the learning environment, teaching methods, curriculum formulation and educational policy development, highlighting how to increase students' satisfaction and intention for the future use of m-learning, like: (i) facilitating conditions are not significant for the model, indicating that it is no longer a challenge to own a smartphone or tablet, even considering the public university public; (ii) the high influence of hedonic motivations indicate that interaction strategies, such as dynamics and quiz, increase the effectiveness of remote teaching; (iii) price having a positive influence indicates that students consider m-learning a good investment for educational purposes.

Especially for educators and policymakers, mainly in emerging economies, we recommend: *first*, partnerships with telecom companies and government initiatives can help expand network coverage and reduce data cost; *second*, the provision of affordable devices, comprehensive training for educators on how to effectively use m-learning tools; *third*, ensure that educational content is relevant and accessible in local languages and culturally appropriate; *fourth*, comprehensive training for educators on how to effectively use m-learning tools; *fifth*, encourage collaboration between government agencies, educational institutions, technology providers, and community organizations; and establish clear policies and guidelines for the implementation and management of m-learning initiatives.

Our additional findings provide theoretical validation for previous studies by confirming the applicability of the UTAUT model in the context of m-learning across both developed and developing societies. Furthermore, these findings contribute to the existing literature on information technology, particularly in developing contexts. From a managerial perspective, the implications of our findings extend to the formulation of policies pertaining to educational technology within learning institutions. For instance, our study highlights the emergence of m-learning as a valuable method of academic instruction, and in light of the COVID-19 pandemic, we recommend a greater emphasis on digital education. Additionally, our literature review underscores the effectiveness of m-learning as a tool for enhancing knowledge within society.

Ultimately, the findings make a valuable contribution to Sustainable Development Goal (SDG) 4, 'Quality Education', by fostering new learning opportunities. This contributes to ensuring equitable access to affordable, quality higher education and significantly increasing the number of youth and adults with relevant skills.

It is important to acknowledge the limitations of our findings. Firstly, the study relied on a single cross-sectional data collection in the latter half of 2022, which may not capture the evolving opinions of respondents over time. Secondly, the sample size was limited to students from only six undergraduate courses at a specific educational institution, potentially introducing a significant bias. Lastly, the model examined only a limited number of antecedents, and there may be additional antecedents that yield different outcomes.

Therefore, future studies should: (i) test the model in different courses and types of educational institutions; (ii) test the model in different cultural and educational contexts; (iii) test multigroup and moderation analyses, such as gender, age, region, and income; (iv) carry out longitudinal or qualitative research, complementing the results with information that considers a longer analysis time; (v) finally, it may be recommended to repeat the data after the epidemic.

Declaration of interest statement

The authors report that there are no competing interests to declare.

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References

Abdelwahed, N. A. A., & Soomro, B. A. (2023). Attitudes and intentions towards the adoption of mobile learning during COVID-19: Building an exciting career through vocational education. *Education and Training*, *65*(2), 210–231. https://doi.org/10.1108/ET-02-2022-0048

Ahmed, S. A. M., Suliman, M. A. E., AL-Qadri, A. H., & Zhang, W. (2024). Exploring the intention to use mobile learning applications among international students for Chinese language learning during the COVID-19 pandemic. *Journal of Applied Research in Higher Education*, *16*(4), 1093–1116. https://doi.org/10.1108/JARHE-01-2023-0012

Alalwan, A. A. (2020). Mobile food ordering apps: An empirical study of the factors affecting customer e-satisfaction and continued intention to reuse. *International Journal of Information Management*, *50*, 28–44. https://doi.org/10.1016/j.ijinfomgt.2019.04.008

Alanya-Beltran, J., & Panduro-Ramirez, J. (2021). Mobile Learning in Business English its Effect to South American Students' Learning Styles in the COVID 19 Pandemic Era: Its Economic Implications. *Studies of Applied Economics*, *39*(12), 1-14. https://doi.org/10.25115/eea.v39i12.6394

Aldholay, A. H., Abdullah, Z., Ramayah, T., Isaac, O., & Mutahar, A. M. (2018). Online learning usage and performance among students within public universities in Yemen. International *Journal of Services and Standards, 12*(2), 163-179. https://doi.org/10.1504/IJSS.2018.10012964

Ali, Q., Abbas, A., Raza, A., Khan, M. T. I., Zulfiqar, H., Iqbal, M. A., Nayak, R. K., & Alotaibi, B. A. (2023). Exploring the Students' Perceived Effectiveness of Online Education during the COVID-19 Pandemic: Empirical Analysis Using Structural Equation Modeling (SEM). *Behavioral Sciences*, *13*(7), 578-591. https://doi.org/10.3390/bs13070578

Alismaiel, O. A., Cifuentes-Faura, J., & Al-Rahmi, W. M. (2022). Online Learning, Mobile Learning, and Social Media Technologies: An Empirical Study on Constructivism Theory during the COVID-19 Pandemic. *Sustainability*, *14*(18), 1-15. https://doi.org/10.3390/su141811134

Almaiah, M. A., Ayouni, S., Hajjej, F., Lutfi, A., Almomani, O., & Awad, A. B. (2022). Smart Mobile Learning Success Model for Higher Educational Institutions in the Context of the COVID-19 Pandemic. *Electronics*, *11*(8), 1–13. https://doi.org/10.3390/electronics11081278

Al-Qora'n, L. F., Al-odat, A. M., Al-jaghoub, S., & Al-Yaseen, H. (2023). State of the Art of Mobile Learning in Jordanian Higher Education: An Empirical Study. *Multimodal Technologies and Interaction*, *7*(4), 1-19. https://doi.org/10.3390/mti7040041

Al-Rahmi, A. M., Al-Rahmi, W. M., Alturki, U., Aldraiweesh, A., Almutairy, S., & Al-Adwan, A. S. (2022). Acceptance of mobile technologies and M-learning by university students: An empirical investigation in higher education. *Education and Information Technologies*, *27*(6), 7805–7826. https://doi.org/10.1007/s10639-022-10934-8

Alsswey, A., & Al-Samarraie, H. (2019). M-learning adoption in the Arab gulf countries: A systematic review of factors and challenges. *Education and Information Technologies*, *24*(5), 3163–3176. https://doi.org/10.1007/s10639-019-09923-1

Alturki, U., & Aldraiweesh, A. (2022). Students' Perceptions of the Actual Use of Mobile Learning during COVID-19 Pandemic in Higher Education. *Sustainability*, *14*(3), 1-17. https://doi.org/10.3390/su14031125

Alzaidi, M. S., & Shehawy, Y. M. (2022). Cross-national differences in mobile learning adoption during COVID-19. *Education and Training*, *64*(3), 305–328. https://doi.org/10.1108/ET-05-2021-0179

Braga, J. de C. F., & Martins, A. C. S. (2020). When Teacher Education Goes Mobile: A Study on Complex Emergence. *Revista Brasileira de Linguística Aplicada*, *20*(2), 353–381. https://doi.org/10.1590/1984-6398201914819

Buarque, B., Santos, A. C. B. dos, Lucena, N. F. de, Magalhães, R. C., & Machado, H. O. (2021). O Papel das Redes e da Capacidade de Conversão de Conhecimento no Desenvolvimento de Spin-Offs Acadêmicas. *Revista Ciências Administrativas*, *27*(3),1-14. https://doi.org/10.5020/2318-0722.2021.27.3.11811

Chen, Y., Zheng, B., Zhang, Z., Wang, Q., Shen, C., & Zhang, Q. (2020). Deep Learning on Mobile and Embedded Devices. *ACM Computing Surveys*, *53*(4), 1–37. https://doi.org/10.1145/3398209

Cohen, J. (2013). *Statistical Power Analysis for the Behavioral Sciences*. Routledge. https://doi.org/10.4324/9780203771587

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

DeLone, W. H., & McLean, E. R. (2016). Information Systems Success Measurement. *Foundations and Trends® in Information Systems*, *2*(1), 1–116. https://doi.org/10.1561/2900000005

Dias, D. D. S. F., & Ramalho, B. L. (2021). Mobile Learning no Ensino de Didática: caminhos na pandemia. *Informática Na Educação: Teoria & Prática*, *24*(2), 66-76. https://doi.org/10.22456/1982-1654.110831

Santos, V. M. dos, Cernev, A. K., Saraiva, G. M. M., & Bida, A. G. (2022). Faculty experience and digital platforms in education. *Revista de Gestão*, *29*(3), 252–266. https://doi.org/10.1108/REGE-05-2021-0090

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.2307/3151312

Garzón, J., & Lampropoulos, G. (2023). Mobile learning for science education: Meta-analysis of K-12 research. *Interactive Learning Environments*, 1–16. https://doi.org/10.1080/10494820.2023.2280973

Gunter, G. A., & Braga, J. de C. F. (2018). Connecting, swiping, and integrating: Mobile apps affordances and innovation adoption in teacher education and practice. *Educação em Revista*, *34*, 1-22. https://doi.org/10.1590/0102-4698189927

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

Hair, J. F., Jr, Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2018). *Advanced Issues in Partial Least Squares Structural Equation Modeling.* SAGE Publications.

Hair, J. F., Jr, Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2009). *Análise multivariada de dados* (6th ed.). Bookman.

Hong, W., Thong, J. Y. L., Chasalow, L. C., & Dhillon, G. (2011). User Acceptance of Agile Information Systems: A Model and Empirical Test. *Journal of Management Information Systems*, *28*(1), 235–272. https://doi.org/10.2753/MIS0742-1222280108

Khan, R. M. I., Ali, A., & Alouraini, A. (2022). Mobile Learning in Education: Inevitable Substitute during COVID-19 Era. *SAGE Open*, *12*(4), 1–10. https://doi.org/10.1177/21582440221132503

Kim, J. (2020). Voices of youth in reconceptualising and repositioning the role of mobile learning for sustainable development. *Information Technology for Development*, *26*(4), 711–727. https://doi.org/10.1080/02681102.2020.1749537

Klimova, B. (2019). Impact of Mobile Learning on Students' Achievement Results. *Education Sciences*, *9*(2), 90-98. https://doi.org/10.3390/educsci9020090

Li, Z., Islam, A. Y. M. A., & Spector, J. M. (2023). Unpacking Mobile Learning in Higher Vocational Education During the COVID-19 Pandemic. *International Journal of Mobile Communications*, *20*(2), 129-149. https://doi.org/10.1504/ijmc.2023.10042533

Lima, T. V. de, Freitas, A. S. de, Ferreira, J. B., & Filardi, F. (2018). O M-Learning como Apoio ao Ensino em Administração. *Revista de Administração FACES Journal*, *17*(3), 28–47.

Maiden, N. (2008). User Requirements and System Requirements. *IEEE Software*, *25*(2), 90–91. https://doi.org/10.1109/MS.2008.54

Marinković, V., Đorđević, A., & Kalinić, Z. (2020). The moderating effects of gender on customer satisfaction and continuance intention in mobile commerce: A UTAUT-based perspective. *Technology Analysis & Strategic Management*, *32*(3), 306–318. https://doi.org/10.1080/09537325.2019.1655537

Marinković, V., & Kalinic, Z. (2017). Antecedents of customer satisfaction in mobile commerce: Exploring the moderating effect of customization. *Online Information Review*, *41*(2), 138–154. https://doi.org/10.1108/OIR-11-2015-0364

Pebriantika, L., Wibawa, B., & Paristiowati, M. (2021). Adoption of Mobile Learning: The Influence And Opportunities For Learning During The Covid-19 Pandemic. *International Journal of Interactive Mobile Technologies*, *15*(5), 222-229. https://doi.org/10.3991/ijim.v15i05.21067

Pires, A. (2021). Covid 19 y la educación superior en Brasil: Usos diferenciados de las tecnologías de la comunicación virtual y las desigualdades educativas. *Educación*, *30*(58), 1-21. https://doi.org/10.18800/educacion.202101.004

Qamar, Md. T., Ajmal, M., Malik, A., Ahmad, J. J., & Yasmeen, J. (2023). Mobile learning determinants that influence Indian university students' learning satisfaction during the COVID-19 pandemic. *International Journal of Continuing Engineering Education and Life-Long Learning*, *33*(2/3), 1-30. https://doi.org/10.1504/IJCEELL.2023.129212

Romero-Rodríguez, J-M., Aznar-Díaz, I., Hinojo-Lucena, F-J., & Cáceres-Reche, M-P. (2020). Models of good teaching practices for mobile learning in higher education. *Palgrave Communications*, *6*(80), 1-7. https://doi.org/10.1057/s41599-020-0468-6

Saikat, S., Dhillon, J. S., Ahmad, W. F. W., & Jamaluddin, R. A. (2021). A systematic review of the benefits and challenges of mobile learning during the covid-19 pandemic. *Education Sciences*, *11*(9), 1-14. https://doi.org/10.3390/educsci11090459

Sigahi, T. F. A. C., Sznelwar, L. I., Rampasso, I. S., Moraes, G. H. S. M. de, Girotto, G., Jr., Pinto, A., Jr., & Anholon, R. (2022). Proposal of guidelines to assist managers to face pressing challenges confronting Latin American universities: A complexity theory perspective. *Ergonomics*, *66*(9), 1–16. https://doi.org/10.1080/00140139.2022.2126895

Singha, C., & Mohapatra, R. L. (2023, November 15-17). *Student Satisfaction on Online Learning During Covid-19 Using Machine Learning Techniques*. [Conference presentation abstract]. International Conference on Sustainable Communication Networks and Application (ICSCNA), Theni, India. https://doi.org/10.1109/ICSCNA58489.2023.10370345

Thanh, L. P., Trang, T. N. Q., Minh, N. N., & Van Hai, H. (2024). Key Determinants of Student Satisfaction in Online Learning During COVID-19: Evidence From Vietnamese Students. *Human Behavior and Emerging Technologies*, *2024*(1), 1–14. https://doi.org/10.1155/2024/5560967

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Voicu, M. C., & Muntean, M. (2023). Factors That Influence Mobile Learning among University Students in Romania. *Electronics*, *12*(4), 1-18. https://doi.org/10.3390/electronics12040938

Wairiya, M., Sahu, G. P., & Tyagi, N. (2022, January 27-28). *Identifying Critical Success Factor for Effective Adoption of Mobile Learning Application: An Empirical Study in Indian Context*. [Conference-presentation abstract]. Twelfth International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India. https://doi.org/10.1109/Confluence52989.2022.9734229

Yalcinkaya, T., & Yucel, S. C. (2023). Determination of nursing students' attitudes toward and readiness for mobile learning: A cross-sectional study. *Nurse Education Today*, *120*, 1-6. https://doi.org/10.1016/j.nedt.2022.105652

Yuan, Y-P., Tan, G. W-H., Ooi, K-B., & Lim, W-L. (2021). Can COVID-19 pandemic influence experience response in mobile learning? *Telematics and Informatics*, *64*, 1-14. https://doi.org/10.1016/j.tele.2021.101676

Zaidi, S. F. H., Osmanaj, V., Ali, O., & Zaidi, S. A. H. (2021). Adoption of mobile technology for mobile learning by university students during COVID-19. *International Journal of Information and Learning Technology*, *38*(4), 329–343. https://doi.org/10.1108/IJILT-02-2021-0033

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