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Approach to M-learning Acceptance Among University Students: An Integrated Model of TPB and TAM

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Abstract

A growing number of higher education institutions have adopted tools to promote mobile learning. However, studies into the driving factors of its adoption are insufficient. This article identifies the aspects that have an effect on the adoption of mobile learning (m-learning) among university students. The theory of planned behavior (TPB) and technology acceptance model (TAM) have been shown to be valid and powerful models in the research on the adoption of learning technologies. Based on TPB and TAM, we propose a model to explain how perceptions influence m-learning adoption among Colombian university students. To confirm the acceptability of the model, a self-administered questionnaire was applied to 878 undergraduate university students from the Instituto Tecnológico Metropolitano (ITM), a higher education institution in Colombia. The results suggest that all of the constructs of TPB and TAM have a moderate impact on the intention to adopt m-learning. Specifically, perceived usefulness and attitude have a significant influence on students' acceptance of m-learning. These results can stimulate future research and promote an effective diffusion of m-learning in developing countries.

Keywords: mobile learning, adoption factors, TPB, TAM, university students

Introduction

Education is key to social and economic change. However, for higher education students, there are problems of coverage, relevance, and methodology in the educational process. This is where new information and communication technologies, as well as the development of applications for mobile devices, have generated extraordinary changes not only in education, but also in society (El-Hussein & Cronje, 2010).

Consequently, educators have sought to use mobile technologies to facilitate the learning process among students and to create new innovative learning opportunities (Jeng, Wu, Huang, Tan, & Yang, 2010). New mechanisms have emerged, such as mobile learning (m-learning), one of the most useful tools in the adoption and appropriation of information and communication technologies (ICT) in learning processes. m-learning seeks to include the requirements of mobility, accessibility, and interactivity that traditional teaching mechanisms lack. Although this type of learning has multiple advantages and has evolved rapidly in different places around the world, studies that analyze the driving factors of m-learning adoption are limited (Sarrab, Al Shibli, & Badursha, 2016), especially in emerging economies.

This article therefore examines key factors and variables in the process of acceptance and use of m-learning by students of the Instituto Tecnológico Metropolitano (ITM) through the application and verification of the theory of planned behavior (TPB) and the technology acceptance model (TAM). The descriptive research is presented through a quantitative methodological design (self-administered questionnaires). The results verify the explanatory capacity of the TPB and TAM for evaluating the incidence of each factor in the level of acceptance of this new technology among university students.

Theoretical Background

Mobile, Open, and Distributed Learning

The use of ICT has dynamically changed the way human groups interact among themselves. One of these changes has occurred in the education context due to mobile technology use. It is important to note that mobile technology directly affects students' learning process and creates innovative learning opportunities (Jeng et al., 2010). In fact, technological advances have allowed the development of open and distributed learning (Downes, 2017), and driven learning initiatives like mobile learning to improve educational outcomes (Akinwamide & Adedara, 2012).

Mobile devices are widely used to support open and distributed learning (Aghaee, Jobe, Karunaratne, Smedberg, Hansson, & Tedre, 2016). m-learning is full of promise and offers thrilling opportunities (Brown & Mbati, 2015) and has reduced study restrictions in terms of time and space (Adebayo, 2010), as well as allowing free access for all (Moreno-Agudelo & Valencia-Arias, 2017).

As noted by Kukulska-Hulme (2010) "learning is open to all when it is inclusive, and mobile technologies are a powerful means of opening up learning to all those who might otherwise remain at the margins of education" (p. 184). A new era of distributed learning is therefore being established with the progressive development of machine learning in mobile devices (Bach, Tariq, Mayer, & Rothermel, 2017).

The literature also shows that information systems for mobile and open learning provide the user with an autonomous learning experience (Cao & Li, 2013; Díez-Echavarría, Valencia, & Cadavid, 2018). As a result, open, technology-based education is moving from being simply an opportunity to a necessity in the education landscape. Students must develop digital skills in order to adequately respond to future challenges (Ossiannilsson, 2015). For this reason, teachers should take advantage of available methodologies in order to meet the demands of the global era and respond appropriately to these social changes (Cadavieco, Goulão, & Costales, 2012).

With the use of mobile technologies, it can be argued that students are not passive agents, but are rather able to pursue activities with greater motivation and interest than with traditional processes (Ozdamli & Cavus, 2011). Mobile technologies also influence the lives of individuals by connecting them with various sources of information, and by providing learners with independence in terms of location and time (Vinu, Sherimon, & Krishnan, 2011). As a result, the use of m-learning changes many educational dynamics of the past into new dynamics based on communication between people and access to information (Gong & Wallace, 2012).

The term m-learning defines the practices that use mobile devices and wireless data transfer technologies to promote and extend the reach of teaching and learning processes (Pardo & Balestrini, 2010). m-learning, combined with a virtual educational environment, is one of the tools derived from mobile technology and Web 2.0. This new educational mechanism has several advantages, including personalization of learning experiences, which allows students to choose the device, place, and time that best fit their learning pace and needs. m-learning also improves the design of instructional environments that promote experiences according to the student's reality (Depetris, Tavela, & Castro, 2012).

The use of mobile devices in the classroom has great educational possibilities because they encourage and stimulate the development of basic skills. m-learning promotes a more atomized organization of content, similar to that obtained with learning objects (Ramírez, 2007, cited by Cataldi & Lage, 2012). Mobile technologies can also provide access to education for students normally excluded by reason of location, social status, or technological infrastructure (Serbanescu, 2010).

A greater understanding of how students perceive and react to the use of virtual learning tools is therefore required. This will allow the creation of mechanisms to attract more students to enter these virtual environments; the success of virtual learning systems depends on their acceptance and use by students (King & He, 2006).

Technology Adoption Models

One issue that has received special attention in the research on m-learning tools is the analysis of the factors that influence students to adopt these technologies (Cheon, Lee, Crooks, & Song, 2012). This includes the exploration of the primary predictors of students' intention to use virtual learning tools (Valencia-Arias, Chalela, & Bermúdez, 2018). There have been different proposals and models that incorporate the most relevant dimensions in the process of adopting mobile devices within the classroom.

Two behavioral theories have been widely applied to investigating the use of technological tools. One is the theory of planned behavior (TPB; Ajzen, 1991), which concerns how behavioral intentions are formed to act. The other is the norm activation model (Schwartz, 1977) and its successors, which explain how personal rules are activated and determine pro-social behavior. There have been numerous empirical studies based on models of m-learning adoption, such as: (a) Hamidi and Chavoshi (2018), who predict the impact of mobile phone use in higher education; (b) Al-Hunaiyyan, Alhajri, and Al-Sharhan (2016), who explore the many challenges that affect the implementation of mobile devices in learning; and (c) Spiegel and Rodríguez (2016), who also incorporate socializing constructions to determine the requirements for technologies becoming a teaching support tool. The common characteristic of these and other relevant studies is that behavioral intent is treated as the most predictive and proximal predictor of behavior. That is to say, no mediator was introduced between behavioral intent and the effective behavior.

Among these approaches, research based on the beliefs and attitudes of individuals acquire singular relevance, and in particular, those based on TPB (Schifter & Ajzen, 1985). This theory aims to explain the behavior of individuals on the basis of the belief–attitude relationship and intention behavior. It is an extension of the theory of reasoned action (TRA) (Sampedro, Fernández-Laviada, & Herrero, 2014). TPB has been widely used to analyze behaviors as diverse as the acceptance of the World Wide Web, the adoption of mobile technologies, and the use of online services (Herrera & Fennema, 2011).

Figure 1 shows an outline of TPB for an individual. According to this model, an individual’s behavior is determined by the intention to perform the particular behavior. This intention is a function of attitude, subjective norms, and perceived behavioral control, which go back to attitudinal, normative, and control beliefs, respectively. More explicitly, intention describes the force of the purpose for performing a particular behavior, while attitude represents the individual’s positive or negative feelings about the performance of the particular behavior (Fishbein & Ajzen, 1975). Subjective norms can be seen as the social pressure that individuals perceive to perform a certain behavior. Finally, perceived behavioral control refers to the perception that people have about the ease or difficulty of performing the behavior (Ajzen, 1991).

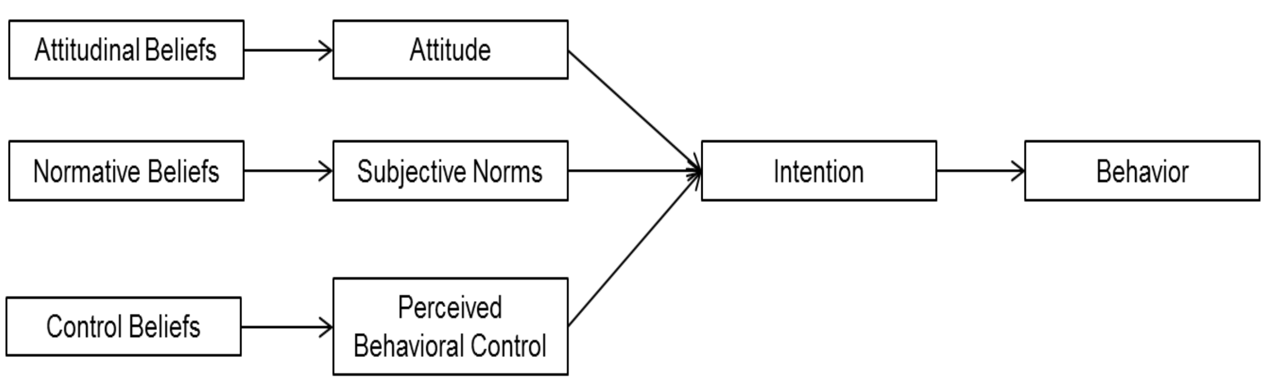

Figure 1. Theory of planned behavior model. From “The theory of planned behavior”, by I. Ajzen, 1991, *Organizational Behavior and Human Decision Processes*, *50*(2). Copyright 1991 by Academic Press Inc.

Cheon et al. (2012) propose specific antecedents to subjective norms and the control of perceived behavior in the context of m-learning. First, they argue that subjective norms are determined by normative beliefs that explain the influence of others' expectations on an individual's intention. Due to the divergence of opinions that may exist among groups of individuals, it is suggested that normative beliefs can be decomposed into different referent groups (Taylor & Todd, 1995). In this sense, the most relevant referent groups in the educational field are students and instructors (Taylor & Todd, 1995), so they propose the readiness of students and readiness of instructors as antecedents of the subjective norms, as shown in Figure 2.

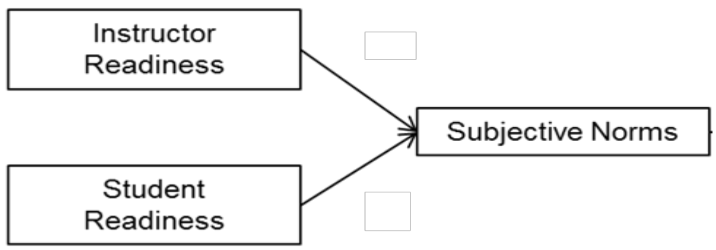

*Figure 2***.** Subjective norms antecedents. From "An investigation of mobile learning readiness in higher education based on the theory of planned behavior", by J. Cheon, S. Lee, S. M. Crooks, and J. Song, 2012, *Computers & Education, 59*(3). Copyright 2012 by Elsevier Ltd.

Second, perceived behavioral control depends on "beliefs about the presence of factors that may favor or hinder the performance of behavior" (Ajzen, 2002, p. 665). Thus, two fundamental concepts are associated within the beliefs of control: perceived self-efficacy and learning autonomy, as shown in Figure 3. Bandura (1997, cited by Cheon et al., 2012) defines self-efficacy as the perception people have of their abilities and motivations in carrying out specific tasks. Learning autonomy, which refers to the extent to which individuals have sufficient control of their learning process (Yeap, Ramayah, & Soto-Acosta, 2016), has also been shown to be an antecedent of control beliefs.

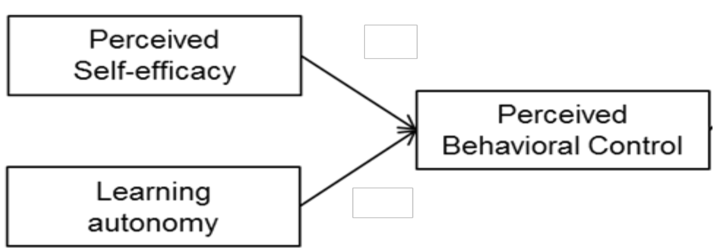

Figure 3. Perceived behavioral control antecedents. From "An investigation of mobile learning readiness in higher education based on the theory of planned behavior", by J. Cheon, S. Lee, S. M. Crooks, and J. Song, 2012, *Computers & Education, 59*(3). Copyright 2012 by Elsevier Ltd.

Several studies on the adoption of technologies have been based on TAM, introduced by Davis (1986), and a variation of the TRA that is focused on the adoption of new technologies. TAM tries to explain the behavior from intention, showing that attitudes lead to intentions, which in turn generate behaviors (Herrera & Fennema, 2011).

As illustrated in Figure 2, TAM establishes causal relationships between perceived usefulness, perceived ease of use, attitude towards the use, and current use of technology (King & He, 2006). Perceived usefulness refers to the extent to which an individual considers that the use of a particular system will improve his or her performance in an activity, whereas the perceived ease of use is the extent to which a potential user expects the use of the technology will not involve great effort (Herrera & Fennema, 2011). Shin and Kang (2015) comprehensively tested factors considered by TAM and demonstrated that students at online universities have begun to use mobile technology as a learning tool, which has improved their learning performance.

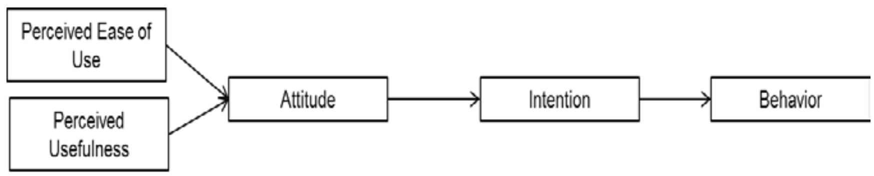

Figure 4. Technology acceptance model (TAM). From *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation), by Davis, 1986, Cambridge, MA: Sloan School of Management, Massachusetts Institute of Technology. Copyright 1986 by the Massachusetts Institute of Technology.

It is important to emphasize that while TPB is a general theory, designed to explain almost any human behavior (Herrera & Fennema, 2011), TAM focuses exclusively on the use of technological innovations and a priori seems more appropriate for analyzing this type of behavior (Davis, 1989).

Park (2009) discusses the importance of analyzing what determines whether students accept or reject virtual learning tools. The different points of view that have emerged on the subject of m-learning suggest that it is relevant to know the opinion of those who have become users, especially students. Many studies have therefore been carried out, such as Gong and Wallace (2012), who identified a series of deficiencies in the academic context, although respondents in general saw m-learning positively. One of the perceived deficiencies is that use of mobile devices concentrates more on entertainment than on education. Many still believe that mobile devices can affect students' concentration and increase the tendency for plagiarism. Therefore, there are still challenges that must be faced in the development of m-learning.

It appears that the new teaching models are based on a constructivist view of learning, where the flow of knowledge in the classroom is increasingly multidirectional. In this sense, it is evident that the new technologies are instruments that can contribute to the acquisition of knowledge, with students continuing to learn outside the classroom (Duarte & Arteaga, 2010). However, there are several obstacles to consolidating the use of instructional technology into higher education, including technological infrastructure, teacher effort, and user satisfaction (Surry, Ensminger, & Haab, 2002). This translates into difficulties for the achievement of successful strategies in terms of acceptance of m-learning.

The increasing reliance on information systems and the vertiginous introduction of new technologies in learning environments means that the identification of critical factors related to user acceptance of this technology becomes an important research problem (Park, 2009). We therefore propose using TAM and TPB as tools to evaluate these technological introduction processes in the educational field in an emergent economy. By limiting the framework of this study to ITM students, we seek to understand student perceptions of m-learning, as well as the factors of use and adoption of this technology. This will permit us to identify key variables in the development of pedagogical processes that are more in line with new social demands and facilitate the acquisition of knowledge.

Research Model and Hypotheses

The model presented in Figure 3 is proposed as the research model, based on constructs related TPB, TAM, and the model proposed by Cheon et al. (2012).

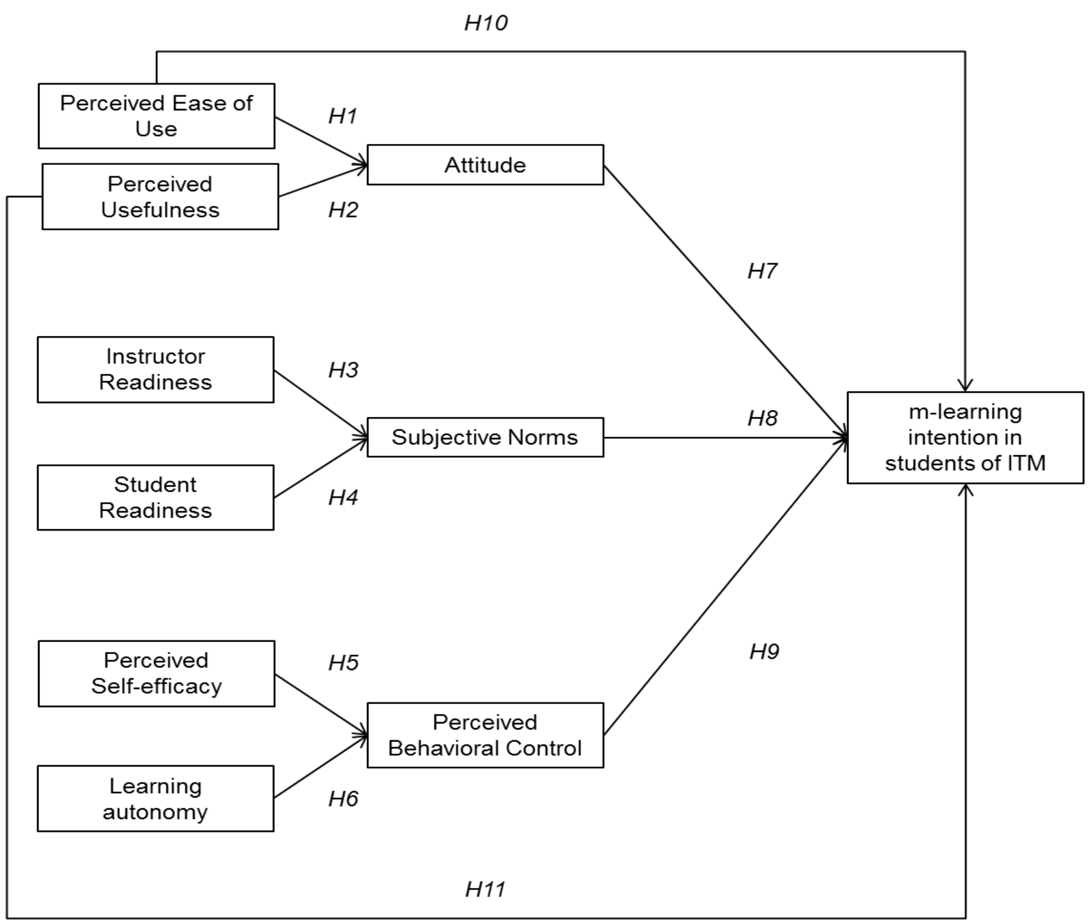

Figure 5. Research model.

It should be clarified that, despite taking as reference point the work developed by Cheon et al. (2012), our article contributes to knowledge from two points. First, concepts can only be understood within the context of their time (Wallerstein, 2011). In that sense, a different temporal horizon between that approached by Cheon et al. and our research produces a different frame within which to understand concepts. Second, although few perspectives are entirely new, novelty may appear in the first serious application of that perspective within a particular context (Wallerstein, 2011). Specifically, there are noticeable differences between developed countries and Colombia that affect the population's behavior and perceptions with respect to areas such as quality of life, education, and others. Therefore, we explore students' behavior in an emergent country to complement the notions and perspectives of preliminary studies conducted with students from developed countries. Subsequently, the following hypotheses were developed:

> H1: ITM students' perceived ease of use of m-learning positively influences their attitude toward m-learning.
>
> H2: ITM students' perceived usefulness of m-learning positively influences their attitude toward m-learning.
>
> H3: ITM students' perceived instructor readiness for m-learning positively influences subjective norms for m-learning.
>
> H4: ITM students' perceived peer student readiness for m-learning positively influences subjective norms for m-learning.
>
> H5: ITM students' perceived self-efficacy toward m-learning positively influences their behavioral control with m-learning.
>
> H6: ITM students' perceived learning autonomy toward m-learning positively influences their behavioral control with m-learning.
>
> H7: ITM students' attitude toward m-learning positively influences their intention to adopt m-learning.
>
> H8: ITM students' subjective norms toward m-learning positively influence their intention to adopt m-learning.
>
> H9: ITM students' perceived behavioral control toward m-learning positively influences their intention to adopt m-learning.
>
> H10: ITM students' perceived ease of use of m-learning positively influences their intention to adopt m-learning.
>
> H11: ITM students' perceived usefulness of m-learning positively influences their intention to adopt m-learning.

According to Venkatesh, Morris, Davis, and Davis (2003) attitude towards behavior is associated with the affective reaction of an individual when using a system, and it can take different nuances depending on the perception experienced by the user. The first of these reactions is part of grading the idea of using the system on a favorable scale (Davis,1989); the second evaluates the level of wisdom (Fishbein & Ajzen, 1975); the third question regards the level of taste; and finally the fourth analyzes the level of liking for technology (Taylor & Todd, 1995). Hypotheses number one, two, and seven fit within the narrative of these authors and their theoretical and experiential verifications. We consider also subjective norms (Ajzen & Driver, 1992) which, according to researchers, means that the majority of people who are important in the life of a person exposed to the action approve of participation in that action (hypotheses three, four, and eight).

Methodology

Sample

University students were the target group of the study because most current m-learning systems are focused on them. The sample was selected based on a non-probabilistic method and consisted of undergraduate students at the Instituto Tecnológico Metropolitano, a public higher education institution in Medellin, Colombia. At this higher education institution, students represent a variety of demographic profiles and degree programs. Therefore, the responses collected from the students provide a holistic and pluralistic view, taking into account a range of disciplines and perspectives from learners in finance, engineering, computer science, business and management, among others. We then analyzed their responses in light of the distinctions between the humanistic and scientific perspectives established by Snow (1993) in his theory of the two cultures, which is a novel aspect of our research. Other studies about m-learning, such as Cheon et al. (2012), only explore the behavior of students enrolled in courses of computer science and information technologies, which is a limit in the scope of their research.

A total of 878 responses were collected. Approximately 52% of respondents were male and 48% were female. Ages ranged between 17 to 55 years, with 66% in the 18 to 25 years old group. Respondents' academic majors included different areas of knowledge. About 93% of the sample had access to a mobile device or devices (81% of the respondents used smartphones with Internet access and 12% used a different Web-enabled mobile device) and around 87% used such devices to support the learning process. The demographic profile of the sample is shown in Table 1.

Table 1

Demographic Profile of the Sample

Characteristics	Frequency	Percent
Gender		
Male	460	47.6
Female	418	52.4
Age		
Below 18 years	3	0.3

18–25 years	581	66.2
26–33 years	215	24.5
34–40 years	37	4.2
Above 40 years	24	2.7
Age not specified	18	2.1
Mobile device		
Smartphone with Internet access	710	80.9
Other mobile device	104	11.8
No device	64	7.3
Mobile device used for learning		
Always	203	23.1
Usually	267	30.4
Sometimes	292	33.3
Rarely	59	6.7
Never	57	6.5

Survey Instrument and Data Collection

The self-administered questionnaire was designed to assess the research model and collect data. The questionnaire was adapted from the examined instrument in Cheon et al. (2012). The questionnaire consisted of two sections. The first included questions about general information related to gender, age, degree program, as well as access to mobile devices and their use for learning purposes (see Table 1). The second section consisted of 25 items measuring the 10 constructs of the research model. A five-point Likert-scale was used and ranged from 1 for "strongly disagree" to 5 for "strongly agree."

The questionnaire was piloted to verify the content and, based on that pilot, we made modifications to clarify the questions. Data collection was then carried out in writing; the questionnaire required approximately 15 to 20 minutes to complete. Students filling out the questionnaire were provided with a brief introduction on m-learning and the purpose of the research project. Participants filled it out based on their own perceptions. A total of 878 students answered, and there were no invalid responses.

Data Analysis

In the measurement model, both convergent and discriminant validity were tested through analysis using the Statistical Package for Social Science (SPSS) software. The convergent validity of the model was evaluated on two levels: the reliability of the observable items and the reliability of the constructs (Calvo, Martínez, & Juanatey, 2013). When an item factor loading is greater than 0.6, this is considered evidence that the model is reliable (Bagozzi & Yi, 1988). The reliability of constructs refers to the degree to which an observable variable reflects a factor, and those constructs with a value greater than 0.7 are considered acceptable (Hair, Anderson, Tatham, & Black, 2001).

With the data collected, a standardized factor load of more than 0.6 was obtained for all constructs, which indicates that the model is reliable. The average obtained from loads on each of the indicator factors was greater than 0.7 for all constructs, which indicates the presence of convergent validity as shown in Table 2.

Table 2

Convergent Validity

Construct	Indicators	Standardized factor loadings	Standardized factor loadings average
Perceived self-efficacy	PS1	0.765	0.765
	PS2	0.755	
	PS3	0.775	
Perceived ease of use	EU1	0.822	0.822
	EU2	0.822	
Attitude	AT1	0.859	0.859
	AT2	0.859	
Perceived usefulness	PU1	0.812	0.830
	PU2	0.827	
	PU3	0.85	
Subjective norms	SN1	0.717	0.719
	SN2	0.722	
	SN3	0.718	
Intention	INT1	0.894	0.894
	INT2	0.894	
Learning autonomy	LA1	0.839	0.813
	LA2	0.814	
	LA3	0.785	
Behavioral control	BC1	0.815	0.815
	BC2	0.815	
Instructor readiness	IR1	0.593	0.716
	IR2	0.744	
	IR3	0.812	
Student readiness	SR1	0.786	0.786
	SR2	0.786	

It should be clarified that prior to performing the above calculations, Bartlett's sphericity test and the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy were calculated to determine the suitability of data for carrying out the analysis. The first of these is a statistical test that detects the presence of correlation between variables; its *p* must be lower than the critical level 0.05 (Manzano, Navarré, Mafé, & Blas, 2011). Similarly, the KMO measure is defined as an index that compares the magnitudes of the correlation coefficients observed with the magnitudes of the partial correlation coefficients, and returns values between 0 and 1. Because in the proposed model Bartlett's values were lower than 0.05 and the KMO coefficient was greater than 0.5, we can affirm that there are significant correlations between the variables.

Discriminant validity refers to the notion that each factor must represent a different dimension: that is, each observable variable must be loaded to only one factor (Ratchford, 1987 cited by Lévy, Martín, & Román, 2006). This is checked by validating "whether the confidence interval around the correlation estimate between the two factors includes 1.0" (Anderson & Gerbing, 1988, p. 416). Figure 6 shows that all cases possess discriminant validity.

	PS	EU	AT	PU	SN	INT	LA	BC	IR	SR
PS	-									
EU	[0.445;0.557]	-								
AT	[0.404;0.521]	[0.403;0.514]	-							
PU	[0.412;0.526]	[0.381;0.501]	[0.542;0.635]	-						
SN	[0.373;0.486]	[0.296;0.425]	[0.375;0.492]	[0.405;0.518]	-					
INT	[0.419;0.534]	[0.384;0.511]	[0.502;0.605]	[0.559;0.653]	[0.431;0.550]	-				
LA	[0.449;0.554]	[0.447;0.563]	[0.605;0.691]	[0.539;0.636]	[0.409;0.525]	[0.578;0.678]	-			
BC	[0.390;0.513]	[0.304;0.433]	[0.364;0.487]	[0.293;0.420]	[0.374;0.489]	[0.418;0.536]	[0.407;0.524]	-		
IR	[0.257;0.384]	[0.306;0.432]	[0.335;0.458]	[0.386;0.502]	[0.373;0.493]	[0.381;0.503]	[0.428;0.538]	[0.346;0.469]	-	
SR	[0.284;0.417]	[0.264;0.405]	[0.362;0.485]	[0.400;0.513]	[0.407;0.521]	[0.465;0.578]	[0.459;0.576]	[0.224;0.355]	[0.358;0.482]	-

Figure 6. Discriminant validity for the measurement model.

The reliability of the measurement scale was determined by Cronbach's alpha. This procedure is necessary because the Cronbach's alpha "is an index used to measure the reliability of the internal consistency of a scale, that is, to evaluate the magnitude in which the elements of an instrument are correlated" (Oviedo & Campo-Arias, 2005, p. 575). Churchill (1979; cited by Manzano et al., 2011) recommends a value higher than 0.70. As shown in Table 3, the measurement instrument's scale appears to have adequate reliability because all Cronbach's alphas are higher than 0.7.

Table 3

Reliability of the Measurement Scale

Construct	Cronbach's alpha
Perceived self-efficacy	0.825
Perceived ease of use	0.841
Attitude	0.879
Perceived usefulness	0.885
Subjective norms	0.778
Intention	0.910
Learning autonomy	0.870
Behavioral control	0.830
Instructor readiness	0.769
Student readiness	0.804

Consequently, the results of the analysis indicate the presence of a factorial model to analyze the acceptance and use of m-learning by ITM students. Moreover, the convergent validity, discriminant validity, and reliability of the measurement scale shows that the instrument includes the principal variables that have a direct or indirect influence on the adoption and use of m-learning.

Results

Following the statistical analysis, the proposed model of adoption of m-learning by the ITM students was estimated by measuring the degree of association in the hypotheses with Somers' D statistic. This corresponds to a measure of association between two ordinal variables that takes a value between −1 and 1, where values close to 1, in absolute value, indicate a strong relationship between the two variables and values close to zero indicate that there is little or no relationship between the two variables (Kaplan, 2000). Because Somers' D is a measure of directional association, it was used in the test of the proposed model. The results obtained for each hypothesis are presented in Table 4, and Figure 7 shows the graphical description of associations of the research model.

Table 4

Degrees of Association in the Research Model

Hypothesis	Somers' D
H1: Perceived ease of use → Attitude	0.429
H2: Perceived usefulness → Attitude	0.565

H3: Instructor readiness → Subjective norms	0.373
H4: Student readiness → Subjective norms	0.410
H5: Perceived self-efficacy → Behavioral control	0.432
H6: Learning autonomy → Behavioral control	0.417
H7: Attitude → Intention	0.502
H8: Subjective norms → Intention	0.479
H9: Behavioral control → Intention	0.463
H10: Perceived ease of use → Intention	0.415
H11: Perceived usefulness → Intention	0.578

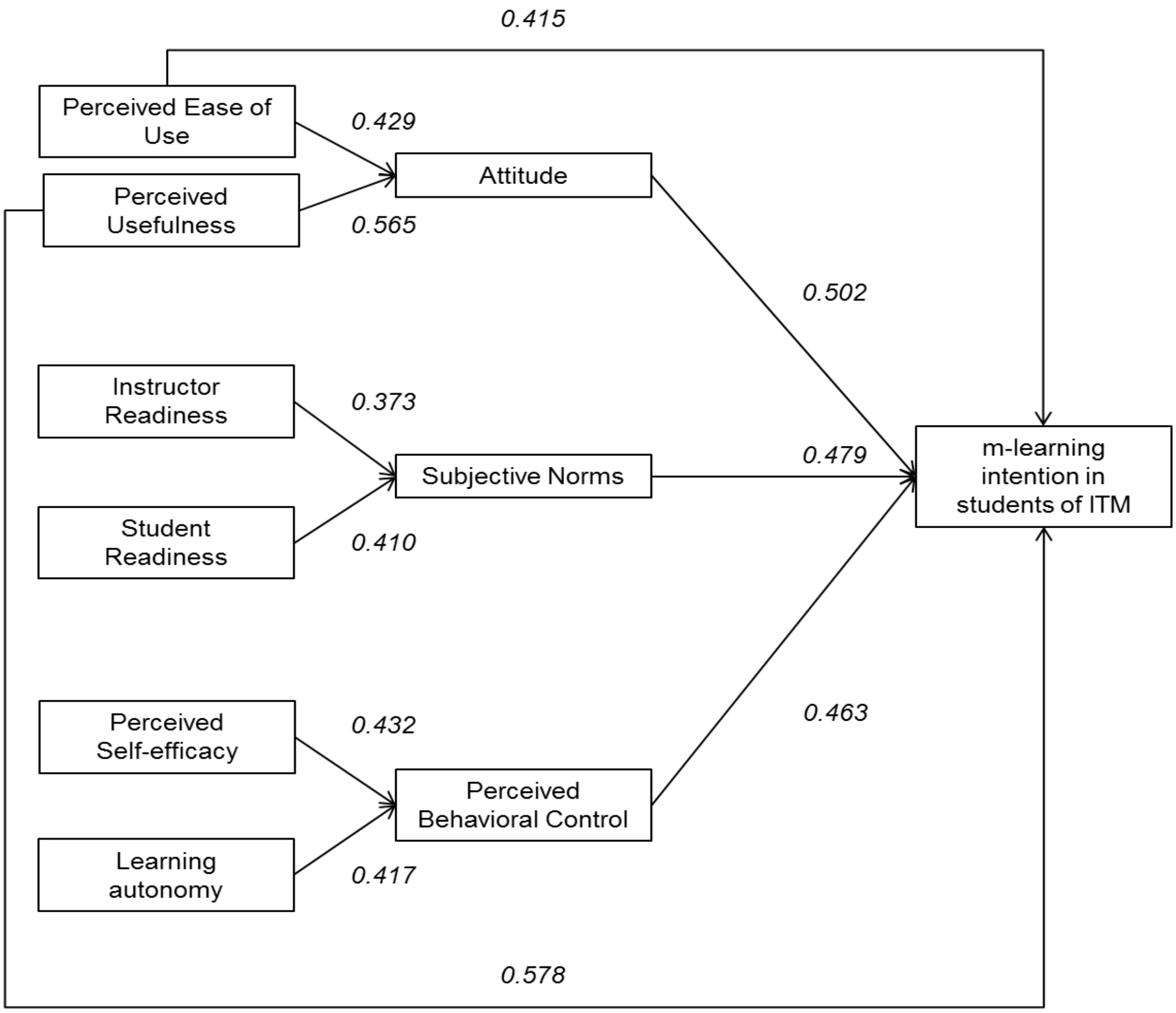

Figure 7. Degrees of association in the research model.

Figure 7 shows that for TPB attitude (0.502), subjective norms (0.479), and perceived behavioral control (0.463), there is an association with intention to use m-learning in ITM students. Specifically, attitude has the closest relationship, followed by subjective norms, and then perceived behavioral control. In terms of TAM, perceived usefulness has a higher association with intention than does perceived ease of use, and it is also the construct with the highest value and an important association with attitude. Perceived usefulness has both a direct and an indirect impact on the m-learning intention of ITM students. This is consistent with the findings of Huang, Hsiao, Tang, and Lien (2014), who noted that perceived usefulness and subjective norms could be connected with m-learning intention.

In general, the strongest relationships corresponded to hypotheses two, seven, and eleven, with a Somers' D of 0.565, 0.502, and 0.578, respectively. The other hypotheses had intermediate relationships between observable and latent variables, with the weakest association occurring between instructor readiness and subjective norms.

Discussion

The analysis of theoretical frameworks in m-learning intention lead to the conclusion that pedagogical dynamics and didactic approaches should be implemented in the classroom based on students' vision for and evaluation of the mobile devices.

Irina Bokova, the former Director-General of UNESCO, has said that pedagogical practices must be transformed according to current needs and argues that the way we conceive education must fundamentally change. Now more than ever, education has a responsibility to promote the right kind of skills, attitudes, and behaviors that lead to sustainable and inclusive growth. The Agenda 2030 for Sustainable Development encourages us to conceive of comprehensive and integrated responses to the many social, economic, and environmental challenges we face. This means going beyond our traditional boundaries and creating effective intersectoral partnerships and alliances (UNESCO, 2016).

The new generation's practical relationship between play and work through the use of technology cannot be ignored. According to the results we obtained, the perceived usefulness of mobile devices for learning processes has an important impact on intention to use. It is therefore necessary to ensure that these processes generate cognitive, playful, and tangible benefits to students in both the long and short term.

One should consider that the development of tools that provide significant advantages to promote m-learning would directly influence the acceptance of those tools. As with perceived utility, ease of use is also perceived as having a direct influence on the acceptance of m-learning.

It is possible that the information circulating in the virtual environment, and to which students have access, can block the learning process because students do not know how to categorize the information that is required. This issue is related both to the personal dimension in the use of technology for learning, understood as the attitude factor, where not only is respect for information necessary, but also a sense of responsibility for the source, whether that is research, a video, or an image.

Although the attitude factor had the greatest influence on acceptance, it was not the only influential factor, because it was found that the subjective norms also possessed a similar degree of influence. This clarifies that both instructor and student preparation can be nearly as much a of determinant as can attitude or the control of perceived behavior.

In this sense, the various possibilities that the virtual space offers (from the point of view of didactic aids) and from the offer of information from other academic spaces cannot be ignored. In both models, this coincides in the valuation of the time, the discipline, and the rational use of the technological mediator. This demonstrates the coexistence that must exist in autonomous learning, highlighting the interactive possibilities that facilitate the teacher–student approach in unplanned projects and spaces.

Conclusions

Despite the increase in the use of mobile devices among students, cultural differences in teaching practices and current social tendencies are key factors for the acceptance and use of this technology. Higher education institutions must develop a policy of institutional transformation because only interconnected structures that involve their employees in the planning, control, and improvement of their operations are essential in order for institutions to be competitive in an environment of constant change. Consequently, it is increasingly necessary to emphasize the importance of the human factor within universities, including the application of models that defend the philosophy that the organization is a human group, a collective.

This study used TAM and TPB to analyze the driving factors related to m-learning intention. It validated that the integration of both models constitutes a fundamental tool when identifying and analyzing the factors, variables, and relationships that inhibit or motivate processes of technological introduction in the educational field in emerging countries such as Colombia.

The proposed model incorporated not only the positive or negative evaluation of an individuals' performance of an individual's behavior, but also the social pressures and benefits of performing or not performing such behavior. This revealed a bigger picture based on the large amount of information collected, while also presenting adequate levels of association for each of the hypotheses.

The adoption of mobile technologies has generated a profound transformation of the university and has affected processes and operations, as well as organizational structures, by presenting new concepts of management. Higher education institutions are therefore called to align the functional structures through which they operate with a mobile education policy in line with their administrative and operational capacity available and culture.

The model can be explained as follows: increasing the degree of favorability of the observable variables will increase the likelihood that there will be greater intention to use m-learning by the students. When presenting adequate margins of association between the related variables, it is correct to say that the model meets the objective set in the research.

The results provide a greater understanding of factors that affect m-learning and should be taken into account in the application of new m-learning initiatives. In developing countries, m-learning also has immense potential and offers new opportunities compared to traditional methods of education. It is therefore necessary for new educational paradigms to include all key factors of the process of technology adoption in devising strategies for the successful dissemination of m-learning in these countries.

M-learning has moved the educational space from the classroom to the screen of a mobile device. This decentralization is the challenge to face when designing teaching-learning processes that take advantage of this virtual space and optimize the communication and didactics on a specific topic. Curricular content and didactic support should stimulate the user to continue learning through research, socialization, as well as deepening knowledge through other learning tools.

Beyond the technical difficulties, an even more significant aspect of m-learning adoption lies in identifying how to approach institutional transformation in higher education; the importance of integrating new and more agile tools of communication, information dissemination, and knowledge transmission will only be possible when institutions clarify and understand the organizational landscape that defines them. Moreover, recognizing the importance of technology in academic life requires that institutions support the strategic decisions related to m-learning at all managerial levels, which will send the appropriate message to the other institutional axes.

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