

**EMPIRICAL ARTICLE**

# Mobile learning acceptance in social distancing during the COVID-19 outbreak: The mediation effect of hedonic motivation

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**Abstract**

M-learning is a trending field in educational organizations, companies, and also for individual study. However, in some regions the ampleness of the phenomenon is not quantifiable or comparable due to the lack of an adequate framework and reliable metrics. Our research intends to make a little light by assessing the degree of m-learning adoption in students at a moment when face-to-face education moved suddenly online due to the COVID-19 outbreak's rapid and unpredictable spread. A new model relying on the Unified Theory of Acceptance and Use of Technology (UTAUT) was built to investigate and explain relationships between constructs. It reveals the key factors affecting technology adoption by considering hedonic motivation a mediator instead of an exogenous variable as in UTAUT2. Based on an analysis of 311 higher education learners, the way how performance expectancy, effort expectancy, social influence, and facilitating conditions influence directly or indirectly the behavioral intention is researched. The analysis was conducted employing partial least squares structural equation modeling. The strongest relationship is between hedonic motivation and behavioral intention followed by the one between perceived effectiveness and hedonic motivation. Age, gender, and experience moderate the model's relationships. Research contributes to theory development by successfully adjusting the original UTAUT model. Results indicate that universities may offer learners an enjoyable m-learning experience by activating social support groups and inserting gameplay elements into the learning system.

**KEYWORDS**

acceptance technology, behavioral intention, COVID-19, facilitating conditions, hedonic motivation, mobile learning, performance expectancy, social influence, structural equation modeling, UTAUT

## 1 | INTRODUCTION

The area of mobile or m-learning is attracting increasing attention in the recent few years. M-learning is a synergy between every nation's development foundation—education—and the trending mobile technology. Education is critical in an individual's life and for the whole society (Sandri, 2020). Sometimes it is criticized for preserving the

brick-and-mortar approach, but in recent decades it substantially evolved (Palagi et al., 2015). However, many times modern education is still seen as an unsuccessful replica of the traditional form (Lee et al., 2021). Data democratization—that is, everybody with average nontechnical skills can use data anytime and from anywhere without access or know-how restrictions—has many positive aspects (Alexander & Joshi, 2016), including the enabling of m-learning.

Mobile technology's high rate of acceptance and the Internet's global spread and its near-ubiquitous accessibility (public and public wi-fi outspread and mobile data traffic cheapening) contributed to extensive development in almost every field, including technology-enhanced learning (Chiu, 2020). Alternatively, distance and online learning's demands have accelerated the integration of mobile technology.

It is well known that m-learning is a natural evolution of e-learning caused by the ubiquitous character of mobile devices (Barnes et al., 2019; Zhai & Shi, 2020). The users, who are familiar with, or even addicted (Andrade et al., 2020; Kuem et al., 2020; Tangmunkongvorakul et al., 2020) to mobile gadgets, do not have to change anymore the device when shifting from basic phone-related activities (calls, messaging, and emails) to personal needs (order food, shopping, booking for various services), entertainment (social media, games, movies, news), but also working or learning (Fu et al., 2020). Moreover, studies like (Buchmann & Karagiannis, 2017) demonstrate that m-learning is not exclusively designed for schools or universities. Buchmann and Karagiannis show the use of mobile app-based platforms for training employees in a knowledge management context. Now, access to all kinds of resources is in the palm of our hands, wearable, with flexible location and time constraints. Accordingly, the e-learning sites have a mobile version or some providers offer dedicated apps (e.g., Coursera, Moodle, Udemy, and edX). Additionally, the smartphone or tablet's screen sizes are growing and can offer a more exciting experience than the regular personal computer (Park et al., 2018). M-learning becomes a cheap and simple solution for current learning, but its implications go beyond data accessibility and technology. Hardware, software, data, and all human resources (Chen & Keng, 2019), social environment, behaviors, attitudes, and perceptions are generic factors that contribute to ensuring an effective, versatile, and performing educational digital ecosystem (Olsen et al., 2020; Venkatesh et al., 2003). However, the adoption of any technology has to be studied individually for every single case, with clear temporal, space, and target user category demarcation.

The literature mentions several theories able to explain the acceptance and/or use of technology. The aim of this work is to extend our knowledge of the Unified Theory of Acceptance and Use of Technology (UTAUT) originally developed by (Venkatesh et al., 2003), a framework that combines a set of other theories able to provide a comprehensive modeling perspective. The UTAUT model was subjected to several extensions leading to the release of UTAUT2 (Venkatesh et al., 2012). However, the newer framework is criticized for its unnecessary complexity (Al-Fraihat et al., 2020). One of the important features that characterize mobile technology is the high degree of enjoyment (Mehta et al., 2019), the pleasure to accept using it. Our research focuses on UTAUT but extends it only with hedonic motivation (HM) borrowed from UTAUT2.

Mobile technologies in general and m-learning in special have plenty of advantages, but they also have downsides (Ajzen, 2020; Benlian, 2020). Mobile technology use is generally regarded as the primary cause of addiction. Addiction and related effects are major concerns (Catone et al., 2020), although not directly linked to m-learning;

adding learning in the already complex mobile systems' use equation, the addiction risk increases (Saiful, 2020), indirectly, due to the screen-time growth. M-learning is disapproved for the lack of a suitable theoretical and technological foundation (Singh & Miah, 2020) or for the failure in adapting the traditional learning style to the modern fashioned one (Palagi et al., 2015).

More recently, humankind is facing a severe health emergency crisis caused by the COVID-19 explosive worldwide spread. Once with the institution of lockdown pandemic-related measures, universities are forced to make an abrupt shift to online education. E-learning—especially the mobile version due to the technological trend—looks to be the sole viable approach. Despite the recognized technology role in supporting ordinary people in ordinary conditions (Yan, 2020), it remains unclear if technology is able to respond to their needs in extreme circumstances (Gaspar et al., 2019). In this context, this study reports findings on the subsequent research questions:

- RQ1.** Is the existing degree of m-learning adoption in students before the lockdown caused by the COVID-19 outbreak at a level that supports the online learning shift in higher education?
- RQ2.** Does hedonic motivation successfully play the mediator role in the UTAUT framework, by improving the research model performance?

## 2 | THEORETICAL FRAMEWORK

In the country where the study was developed, the mobile technology has good penetration. The last few years have witnessed an increase in this domain. For example, in 2019, according to (Euromonitor International, 2020), 4,640,000 mobile phones were bought. It is 5.98% of all 22 Eastern European countries' purchases of this type, including Russia with 50.24%. Alternatively, in young people, the percentage of households possessing at least one mobile telephone is 90.9% for under 20 years old ones and 99.1% in 20–29 range. These are premises that sustain a high adoption rate for m-learning together with the large variety of involved devices (Arthur-Nyarko et al., 2020). In the beginning m-learning, although challenging, was optimistically embraced as a technological perspective, but with reticence concerning its implementation (Pocatilu et al., 2012). Universities invest consistent resources in e-learning solutions (Chen & Keng, 2019) to effectively sustain their distance learning programs and student's interest. M-learning is just an option for teachers and students, not necessarily a policy of the educational institutions.

### 2.1 | Background of UTAUT

Developed by (Venkatesh et al., 2003), UTAUT is the most popular framework for quantifying the degree of acceptance and/or use of any technology. As the name suggests, it unifies several preexistent theories (Yonkers, 2020): the Technology Acceptance Model (TAM;

Davis, 1989), Theory of Planned Behavior (TPB; Ajzen, 1991), then their mixture of Combined TAM and TPB (Taylor & Todd, 1995), Model of PC Utilization (Triandis, 1980), Theory of Reasoned Action (Fishbein & Ajzen, 1975), Diffusion of Innovation Theory (Rogers, 2003; Yan, 2020), Social Cognitive Theory (Bandura, 1986), and Motivational Model (Deci & Ryan, 1985). Natively or adapted, UTAUT is used in various fields. Some studies address the mobile application's adoption for persons with visual impairment (Moon et al., 2020), mobile payment (Al-Saedi et al., 2020), or other wearable devices (Wang et al., 2020), but the major body of literature focuses on learning technologies. Thus, m-learning is assessed in (Almaiah et al., 2019; Chao, 2019; Hoi, 2020), e-learning in (Abdou & Jasimuddin, 2020; Zhang et al., 2020), also in the isolation context dictated by COVID-19 (Raza et al., 2021).

The UTAUT model tackles the acceptance of technology by considering the following complex factors: performance expectancy (PE), effort expectancy (EE), social influence (SI), or social factors (Šumak & Šorgo, 2016), facilitating conditions (FCs), and behavioral intention (BI). The original UTAUT model has an additional construct called use behavior (UB), which is the final endogenous variable. UB is involved in studies dealing with the use of the system and considers the confirmed BI as actual use. In many studies like (Hoi, 2020), UB is omitted due to a partial semantic overlapping with BI, or subjective interpretation, and construction of the measures. BI is the endogenous construct of our model, which captures and predicts the impact of other factors on m-learning acceptance. Additionally, age, gender, and experience are moderators in UTAUT.

UTAUT2 (Venkatesh et al., 2012) represents an updated and more complex version of UTAUT in which three new constructs are added, novel relationships are considered, whereas moderators remain the same. The new entries are HM, attitude (García Botero et al., 2018), or intrinsic motivation (Mehta et al., 2019); Price/Learning Value (Ali, 2019), and Habit. Even if it is a newer and more comprehensive model, UTAUT2 is less popular in scientific research. Sometimes its complexity is disapproved due to the confusing nature of some items and to the low impact on the overall performance of the outputs compared to UTAUT (Abdullah & Ward, 2016). Moreover, concerning the role of HM, UTAUT2 is criticized because it avoids identifying factors that bring enjoyment (Choi, 2016; Tamilmani et al., 2017).

## 2.2 | An adapted UTAUT model for m-learning

The research model uses UTAUT-genuine constructs, while excluding UB. Furthermore, HM from UTAUT2 was added as a mediator instead of an exogenous variable. The list of possible moderators was extended with GPA. HM is related to the level of enjoyment, fun, or pleasure to use a specific technology (Mehta et al., 2019; Venkatesh et al., 2012). Literature knows only a few successful tries of reinterpreting the role of the attitude in the UTAUT framework, like in (García Botero et al., 2018; Šumak & Šorgo, 2016). The reasoning

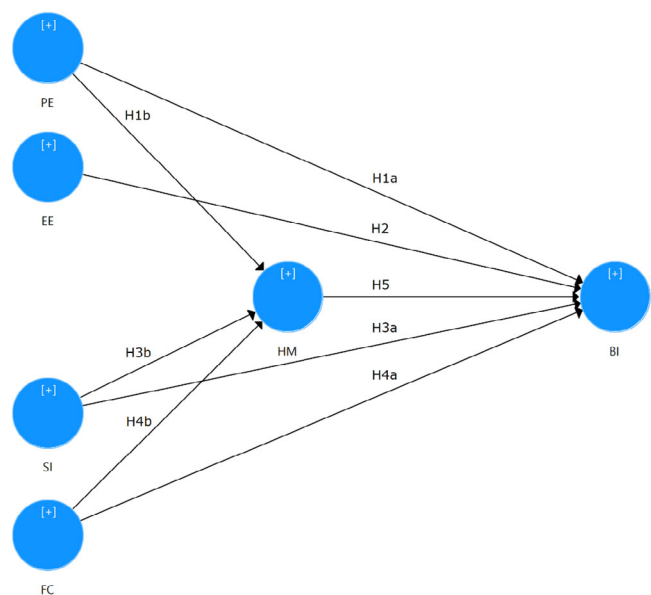
behind considering HM was that mobile phones rely intensively exactly on the users' appeal for entertainment.

In the social distancing time, citizens of each country encounter various ranges of feelings, most of them are negative (Xiong et al., 2020), due to these unprecedented circumstances. The business and education institutions suddenly move their activities online, which complicates the way of living for most of the population. In this complex equation, attitude plays an important role. We believe that the user would adopt m-learning (BI) only if they achieve the desired learning goals in an entertaining way in a pleasant environment (HM). Additionally, we consider HM in using m-learning or other technology-enabled activities as a critical factor that may contribute not only to the acceptance of the system, but also to the overall well-being of the user and a support facilitator.

## 2.3 | Research hypotheses and the proposed model

Our study tests some UTAUT/UTAUT2-related assertions, but also several new ones created by HM's mediation. A list of eight hypotheses is considered, the grouping and numbering criterion is the predictor. Further analysis is done later to investigate potential moderated relationships for a given set of control variables. The model and relationships' network between constructs are symbolized in Figure 1.

PE or perceived usefulness (Zhai & Shi, 2020) is usually defined as the amount of usefulness associated with the use of a new system (Venkatesh et al., 2003), or the perception of how we can help improve work performance by using new technology (Hwang & Lee, 2018). An important body of UTAUT literature considers it a major variable that controls BI (Hoi, 2020; Mehta et al., 2019; Zhai & Shi, 2020). Concerning the same predictor, but at the opposite pole,



**FIGURE 1** Research model portraying the impact of various constructs on BI

HM is rarely seen (García Botero et al., 2018; Hoi, 2020) as an endogenous factor, being rather an exogenous one as in the UTAUT2-related framework. Even if not all attempts were concluding—such in (Mehta et al., 2019)—we investigate this relationship. Therefore, the two PE-related impacts are questioned:

**H1a.** *Performance expectancy impacts positively hedonic motivation regarding m-learning.*

**H1b.** *Performance expectancy positively affects behavioral intention to use m-learning.*

The term EE, the simplicity of use, or usability has been used to denominate the extent of how intuitively or easy it is to operate the system (Venkatesh et al., 2003). Sometimes this variable is not used in learning systems' acceptance studies (Zhang et al., 2020). Both UTAUT and UTAUT2 proved that EE significantly and positively impacts BI, but this position is not unanimously sustained (Salloum et al., 2019). Since there is no consensus regarding the relationship between EE and HM—UTAUT2 does not count on it, (García Botero et al., 2018) do not confirm it, while (Šumak & Šorgo, 2016) state it is positive—we do not explore it. In this context, the following hypothesis is offered:

**H2.** *Effort expectancy has a negative influence on behavioral intention to use m-learning.*

SI should be important in a crisis, when social support (Lin et al., 2020) plays an important role. SI is an UTAUT-genuine factor and in this article, the term will be used to refer to the weight of others' behavior over the personal one (Venkatesh et al., 2003). In line with other authors (García Botero et al., 2018), we study the SI's impact on BI. Consequently, the next hypothesis is created:

**H3a.** *Social influence motivates behavioral intention to use m-learning.*

**H3b.** *Social influence enables hedonic motivation.*

FCs represents a UTAUT exogenous factor. In this study, it captures the readiness of the institution and how supportive is the technical assistance to encourage the system's acceptance (Venkatesh et al., 2012). It reflects the degree of support's perceptiveness (Yakubu & Dasuki, 2018). Even if it is one of the classic UTAUT frameworks' constructs, a part of the literature (Mehta et al., 2019) ignores it due to the subjectivism dose of realistic assessment that comes from the user side. Classic UTAUT models do not identify any relationship among FC and HM, but there are some occurrences, such as (Hoi, 2020), where it is positive. Besides, FC positively impacts BI (Zhang et al., 2020). In line with this, the following hypotheses have been launched:

**H4a.** *Facilitated conditions enable behavioral intention.*

**H4b.** *Facilitated conditions positively control hedonic motivation to use m-learning.*

HM or attitude is the fun or enjoyable part assigned to the system's acceptance and possible use. It was introduced by UTAUT2 (Venkatesh et al., 2012) as an independent variable. UTAUT2 indicates that HM has a major effect on BI. If something brings entertainment or joy, then individuals are more probable to use it and meet their private or career goals. HM impacted BI in many cases (Çera et al., 2020; Ching-Ter et al., 2017; García Botero et al., 2018; Salloum et al., 2019), but in other situations, it does not (Mehta et al., 2019; Venkatesh et al., 2003). HM also impacts UB (Hoi, 2020; Šumak & Šorgo, 2016). Consequently, to discover the role of HM in m-learning acceptance, the subsequent assertion is provided:

**H5.** *Hedonic motivation triggers the behavioral intention to use m-learning.*

*Moderating effects.* Starting from the classic moderators—age, gender, experience, and voluntariness—met in UTAUT models (Venkatesh et al., 2003, 2012), we propose a similar control variable list to check if significant influences are identified in some relationships. Because voluntariness is questionable in our students in these pandemic circumstances and somehow the teachers/managers' requests altered it (Zhang et al., 2020), it was replaced with a new, but learning-related variable, which is GPA. We believe m-learning acceptance is differently perceived in student groups with different learning performance degrees. Some significant behavior variance may also occur between the gender groups, as the literature indicates, such as a different effect of FC (Venkatesh et al., 2012), HM (Zhai & Shi, 2020), and SI (Zhang et al., 2020) on m-learning acceptance. We suspect minor behavioral discrepancies related to the age and experience, since the first year of study students are omitted from the study. However, the small sample of students enrolled in distance learning programs creates heterogeneity concerning these two aspects. Because of the homogeneity of the sample in some variables, and the experimental addition of the GPA, we will not enounce specific hypotheses to test possible moderations.

## 3 | METHOD

### 3.1 | Participants

Data for our survey were gathered in the early 2020s, at the beginning of lockdown and social distancing measures installation in our country. Even if the COVID-19 outbreak seriously spread in a few globe regions, here, at that moment, the authorities' measures were considered rather precautionous than alarming. However, the businesses were seriously impacted, many of them being moved online, including education. This radical and unpremeditated change occurred instantaneously. Thus, our survey captures the m-learning subjects' acceptance in its genuine status without any additional specific training or preparation.

Google Forms and the faculty's Moodle platform offered technological support to manage the survey, which targeted undergraduate students, enrolled both for full attendance and distance learning. The

m-learning users' pool was represented by the students from the biggest faculty from a large EU country.

Subjects filled in the questionnaire willingly and with no identity disclosure. The output data was preprocessed by removing missing data records and straight-liners. A reliable sample ( $N = 311$ ) remained to continue analyses, by following the research goal. The demographic distribution indicates that there are 197 (63.34%) females and 114 males (36.66%). In addition, 226 responders are under 22 years since 85 are at least 22 years old. 178 (57.23%) participants appreciate having a high experience in e-learning tools use, since 133 (42.77%) are less experienced. Regarding the learning

performance, 168 (54.02%) declared a GPA above 7.49, but 143 (45.98%) have a GPA in [5, 7.5] range.

### 3.2 | Questionnaire design and coding

The survey items are found and assembled after a solid UTAUT literature review, as Table 1 shows. The survey supporting our m-learning adoption study contained 26 items, plus age, gender, experience, and GPA as control variables. All questions were devised simply and clearly, additional explanations and context are presented at the

**TABLE 1** The adapted UTAUT survey items

Construct and sources	Latent variable coding. Item wording
<i>Behavioral Intention</i> <sup>UTAUT</sup> (Ali, 2019; Chopra et al., 2019; García Botero et al., 2018; Hoi, 2020; Mehta et al., 2019; Šumak & Šorgo, 2016; Venkatesh et al., 2003, 2012; Zhang et al., 2020)	BI1. I intend to continue using m-learning in the near future BI2. I will always try to use m-learning in my daily life BI3. I plan to continue to use m-learning frequently
<i>Effort Expectancy</i> <sup>UTAUT</sup> (Ali, 2019; Hoi, 2020; Mehta et al., 2019; Šumak & Šorgo, 2016; Venkatesh et al., 2003, 2012)	EE1. Learning how to use m-learning is easy for me EE2. My interaction with m-learning is clear and understandable EE3. I find m-learning easy to use EE4. It is easy for me to become skillful at using m-learning <sup>a</sup> EE5. Using m-learning is as easy as using any other systems I have previously used <sup>a</sup>
<i>Facilitating Conditions</i> <sup>UTAUT</sup> (Al-Fraihat et al., 2020; Ali, 2019; Hoi, 2020; Mehta et al., 2019; Šumak & Šorgo, 2016; Venkatesh et al., 2003, 2012; Zhang et al., 2020)	FC1. In general, my University has support for m-learning <sup>a</sup> FC2. In general, the Country in which my university is located has support (infrastructure, policies, etc.) for m-learning <sup>a</sup> FC3. I have the resources necessary to use m-learning FC4. I have the knowledge necessary to use m-learning FC5. I can get help from others (instructor, technical support) when I have difficulties using m-learning <sup>a</sup> FC6. M-learning is compatible with other technologies I use <sup>a</sup>
<i>Hedonic Motivation</i> <sup>UTAUT2</sup> (Al-Fraihat et al., 2020; Ali, 2019; Davis et al., 1992; Hoi, 2020; Mehta et al., 2019; Šumak & Šorgo, 2016; Venkatesh et al., 2003, 2012)	ATT1. It is a good idea to use m-learning ATT2. I would like to use m-learning technologies ATT3_HM1. Using m-learning is enjoyable HM2. Using m-learning is fun HM3. Using m-learning is very entertaining <sup>a</sup>
<i>Performance Expectancy</i> <sup>UTAUT</sup> (Al-Fraihat et al., 2020; Mehta et al., 2019; Šumak & Šorgo, 2016; Venkatesh et al., 2003, 2012)	PE1. I find m-learning useful in my daily life PE2. Using m-learning increases my chances of achieving things that are important to me PE3. Using m-learning helps me accomplish things more quickly PE4. Using m-learning increases my productivity
<i>Social Influence</i> <sup>UTAUT</sup> (Ali, 2019; Hoi, 2020; Mehta et al., 2019; Šumak & Šorgo, 2016; Venkatesh et al., 2003, 2012; Zhang et al., 2020)	SI1. People who influence my behavior think that I should use m-learning SI2. People who are important to me think that I should use m-learning SI3. People/professors whose opinions that I value prefer/encourage that I use m-learning <sup>a</sup> SI4. In general, the organization has supported the use of the system.

Note: Latent variables measurement items.

Abbreviations: <sup>UTAUT</sup>, UTAUT model source; <sup>UTAUT2</sup>, UTAUT2 model source.

<sup>a</sup>Dropped from the model due to lower than 0.7 outer loadings.

beginning of the form and for each section. For instance, BI items comprise assertions such as “I will always try using m-learning in my daily life,” which points to BI2. For HM, the HM2 measure tells “Using m-learning is fun.” All model measures, excepting the possible moderators, rely on a five-point Likert scale, where one means “Totally disagree/inadequate/unimportant” and five is for “Totally agree/adequate/important.” These items are converted into indicators grouped in constructs to ground an empirical PLS-SEM model.

## 4 | ANALYSIS AND RESULTS

Partial least squares SEM (PLS-SEM) (Hair et al., 2017; H. Wold, 1982, 1985) has positively impacted the research output of late years and is still increasingly used in many fields like marketing studies (Kwiatek et al., 2020), recommender systems research (Mican et al., 2020), health systems acceptance (Ho et al., 2019), but extensively in education (Hernandez-Selles et al., 2019; Mehta et al., 2019; Nikou & Economides, 2017). It supports both exploratory model development and confirmatory analysis. Besides, PLS-SEM is fitting well for constructing intricate models and for forecasting and assessing the interactions between latent factors. It can manage effectively small samples and normalization testing is not required (Hair et al., 2017).

Our empirical study relies on the PLS-SEM modeling multivariate method, which uses variance as the estimation method, applied here through the dedicated software SmartPLS version 3.3.2 (Ringle et al., 2015). PLS-SEM methodology implies a two-phase assessment approach, one for the measurement model and the second for the structural model (Hair et al., 2017).

The first phase manages the model validation considering the reliability and validity of the factors and their assigned manifest variables (Hair et al., 2019). This procedure implies computing outer loadings, Cronbach's alpha ( $\alpha$ ), composite reliability (CR), average variance extracted (AVE), and heterotrait-monotrait ratio (HTMT; Hair et al., 2019). The outer loadings are used in reflective models, to investigate the links among constructs and indicators. The metrics for inner consistency reliability (Hair et al., 1987) are  $\alpha$  and CR. AVE (Fornell & Larcker, 1981) quantifies the convergent efficiency of the factor degree since HTMT (Henseler et al., 2015) performs a statistical discriminant validity check. The collinearity assessment between the values of all predictor constructs is a complementary test indicated by the inner VIF values.

The second phase establishes the level of significance of the correlations among constructs, namely, the structural model validation by assessing the offered hypotheses. At this level, the path coefficients,  $p$ - and  $t$ -values for the structural model are computed. This validation is first performed at the global level, then among data subsets using multi-group analyses for each control variable. The model's goodness of fit is given by the standardized root mean square residual (SRMR) measure (Henseler et al., 2016). However, all indicators and steps performed until now from both stages are irrelevant without reasonable outputs for the predictive capability of the inner model assessment (Hair et al., 2019). For this purpose,  $R^2$  and  $Q^2$  values of the final

endogenous variable are calculated and the PLSpredict algorithm (Shmueli et al., 2016) is used.

Additionally, the mediation effects and their role in model optimization are assessed. The mediation is tested based on the procedure depicted in (Zhao et al., 2010). To select which model performs better from two or more competing methods, Akaike's (AIC), Bayesian (BIC), and Meese's (GM) information criteria are recommended to be considered (Sharma et al., 2019).

### 4.1 | The measurement model assessment

Table 2 shows the values of  $\alpha$ , CR, AVE, and outer loading measures that quantify the convergent validity and inner consistency test for the reflective variables. We note that the outer loadings are above the minimum limit of 0.7 (Hair et al., 2019). Hence, the indicator reliability is validated. All composite reliability and  $\alpha$  values are noticeably above the reference value of 0.7 (Hair et al., 1987). This proves that all constructs are internally consistent. Since all AVE values are above the limit of 0.5 (Fornell & Larcker, 1981), the convergent validity is confirmed in this model.

All HTMT values, that indicate the discriminant validity, are in the interval of [0.217, 0.820], satisfying the conservative constraint to be lower than 0.85 (Henseler et al., 2015). Table 3 reflects this statement, confirming that each construct is distinct from the rest of the constructs, according to the empirical standards (Hair et al., 2017).

Table 4 shows the VIF scores for all construct combinations. The highest value is 2.155, being under the conservative upper boundary of 3 (Becker et al., 2015). Therefore, no collinearity problems between predictor constructs were discovered.

### 4.2 | The structural model assessment

In this phase, the inner model is evaluated. For intuitiveness, the outputs are presented visually as a complementary picture-table pair. Figure 2(a) relates to the UTAUT model. Figure 2(b) reveals  $R^2$  for the latent variables, the indicators' outer loadings for each construct, and the path coefficients (strength and direction) between the structural model's factors. The latter aspect is emphasized in Table 5 that surprises the direct effects concerning each offered hypothesis.

Table 5 shows that all hypotheses are supported. In summary, H1a, H1b, H4b, and H5 are validated with  $p < .001$ , H2, H3b, and H4a with  $p < .01$  since H3a with  $p < .05$ . All relationships reveal moderation effects, excepting H1b and H5, the strongest relationships. These aspects will be detailed in Section 5.

Regarding the model's goodness of fit, the SRMR value for both the saturated and estimated model are 0.064. This is lower than the conservative upper threshold of 0.08 (Henseler et al., 2016). The output indicates a good fit for the research model.

Concerning the predictive capability of our model, the scores for the final endogenous variable in our model are  $R^2 = .576$  and  $Q^2 = 0.405$ , proving high predictive accuracy and power (Hair

**TABLE 2** Convergent validity and internal consistency evaluation of the reflective variables

Latent reflective variable	Reflective indicators	Outer loadings	Mean	Deviation	Cronbach's alpha	Composite reliability	AVE
BI	BI1	0.845	4.170	0.837	.814	0.890	0.729
	BI2	0.846	4.588	0.655			
	BI3	0.870	4.145	0.890			
EE	EE1	0.772	4.492	0.721	.800	0.881	0.713
	EE2	0.866	4.248	0.802			
	EE3	0.891	4.244	0.821			
FC	FC3	0.891	4.624	0.654	.787	0.903	0.823
	FC4	0.923	4.566	0.677			
HM	ATT1	0.845	4.569	0.647	.902	0.932	0.774
	ATT2	0.879	4.434	0.736			
	ATT3_HM1	0.894	4.209	0.813			
	HM2	0.899	4.26	0.773			
PE	PE1	0.742	4.537	0.609	.780	0.859	0.604
	PE2	0.734	4.473	0.716			
	PE3	0.828	4.061	0.852			
	PE4	0.801	4.077	0.845			
SI	SI1	0.941	3.643	0.984	.892	0.949	0.902
	SI2	0.958	3.633	1.015			

**TABLE 3** Discriminant validity evaluation for the reflective variables by HTMT criterion

	BI	EE	FC	HM	PE	SI
BI						
EE	0.371					
FC	0.539	0.449				
HM	0.820	0.508	0.527			
PE	0.761	0.680	0.450	0.755		
SI	0.531	0.499	0.217	0.506	0.651	

**TABLE 4** Collinearity evaluation between the predictor constructs by inner VIF values

	BI	EE	FC	HM	PE	SI
BI						
EE	1.557					
FC	1.324			1.142		
HM	1.916					
PE	2.155			1.578		
SI	1.535			1.429		

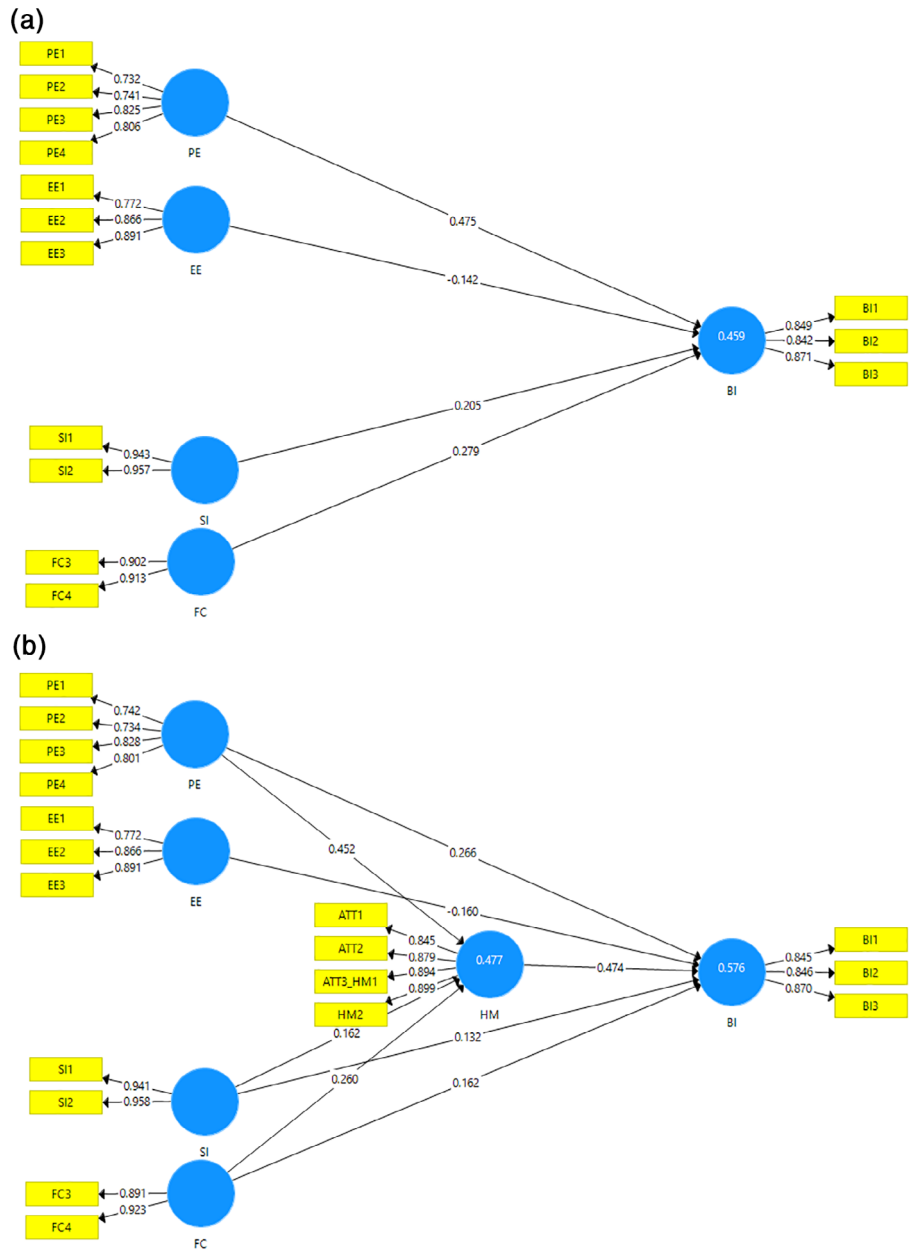
et al., 2019). Additionally, the PLSpredict process is initiated to assess the predictive power (Shmueli et al., 2016). Each indicator of the final endogenous factor has a lower prediction error for our model than LM, considering RMSE (see Table 6). These outputs correlated with the positive  $Q^2$  values for all these indicators lead to the conclusion that our custom model possesses high predictive power.

The moderating effect of HM is considered regarding three relationships, namely, between PE, SI, FC, and BI. For all of them, complementary mediation is revealed (Zhao et al., 2010). It means that both mediated and direct effects are present and have the same sign. The model we have developed has excellent predictive performance. Additionally, the values of AIC of  $-255.85$ , BIC of  $-233.41$ , and GM of  $344.44$  indicate a better model with BI in the position of final endogenous variable and HM as a mediator than the model without mediation—AIC =  $-182.06$ , BIC =  $-163.36$ , and GM =  $338.70$ —because all measures are higher in absolute value (Sharma et al., 2019).

## 5 | DISCUSSION AND IMPLICATIONS

M-learning, an extension and/or alternative of e-learning, evolved considerably in the past few years due to the attractiveness of mobile devices, the Internet, and data availability. There are still discrepancies in this aspect between different regions, developed, and developing countries (Al-Adwan et al., 2018), but even countries from Eastern Europe made noticeable progress (Ching-Ter et al., 2017). Nevertheless, officially in our country, the educational system relies mainly on traditional face-to-face learning. It is assisted almost by e-learning tools and features due to each university's support and teachers' implications. COVID-19's threat put all educational actors in an unprecedented situation. Without prerequisite training, teachers and students are forced to continue the didactic process from their homes using improvised set-ups consisting of various devices they own.

**FIGURE 2** Graphic representation of the comparative structural model relationships between (a) UTAUT and (b) research models



**TABLE 5** Summary and hypothesis testing results

Hypothesized path	Path coefficient	T statistics	Hypothesis
H1a PE → BI <sup>UTAUT</sup>	.266 <sup>***</sup>	4.919	Supported
H1b PE → HM <sup>NEW</sup>	.452 <sup>***</sup>	8.083	Supported
H2 EE → BI <sup>UTAUT</sup>	-.160 <sup>**</sup>	2.627	Supported
H3a SI → BI <sup>UTAUT</sup>	.132 <sup>*</sup>	2.570	Supported
H3b SI → HM <sup>NEW</sup>	.162 <sup>**</sup>	2.744	Supported
H4a FC → BI <sup>UTAUT2</sup>	.162 <sup>**</sup>	2.995	Supported
H4b FC → HM <sup>NEW</sup>	.260 <sup>***</sup>	4.507	Supported
H5 HM → BI <sup>UTAUT2</sup>	.474 <sup>***</sup>	8.546	Supported

Abbreviations: <sup>UTAUT</sup>, UTAUT hypothesis; <sup>UTAUT2</sup>, UTAUT2 hypothesis; <sup>NEW</sup>, non-UTAUT hypothesis.

<sup>\*\*\*</sup> p < .001,

<sup>\*\*</sup> p < .01,

<sup>\*</sup> p < .05.



Indicator	PLS		LM	RMSE <sub>PLS</sub> < RMSE <sub>LM</sub>	Predictive power
	RMSE	Q <sup>2</sup> _predict	RMSE		
BI1	0.696	0.313	0.703	Yes	
BI2	0.545	0.313	0.547	Yes	High
BI3	0.740	0.314	0.749	Yes	

Abbreviations: LM, prediction using a linear model; PLS, prediction using PLS-SEM; RMSE, root mean squared error.

Our research empirically measured the m-learning level of acceptance and readiness in students at the beginning of the quarantine and social distancing period. The model designed to explain the status quo is based on the UTAUT framework. A UTAUT2 construct was introduced as a mediator. This fact leads to the study of two UTAUT2 relationships, but also three new ones. UTAUT and mediation results are discussed separately in the next subsections, which are organized as follows: the first subsection discusses all relevant aspects which are related only to UTAUT framework, since the next one combines UTAUT2 with non-UTAUT/UTAUT2 insights. Each discussed hypothesis is debated in the related subsection first from the theoretical/research point of view, then it is interpreted and pragmatically implications are provided for various stakeholders. Moderation effects were investigated in all relationships, but only the impactful results are presented.

## 5.1 | UTAUT framework

Our model tackles three of five UTAUT original relationships. The setup emphasizes the importance of PE, its positive influence on BI being confirmed. This is one of the major relationships validated by the original model (Venkatesh et al., 2003), but also in specific m-learning acceptance research (Hoi, 2020; Zhai & Shi, 2020). If the users see significant usefulness in using mobile devices to fulfill their learning goals, then the intention to use m-learning is very high. This behavior is manifested with the same intensity in the younger students group since the older ones seem to care less about transforming this perceived usefulness in adoption, but this behavior is inconclusive.

The impact of EE on BI is questioned in many studies. Ours reveals a negative, but weak influence, which means the m-learning usability negatively affects the intention to use the system. Usually, the system's ease of use attracts potential users, but for serious activities—like learning—he or she assigns less importance to this aspect, or it is even considered inappropriate (Salloum et al., 2019). The way how EE influences BI is confirmed in none of the groups, except for the male students. In this group, there is a positive, but still weak relationship. To motivate student engagement in m-learning activities, the direction of EE has to be driven toward gamification (Çera et al., 2020; Durao et al., 2019; Zeng et al., 2020).

The lowest, but positive association has been identified between SI and adoption. The original theory and additional studies like (García

**TABLE 6** Predictive power evaluation using the PLSpredict algorithm

Botero et al., 2018) confirmed our results. We have expected a stronger relationship. The MGA analysis revealed that younger students, especially those with lower e-learning experience, manifested more social engagement concerning use intention. These are groups that require special care from the users' community. During the crisis, universities should pay substantial efforts to form or reactivate social support groups to assist students. They contain key-persons from the university staff, teachers, students, and care specialists (Lin et al., 2020).

The findings exposed above demonstrate that our study partly validates the UTAUT model. Our model confirmed three relationships among the genuine UTAUT constructs PE, EE, SI, and BI.

## 5.2 | Implications of the mediator

By adding HM as a mediator, several UTAUT2 and new relationships need to be assessed. As PE is a fundamental factor in UTAUT frameworks, it offers here, along with HM, a powerful impact. The literature is divided according to the role or significance of this association. For instance, in e-learning or m-learning studies (Hoi, 2020; Šumak & Šorgo, 2016) confirmed a positive relationship since (Mehta et al., 2019) did not reveal a direct one. However, our overall result is shared with similar strengths in all student groups. The output can be explained by the fact that the perceived usefulness toward using m-learning controls the joy or pleasure to use this educational technology.

SI plays a better role in increasing the positive attitude than it has succeeded in BI's case. However, this achievement is minor, considering the slight ampleness of the impact. This non-UTAUT relationship was supported also in (García Botero et al., 2018). In most of the groups, created regarding the control variables, this association is validated. In more mature students, the social aspect leads the effect on attitude to second place as magnitude.

The existence of the following relationship is confirmed in (Hoi, 2020) since the large body of UTAUT-related literature ignores it. FC influences HM with a medium, but positive strength. Similar behavior is met in most of the groups, except for the older students, where the relationship is not supported. The intensity is similar in the rest of the groups, being less important only for students with higher experience in e-learning.

The relationship between FC and BI assessment has no connection with the mediator position of HM. This association belongs to the

UTAUT2 framework (Venkatesh et al., 2012), is validated also by (Zhang et al., 2020), and has the same intensity as between SI and HM. The assessment of the relationship in younger, higher experienced, lower learning performance, and male student groups provided similar results since for the rest of the groups it was not significant. Overall, the university's current technical and logistics facilities represent a predictor of student m-learning adoption. If technical conditions are offered and supporting, contextual, prompt, and specialty assistance is provided to the user (Suárez et al., 2018), he or she is confident with m-learning and comfortable to accept and finally use it.

The last relationship we have studied is between HM and BI, being confirmed in (Hoi, 2020) for the m-learning field. Our study revealed the attitude's major influence on the final endogenous variable, BI. The higher the fun, joyfulness, and rewarded attitude regarding m-learning use, the higher the related acceptance. The assessment of the moderation effect indicates that this relationship is achieved with the same or similar intensity in all groups. The good attitude toward mobile technology adoption, in general, is transferred successfully to m-learning acceptance. This technological enthusiasm may lead to better educational performance (Dar & Bhat, 2016; Zeng et al., 2020), even if the shift from face-to-face learning and desktop computers was abrupt.

In addition to the UTAUT assessment, our study confirms, furthermore, some UTAUT2 relationships, but also new ones, involving traditional UTAUT/UTAUT2 constructs, namely, PE, SI, FC, HM, and BI.

HM is critical, but it does not offer a full mediation effect. It fulfills a complementary mediation. We believe that other UTAUT2 constructs—such as habit, learning value, and UB (Venkatesh et al., 2012)—and/or possible new ones such as personal innovativeness (Sagnier et al., 2020) and information quality (Chopra et al., 2019; Zhang et al., 2020) must be considered.

This research contributes to theory development by adjusting successfully the original UTAUT model. We investigated and confirmed three UTAUT, two UTAUT2, but also three new non-UTAUT/UTAUT2 hypotheses; the MH's mediator role to improve the model's performances; and the moderation capabilities of age, gender, experience, and GPA, the latter's effect being insignificant.

### 5.3 | Limitations

Our UTAUT-based model revealed good performance metrics. It was empirically validated on a 311 students sample survey. However, their habits cannot be extrapolated to the world-scale, especially in such extraordinary and irreproducible circumstances, such as the COVID-19 outbreak. The moment when the lockdown measures have been installed, the duration and their perceived severity, the individual material wealth, homogeneity of the population, and the economic development of the region are factors that may affect HM and acceptance.

## 6 | CONCLUSIONS AND FUTURE RESEARCH

Our research investigated relevant aspects regarding m-learning acceptance in social distancing conditions caused by the COVID-19 outbreak. The study leads to the construction of a new model derived from the classic UTAUT. It was empirically validated and the outputs revealed valuable insights. To inspect the BI, we observed five variables: performance expectancy, SI, EE, FCs, and HM with a mediation key-role in the attitudinal context of lockdown. The resulted model was compared with the UTAUT one. The measurements revealed a better performance in ours. However, HM did not offer a full mediation effect, but a complementary mediation is still accomplished. Our model has high predictive power (by RMSE and  $Q^2$ ) and accuracy (by  $R^2$ ). All eight hypotheses—three from UTAUT, two from UTAUT2 frameworks, and three new ones—were evaluated and successfully confirmed. The moderation of the following control variables, namely, age, gender, experience, and GPA was considered. Only the first three, which are UTAUT-genuine moderator factors, manifested slightly different behaviors in some relationships.

The most influential relationship is between HM and BI, followed closely by perceived effectiveness with hedonic motivation. After perceived usefulness, the next variable that impacts both attitude and m-learning adoption is FCs, since the less important factors are the SI and EE. Surprisingly, a control variable—age—turned the weakest relationships—between SI and attitude—into one of the most powerful ones. In male students, this is the second strong relationship. Beyond variable and relationship rankings, the following insights regarding the status quo and ways to improve m-learning adoption are provided as follows.

The perceived usefulness toward using m-learning controls the joy or pleasure to use this technology. The good attitude toward mobile technology adoption is transferred successfully to m-learning acceptance. The perceived support directly affects the joyfulness of using m-learning. If technical conditions are offered and supporting, contextual, prompt, and specialty assistance is provided to the user, he or she is confident with m-learning and comfortable to accept and use it. To motivate the learner's engagement in m-learning, the usability design has to be tailored toward gamification. Some groups require special care from the users' community; during a crisis, universities should spend substantial efforts to form or reactivate social support groups to assist students. Some supporting measures have to be applied for all students while specific groups should be addressed contextually.

Concluding, the research model highlights promising outputs and findings. All performance indicators prove high prediction and accuracy. This assertion responds to the first research question, confirming that the existing degree of m-learning adoption in students before the lockdown is at a level that effectively supports the online learning shift in higher education. By adding the attitude as a predictor of BI, the UTAUT model capabilities are improved. The custom model constitutes a more trustworthy framework than UTAUT to sustain m-learning acceptance. Thus, the mediation role played by HM is confirmed, and the second research question is also answered.

UTAUT has notable results in various fields but fails to provide a universal model. In the forthcoming research, we propose to validate the model on larger and more heterogeneous samples in pandemic-free conditions. Additionally, the extension to UTAUT2 and beyond, by testing constructs such as personal innovativeness and information quality, is possible.

### CONFLICT OF INTEREST

The author declares there is no conflict of interest.

### PEER REVIEW

The peer review history for this article is available at <https://publons.com/publon/10.1002/hbe2.261>.

### DATA AVAILABILITY STATEMENT

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

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