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Learning with mobile technologies – Students' behavior

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A B S T R A C T

The increasing growth of mobile technology in our Society has become a reality. This paper was designed to research about the different factors and drivers that could influence students' behaviour into the usage of mobile technologies for learning.

The methodology was based on a quantitative survey grounded on the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology. Data were collected from medical students in University of Coimbra.

This model pointed to a behaviour pattern based on the experience and application by medical students, correlating with a strong attitude towards using mobile technology for learning (57%) and willingness to recommend it (40.5%).

In line with previous studies, Social Influence raised to be an important factor towards the Attitude and Behavioural Intention of using Mobile Learning. In addition, according to the results, the student's ease of perception seems to be the main factor affecting the Social Influence (31.9%) and the reliability for recommending this technology for learning was the main factor that affected the Behavioural Intention. Findings provide support for Technology Acceptance Model and the implications of these findings are discussed within the context of Innovation in Education.

1. Introduction

During the last decade, the number of mobile lines in the world has been increased significantly. In fact, according to the last report of International Telecommunications Unit (ITU, 2015) there were more than 7.000 million users in the world with a mobile line by end 2015. In Europe, ITU estimates the mobile users penetration around 125% and the Internet rate will reach 75% by end 2014.

These figures show the importance that these new technologies have in the Society. This trend has affected different sectors as Education, Medicine, and Communication. The way people interact among them and the way they have to communicate each other have evolved completely, incorporating the mobile gadgets and the mobile technologies as part of them.

Due to this reasons, there have been some researches about the inquiries and the use of mobile technologies in education and learning (Briz-Ponce, Juanes-Méndez, & García-Peñalvo, 2014a; Huang, Lin, & Chuang, 2007; Tsinakos & Ally, 2013). This publications report the importance of these resources in the learning process, claiming that many Universities are implementing mobile learning to provide flexibility or even to prepare students and teachers for the developing digital area. The United Nations Educational, Scientific and Cultural Organization (UNESCO) have recommended Governments to adopt technological infrastructure to ensure equal access to mobile connectivity in order to allow students accessing to an important and increasing range of learning possibilities. This Organization has affirmed that m-learning has a great potential in the quality of learning and enhancing the good student's results (UNESCO, 2009).

The drivers that could influence in students' behaviour to use mobile technologies for learning, have been considered an engaging factor to assay in many researches (Arteaga, Duarte, & García, 2013; Briz-Ponce & García-Peñalvo, 2015; Chen, 2011; Hong, Thong, & Tam, 2006; Lee & Lehto, 2013; Sánchez & Hueros, 2010; Sezer, 2016; Thakre & Thakre, 2015).

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For example Thakre and Thakre (2015) explain what are the main uses of smartphones by students, reporting that communication, learning and entertainment are the most popular ones.

Briz-Ponce and García-Peñalvo (2015) makes a description of a TAM model applied to medical students making a confirmatory factorial analysis in order to explain the relationship between the dimensions included in the study. Lee and Lehto (2013) makes a research based on a TAM model as well reporting the determinants that may influence in the behavioural intention to use new technologies.

Sánchez and Hueros (2010) make an analysis of virtual teaching platforms for distance learning and the use of TAM whereas Sezer (2016) reveals that the factors of gender and the academic success affects significantly towards students' attitudes towards e-learning.

The authors Hong et al. (2006) make a comparison between three models in order to understand the usage behaviour of mobile Internet.

Arteaga et al. (2013) investigate the factors that determine the acceptance of WEbCt learning system among students and the findings published by Chen (2011) show that educational compatibility and expectancy are important determinants of e-learning acceptance.

Therefore, healthcare professionals are rapidly changing the use of mobile technologies. Clinicians consider that mobile technologies allow them to enable rapid access to clinical information and communicate among them (Epocrates, 2013). The main benefits reported of using m-learning was the convenience of getting information just when it was needed, accessibility, utility of mobile devices due to their compact size, portability, fast access to information, efficient use of time and flexibility (Boruff & Storie, 2014; Wallace, Clark, & White, 2012).

The purpose of this paper is to enhance the understanding of this issue, providing some insights about the different factors that could influence in students' behaviour using mobile technologies for learning, which will contribute to make Institutions or Universities promote their adoption and improve the needed resources to achieve a better quality in Education. In order to perform this research, it was necessary to design a survey that was distributed to the students of University of Coimbra.

2. Materials and methods

2.1. Participants

The study carried out within this research, performed a survey in University of Coimbra among medical students. One hundred and sixty participants were solicited in this University.

Table 1 presents the detailed analysis of participants' demographic information and other data related with their ownership of mobile devices, operating system, frequency of use and experience.

It is important to notice that about 74.4% of students in the sample who reported gender were female. This percentage is not so strange as there is a majority of women in Medical Schools these days. According to the European Union, the percentage of female physicians has increased between 1996 and 2006 in almost all Member States. In fact, there were 35% of women in Medical Schools in 1996 and 41% in 2006 (Corselli-Nordbald, 2009).

More than half of participants were enrolled in their third year of medicine (51.9%) and most part of the students ranged from 18 to 21 years of age. Another important data is almost all participants (96.9%) owned a mobile device (Smartphone, Tablet or both). The Operating system most used for Smartphones between undergraduate students is the Android, whereas the iOs (iPAd) is more popular for the tablets.

Table 1
Participants' demographic Information and other related characteristics (N = 160).

Variable	Participants' characteristics		
	Descriptive	Frequency	Frequency (percentage)
Gender	Male	41	25.6%
	Female	119	74.4%
Range age	From 18 to 25 years old	150	193.8%
	From 26 to 35 years old	10	6.3%
Year	1° Year of Medicine	38	23.8%
	2ª Year of Medicine	15	9.4%
	3° Year of Medicine	83	51.9%
	4° Year of Medicine	24	15.0%
Ownership	Only Smartphone	45	28.1%
	Only Tablet	9	5.6%
	Smartphone and Tablet	101	63.1%
	None	5	3.1%
Operating system smartphone	iOS (iPhone)	46	28.8%
	Android	95	59.4%
	Windows 8	5	3.1%
	N/A	14	8.8%
Operating system tablet	iOS (iPad)	49	30.6%
	Android	45	28.1%
	Windows 8	13	8.1%
	Other	2	1.3%
	N/A	50	31.2%

2.2. Procedure

The survey was distributed to the participants face-to-face during a class of first year, third and fourth year at University of Coimbra. The sampling method was non probabilistic (non randomly), accidental or convenience type (McMillan & Schumacher, 2001). Previously, it was necessary to request permission to the director of the department and the teacher responsible of the class in order to be allowed to interrupt the class. Therefore, a formal letter was sent to the director explaining all the process and a copy of the questionnaire in order they could check the data that will be collected. Once they received all the documentation, they provide the dates and the classes that could be interrupted in order to obtain data. Also, before filling the test, the students received information in class of this research and the contact email to answer any question they may have.

It is important to notice that all the data collected was anonymously and the participants were volunteer as they could refuse to fill the survey. All the data were obtained from October to November of 2015.

2.3. Instruments

The survey consisted of 53 questions grouped in two sections. The first section included 19 questions related with demographic and context information. This sections covers the main independent variables that were analysed in the result period. The second section included 34 items and was designed based on the TAM published by Davis (Davis, 1989) and the constructs reported by other article published in order to unify the different versions of the model (Venkatesh, Morris, Davis, & Davis, 2003). In addition, this study added one construct more referred to as Reliability and Recommendation (Briz-Ponce, Juanes-Méndez, & García-Peñalvo, 2014b).

In order to quantify the different dimensions or constructs, the survey used a 5-point Likert scale. The participants were asked to respond to each statement in terms of their own degree of agreement of disagreement. Likert scale is based on five possible answers

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ranging from strongly disagree (mapped to number 1) and strongly agree (mapped to number 5).

The instrument was validated through the Think aloud (Lewis, 1982) procedure, using a small group of teachers. This protocol is commonly more and more popular in education researchers due to the potential data that could be obtained using this methodology (Johnstone, Bottsford-Miller, & Thompson, 2006).

Table 2 shows the different constructs used to design the survey.

2.4. Hypothesis

The hypothesis drawn up within this project is described in Table 3. These hypothesis were based on the previous findings of other researchers (Briz-Ponce & García-Peñalvo, 2015; Venkatesh et al., 2003; Zayim & Ozel, 2015).

2.5. Data analysis

In this research, it was necessary to use a structure equation model (SEM) technique. According to Hsu, Chen, and Hsieh (2006), there are two types of SEM Techniques: "-covariance based (e.g. LISREL, EQS or AMOS) and component-based SEM Techniques (e.g. Partial Least Square)" (pp. 356).

One definition of SEM is the following: "… is a very general statistical modelling technique, which is widely used in the behavioural sciences. It can be viewed as a combination of factor analysis and regression or path analysis" (Hox & Bechger, 2009, p. 1).

The PLS technique was basically designed to analyse and determine the values of the variables for predictive purposes (Chin, 1998). Both techniques are considered robust against skewness scenarios, but the component-based SEM techniques are more adequate for investigations with a small sample size or with a predictive purpose. Finally, PLS model was chosen for this research as it was less restrictive than the other techniques and it fit well with the final purpose of this research. It is important to notice that PLS has two components, the measurement model (also referred to as an outer model) and a structural model (also referred to as an inner model). The outer model assess the quality of all constructs taking into account the measurement's reliability and validity. The inner model estimates the relationships between the different constructs of the model (Hair, Celsi, Money, Samouel, & Page, 2015).

The software SmartPLS (V. 3.2.3) and the SPSS (V.21) were used to computerize all the data and to analyse and obtain the main output indicators relevant for this research.

3. Results

3.1. Descriptive statistics

In this section, the authors make a main descriptive statistics of the selected constructs. Table 4 describes the different values for media, mean, standard deviation, standard error and variance. All means are above the midpoint 3.2355. It is important to notice that the standard deviations are within the range from 0.57986 to 0.86457 indicating a narrow spread around the mean (See Table 4). Besides, the values of kurtosis and skewness could be used as a test of normality. Data normality is ensured when their absolute value is within ±1. The results obtained with this study implied the survey was fairly normally distributed in all constructs except for PEOU, FC and SE. The non-normality distribution could distort the results of the analysis. However, the PLS technique minimise this problem and besides, the rule of thumb published by Kline (2005, p. 83) establishes that absolute values of Skewness < 3 and Kurtosis < 10 could be considered as accepted values. Therefore, there is no reason to think that the variable distribution may influence the overall results.

The results obtained from the preliminary analysis of the survey

Table 2
Description of the constructs of the survey.

Construct	Variable name	Description
Performance expectancy or Perceived Usefulness	PU	It measures the usefulness of the technology
Effort Expectancy or Perceived Ease of Use	PEOU	It measures the ease of use of the technology
Attitude toward using technology	ATU	It measures if the new technology is a good idea.
Social Influence	SI	It measures the external influence and the support of External Institutions
Facilitating conditions	FC	It considers the available resources.
Self-efficacy	SE	It measures if the construct can complete the tasks with the new technology
Anxiety	ANX	It measures the apprehension of using the technology (i.e. lack of information).
Behavioural intention to use the new technology	BI	It measures the intention to use the technology in the coming future.
Reliability and Recommendation	RELREC	It measures the necessity of a quality certification for apps and the recommendation of mobile technology

Table 3
Description of hypothesis.

Id	Hypothesis	Dependent variable	Independent variable	Description
H1	ANX → ATU	Attitude	Anxiety	The anxiety dimension could influence in the attitude of participants
H2	ANX → SI	Social Influence	Anxiety	The anxiety dimension could influence in the Social Influence of participants
H3	ATU → REL	Reliability	Attitude	The attitude may influence in participant's reliability
H4	PEOU → ATU	Attitude	Perceived Ease of Use	The Perceived Ease of Use influences in Students' Attitude
H5	PU → ATU	Attitude	Perceived Usefulness	The Perceived Usefulness may influence in Students' Attitude
H6	PU → FC	Facilitating Conditions	Perceived Usefulness	The Perceived Usefulness may influence in facilitating conditions
H7	PU → SI	Social Influence	Perceived Usefulness	The Perceived Usefulness influences in Social Influence of participants
H8	REL → BI	Behavioural Intention	Reliability	The Reliability dimension may affect the Behavioural Intention of participants
H9	SE → REL	Reliability	Self-Efficacy	The Self-Efficacy affect the Reliability
H10	SI → ATU	Attitude	Social Influence	The Social Influence of participants affects the Students' Attitude
H11	SI → BI	Behavioural Intention	Social Influence	The Social Influence of participants may influence in their Behavioural Intention
H12	SI → REL	Reliability	Social Influence	The Social Influence of participants affects the Students' Reliability.

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Table 4
Descriptive statistics.

Construct	$\bar{X} \pm SD$	σ^2	Skewness	Kurtosis
PU	3.2266 ± 0.86457	1.909	−0.430	−0.078
PEOU	4.3906 ± 0.57986	0.336	−1.201	2.998
ATU	3.4672 ± 0.73853	0.545	−0.308	0.336
SI	2.6370 ± 0.82656	0.683	−0.077	−0.294
FC	3.0033 ± 0.59356	0.352	0.144	1.568
SE	3.1965 ± 0.61002	0.372	−0.198	1.921
ANX	3.0932 ± 0.75238	0.566	0.141	0.278
BI	2.9345 ± 0.77657	0.484	−0.225	0.234
RELREC	3.3994 ± 0.78511	0.616	−0.595	0.796

are set out in Fig. 1. This figure illustrates the different percentages of participants' for the Technological Acceptance Model questionnaire based on a five point Likert scale. Besides, on the top of each column, the percentage of participants that have selected the option of Partially Agree or Strongly Agree is been added. Then, this information indicated that most part of participants (94%) considered mobile devices were easy to use. However, only 39% recognized them useful. The students also perceived that the external support or the facilitating conditions are very low (only 13% and 10% of participants respectively). Besides, only 24% of participants thought that they were ready to complete tasks with these technologies and half of the participants would recommend or trust on these new resources for learning. In addition, only 21% was reluctant to use it because they think that they would lose information. Finally, only 14% reported the intention to use them although 43% of them had a positive attitude towards using them.

3.2. Outer model: reliability and validity

The outer model performs an exploratory analysis obtaining the scale reliability and the construct validity.

In order to check the reliability of the survey, it is necessary to calculate the outer loadings using SmartPLS program. Before using it, an analysis with SPSS program was performed and the communalities were obtained. The communalities provide which level of variance is explained by the extracted items. In this case, all the items with communalities less than 0.7 were removed in order to obtain a good convergent validity scale (Gefen, Straub, & Boudreau, 2000; Mohammadi, 2015).

For the reliability, this study follows the criteria suggested by Fornell and Larcker (1981), Chin (1998) and Hair, Hult, Ringle and Sarstedt (2016). First, all indicator factor loadings should be significant and exceed 0.5. Second, the factor loadings should have at least a value of 0.7 and have a t-statistic in excess of ±1.96 at the 5% level. Finally, the composite reliability should be higher than 0.7.

Table 3 provides a detailed view of the main indicators used for the measurement model. It shows that the factor loadings obtained from SmartPLS are significant at the 5% level. Besides, all items set the rule thumb of 0.5 for the indicator reliability and 0.7 for standardized factor loadings except REL1 and SI3.

The survey used in this research was based on a 5-point Likert-type scale, so it is imperative to evaluate the internal consistency reliability, which is necessary to evaluate also the reliability of this study. There are three ways to calculate the internal consistency reliability (Hair et al., 2015). The first one is split-half reliability. Other type is coefficient alpha, also referred to as Cronbach's alpha. This parameter has a value between 0 and 1 and the closer is to 1.0 the greater the internal consistency of the items in the scale (Gliem & Gliem, 2003).

According to Nunnally (1978) the acceptable value of Cronbach's alpha depends on the type of research. It is exploratory analysis, the author states 0.70 as the minimum accepted value of Cronbach's alpha. If the research is not exploratory, then the minimum accepted value of this parameter could be 0.80.

A rule of thumb provided by George and Mallery (2003) is the following:

"$\alpha > 0.9$ – Excellent
$\alpha > 0.8$ – Good
$\alpha > 0.7$ – Acceptable
$\alpha > 0.6$ – Questionable
$\alpha > 0.5$ – Poor
$\alpha < 0.5$ – Unacceptable" (p.231).

The total value of Cronbach's alpha of this research is 0.85, which means that this survey could be considered with an internal consistency acceptable.

The third type of internal consistency reliability is composite reliability, developed by Werts, Lynn, and Jöreskog (1974). This

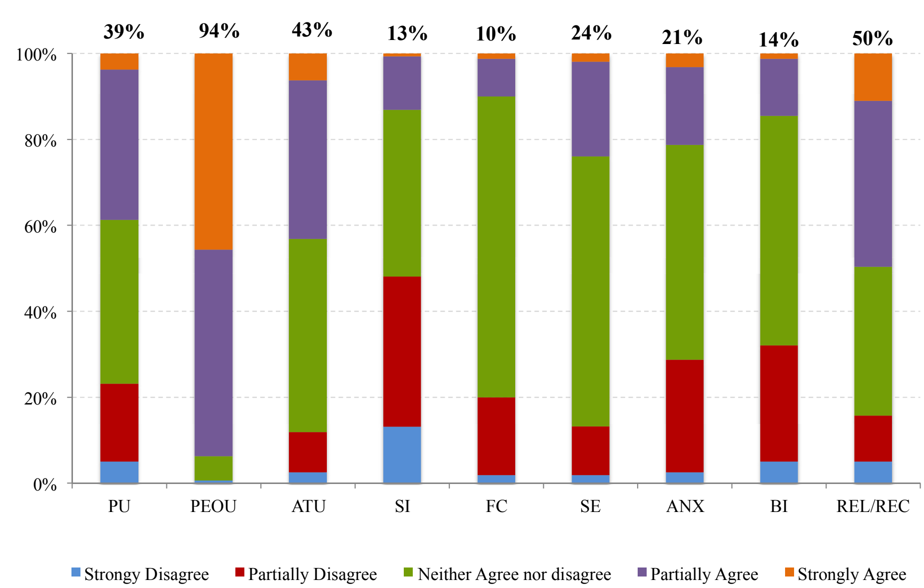

Fig. 1. Percentage of answer selection for each construct.

parameter is similar to Cronbach's alpha, but they are calculated differently. The coefficient alpha assumes that all items weigh equally, whereas composite reliability weighs each item based on the weights for individual items. The minimum accepted value for this parameter is stated in 0.70 (Bagozzi & Yi, 1988, p.82, p.82).

Table 5 shows the measured parameter for the Cronbach's alpha and the composite reliability for each construct. However, "composite reliability is considered a more accurate approach to assessing reliability" (Bagozzi & Yi, 1988, p. 255). Thus, according to the results obtained with the composite reliability, it is possible to say that this study has a good internal consistency reliability.

In order to assess the construct validity, it is necessary to check the convergent and discriminant validity.

The convergent validity "shows the degree to which the items of a certain instrument are related" (Cheung & Vogel, 2013). This is measured by the Average Variance Extracted (AVE) and the accepted values must be 0.50 or higher (Bagozzi & Yi, 1988, p.258). According to the values shown in Table 3, all values of AVE are higher than 0.5, so it is possible to conclude that the convergent validity is evident.

The discriminant validity "is the extend to which the construct does not correlate with other measures that are different from it" (p.258). In order to assess this indicator, it is necessary to compare the squared roots of the AVEs with the factor correlation coefficients. The results are listed in Table 6. This table presents that, for each construct, the square root of AVE is larger than its correlation coefficient with other constructs, which means that the survey exhibits good discriminant validity (Gefen et al., 2000).

In summary, this survey has a good internal consistency reliability. According to the validity indicator, the convergent validity is evident and the survey exhibits a good discriminant validity, so the results suggest the validity of this research.

3.3. Inner model

The inner model "depicts the relationship among latent variables based on substantive theory" (Chin, 1998, p. 312). In this case, for this model, this study follows the steps recommended by Hair et al. (2016). First, it is necessary to calculate the path coefficients and their significance. Then, the R^2 measures the variance for each construct. The third step is to calculate the change of R^2 obtaining the f^2 statistics, which indicates the strength of each independent item for its corresponding factor and finally the indicator of model's predictive relevance calculating the parameter Q^2.

Table 7 shows the path coefficients for all constructs. As it is possible to observe, all T-values exceed ±1.96 at 5% level except the relation between SE and REL, therefore all hypothesis except that one are empirically supported.

Fig. 2 also represents these path coefficients and the R^2 value for each factor. According to it, the 57% of variance of user's attitude

Table 5
The measurement model.

Construct	Indicators	Factor loadings	T-statistics	Reliability			Validity
				Indicator reliability (reliability)	Composite reliability internal consistency reliability	Cronbach's alpha	AVE (convergent validity)
PU	PU1	0.872	40,309	0.760	0.914	0.859	0.780
	PU2	0.925	60,320	0.856			
	PU3	0.852	38,450	0.725			
PEOU	PEOU1	0.933	35,036	0.870	0.954	0.929	0.874
	PEOU2	0.943	25,943	0.890			
	PEOU3	0.929	23,684	0.863			
ATU	ATU1	0.849	33,906	0.720	0.874	0.783	0.699
	ATU2	0.898	47,666	0.806			
	ATU3	0.756	14,679	0.572			
SI	SI1	0.944	77,595	0.892	0.874	0.777	0.707
	SI2	0.947	79,622	0.898			
	SI3	0.576	6637	0.332			
FC	FC1	0.788	7696	0.622	0.826	0.587	0.704
	FC2	0.887	16,555	0.788			
SE	SE1	0.950	3226	0.902	0.898	0.785	0.815
	SE2	0.853	3640	0.727			
ANX	ANX1	0.920	9895	0.846	0.892	0.761	0.805
	ANX2	0.874	9479	0.765			
BI	BI1	0.936	45,090	0.876	0.965	0.946	0.903
	BI2	0.967	108,562	0.934			
	BI3	0.948	47,339	0.899			
REL and REC	REL1	0.542	3728	0.294	0.736	0.410	0.600
	REL2	0.952	39,249	0.906			

Table 6
Square root of AVE (bold at diagonal) and correlation coefficients. Fornell-Larcker Criterion.

	PU	PEOU	ATU	SI	FC	SE	ANX	BI	RELREC
PU	**0 883**								
PEOU	0.171	**0 935**							
ATU	0.659	0.214	**0 836**						
SI	0.524	−0.113	0.590	**0 841**					
FC	0.352	0.366	0.307	0.275	**0 839**				
SE	0.152	−0.131	0.134	0.165	0.067	**0 907**			
ANX	0.015	0.202	−0.177	−0.201	0.039	−0.154	**0 897**		
BI	0.362	0.035	0.371	0.477	0.143	0.179	−0.103	**0 950**	
RELREC	0.486	0.088	0.592	0.513	0.301	0.214	−0.196	0.504	**0 774**

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Table 7
Structural model hypotheses.

Hypothesis	Path coefficients	T-statistics	Supported
ANX → ATU	−0.155	2.773	YES
ANX → SI	−0.209	2.782	YES
ATU → REL	0.438	5.786	YES
PEOU → ATU	0.210	3.828	YES
PU → ATU	0.441	7.072	YES
PU → FC	0.352	4.142	YES
PU → SI	0.528	9.257	YES
REL → BI	0.352	4.517	YES
SE → REL	0.116	1.387	NO
SI → ATU	0.351	5.660	YES
SI → BI	0.296	4.085	YES
SI → REL	0.236	3.402	YES

(ATU) is accounted for by the variables: Anxiety (ANX), Perceived Usefulness (PU), Perceived Ease of Use (PEOU) and the Social Influence (SI). It is difficult to establish the rule thumb of the minimum accepted value of the variance. Some authors consider an adequate range for R^2 between 40% and 70% (Warner, 2012), whereas others describe the R^2 values of 0.75, 0.50 or 0.25 as substantial, moderate or weak, respectively (Hair, Ringle, & Sarstedt, 2011). Thus, following this rule, it is possible to consider that all constructs have moderate level of variance except R^2 result of facilitating conditions (FC), which indicates a weak level of it.

Once that the hypothesis have been evaluated, it is interesting to calculate the effect size (f2) statistics in order to "identify which one of the independent variables accounts for most of the variance in a dependent variable" (Hair et al., 2015, p. 449). Table 8 shows the values obtained for each independent variable. These ones are represented in each row whereas the dependent variables are represented in each column. In this case, the effect size of 0.02, 0.15 and 0.35 indicates small, medium and large effect (Cohen, 1992).

According to the results, the variable that accounts for most of the variance in ATU, BI and RELREC are PU, RELREC and ATU respectively. FC and SI variables only have one independent variable, and the effect of it is medium and small respectively.

Finally, the indicator of model's predictive relevance (Q^2) is shown in Table 9. This parameter "represents a measure of how well-observed values are reconstructed by the model and its parameter estimates" (Esposito, Chin, Henseler, & Wan, 2010, p. 680). According to Hair et al. (2011), if this parameter is higher than zero, the construct exhibits predictive relevance. In this research, the value obtained for Q^2 is positive in all cases, providing support for the model's predictive relevance.

4. Discussion

This study attempts to provide some insights about the different drivers that could affect the behaviour of the undergraduate medical students in order to use mobile technology for their learning.

In this study, 96.8% of participants owned a mobile device (Smartphone, Tablet or both). This data is also very similar as the result collected in four Canadian Universities (Boruff & Storie, 2014), which obtained that 92.6% (n = 1296) of survey respondents owned a mobile device. In addition, other study conducted in the Medical School of Author's University reported that 94.4% of participants owned a mobile device (Briz-Ponce, Juanes-Méndez, & García-Peñalvo, 2014c).

There are several articles (among others) that have analysed the use of mobile devices for learning (Ally & Prieto-Blazquez, 2014; Briz-Ponce & Juanes-Méndez, 2015; Gikas & Grant, 2013; Hasan, Ashraf, Abdullah, & Murad, 2015; Herrington, Herrington, Mantei, Olney, & Ferry, 2009; Huang et al., 2007) and several studies have been measured the acceptance of different technologies for learning in general (Arteaga et al., 2013; Chen, 2013; Mohammadi, 2015; Paluri, 2015; Sánchez & Hueros, 2010). However, the results

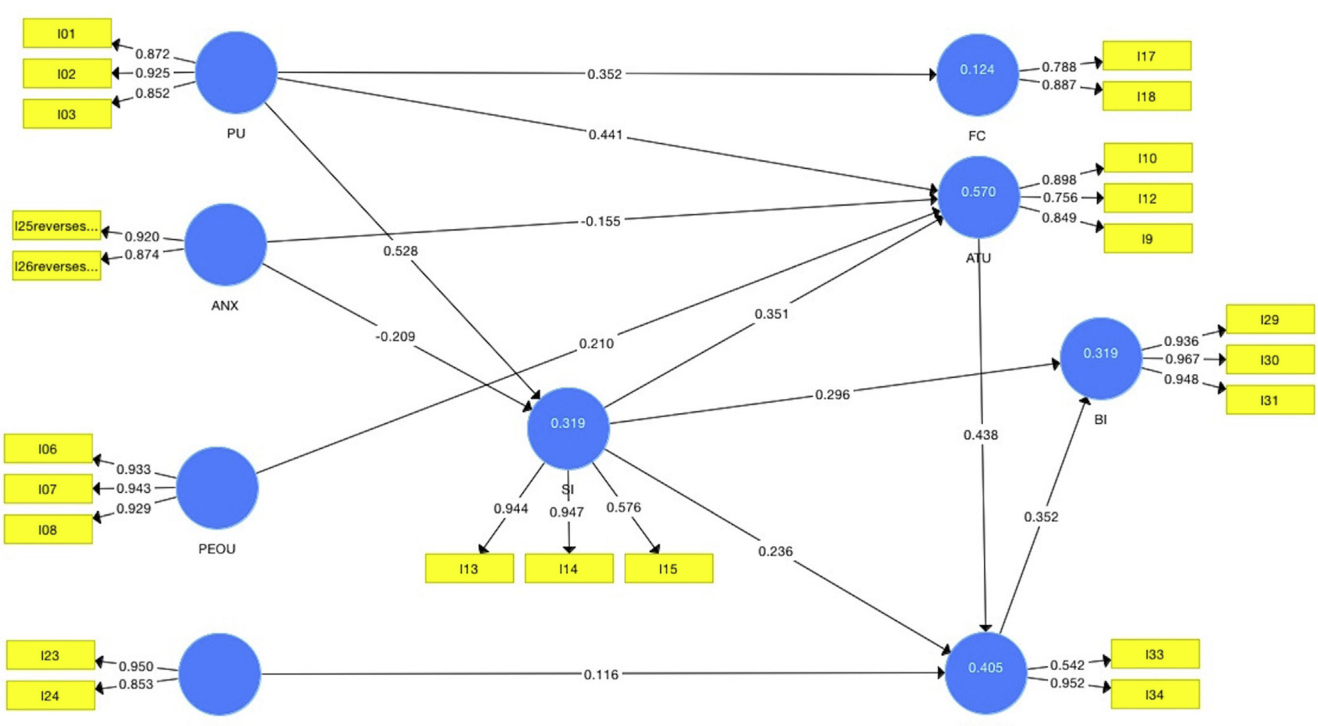

Fig. 2. Path coefficients and R^2 values obtained from SmartPLS program.

Table 8
Effect size for each independent variable.

	ATU	BI	FC	RELREC	SI
ANX	0.051	–	–	–	0.064
ATU	–	–	–	0.210	–
PEOU	0.091	–	–	–	–
PU	0.301	–	0.142	–	0.408
RELREC	–	0.134	–	–	–
SE	–	–	–	0.022	–
SI	0.187	0.095	–	0.060	–

Table 9
Indicator of model's predictive relevance.

	Construct crossvalidated redundancy
ATU	0.389
BI	0.281
FC	0.065
RELREC	0.210
SI	0.220

need to be interpreted with caution to extend the results to different sectors as it is well reported by other authors (Huang et al., 2007).

The Innovation has been regarded as a crucial factor to enhance the ability to adapt to changing environments (Damanpour & Gopalakrishnan, 1998). This term is also applied into the Education field. According to the Organization for Economic Co-operation and Development (OECD), the Innovation in Education could be employed introducing new products and services, new processes (for example the use of new technologies in e-learning), new methods of organising their activities (use of new technologies to communicate with students and parents) and finally, new marketing techniques (for example, differential pricing of postgraduate courses) (OECD, 2014). Therefore, in the context of Innovation Education, this research aims to be considered as a first-stage evaluation working towards a framework to demonstrate that individual characteristics and external variables may have a significant influence on individuals to predict Behavioural Intention (BI) and in the meantime could foster the behaviour of medical students towards the use of mobile devices and mobile technologies for their curriculum, which are perceived as potential tools to enhance and improve the learning process.

There are few studies that investigate specifically the medical education area (Briz-Ponce & García-Peñalvo, 2015; Chatterley & Chojecki, 2010; Fayaz-Bakhsh & Geravandi, 2015; Sezer, 2016; Thakre & Thakre, 2015; Vafa & Chico, 2013), so this discussion consider not only the studies performed with medical students, but also the general studies performed with the student's attitudes for e-learning or m-learning.

Hence, this research suggests that the Perceived Usefulness (PU) is important to predict the Attitude towards Use of Technology (ATU). In fact, this result also agree with the one reported by Davis (forefather of the TAM theory), who assumed that the Perceived Usefulness (PU) is one main indicators of user's attitudes (ATU) (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). Also, the Perceived Ease of Use (PEOU) has a positive impact on the user's attitude, which also agrees with the results of the Davis' study (Davis et al., 1989). Also, a study about mobile learning in Higher education, performed in three important Chinese universities (Zhu, Guo, & Hu, 2012), reported that Perceived Usefulness (PU) exerts more influence on user's attitude (ATU) than Perceived ease of use (PEOU).

Another important contribution to highlight is the introduction of Social Influence (SI) as an important factor to affect the user's attitude (ATU), whereas other author revealed that this factor affects directly the Behavioural Intention (Venkatesh, Thong, & Xu, 2012). In this research, the Social Influence also affects the Behavioural Intention, however, it is not very relevant for the final contributions.

This research, also, introduces a new dimension referred to as Reliability and Recommendation of Mobile Technology. User's attitude (ATU) significantly increases the degree of recommendation or the necessity of an app certification (RELREC). This is the same result obtained for other research which conducted the same survey at Authors' University (Briz-Ponce & García-Peñalvo, 2015). Finally, this study found that overall one construct (Reliability and Recommendation) is a key determinant for the Behavioural Intention of using apps for learning (f^2 is higher than 0.30).

5. Conclusions

According to the data analysis, this study presents a good internal consistency reliability and also suggests the validity of this research. Besides, it seems that medical students perceive mobile learning and the use of apps moderately positive. They have a strong attitude towards using it (57%) and they are very willing to recommend it (40.5%). However, they have a medium willingness to adopt it (Behavioural intention has a variance of 31.9%).

Social Influence is an important factor that could affect the Attitude and the Behavioural Intention of using Mobile Learning. Besides, the student's ease of use perception is the main factor affecting the Social Influence (31.9%) and finally, the new factor related with the reliability of recommendation of this technology for learning is the main factor that may affect the Behavioural intention.

Future research can be conducted to analyse the score results obtained and the benefits and drawbacks to encourage the use of mobile devices and apps for learning and then contribute to the innovation in education area. In addition, it should be recommended to compare the collected data by using different subgroups such as profile, age or gender to dwell on the impact of these external variables to the model.

In summary, the understanding of the drivers to motivate the use of new technologies could enhance the quality of learning process, allow students benefit their potential pedagogical and instructional uses and, in short, promote and encourage the adoption of these original resources as innovative ways of teaching and learning.

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Appendix

A. Survey employed in this research.

Construct	Id	Items
PU	PU1	I would find the system useful in my job
	PU2	Using the system enables me to accomplish tasks more quickly
	PU3	Using the system increases my productivity
	PU4	If I use the system, I will increase my chances of getting a raise
PEOU	PEOU1	My interaction with the system would be clear and understandable
	PEOU2	It would be easy for me to become skilful at using the system
	PEOU3	I would find the system easy to use
	PEOU4	Learning to operate the system is easy for me
ATU	ATU1	Using the system is a bad/good idea
	ATU2	The system makes work more interesting
	ATU3	Working with the system is fun
	ATU4	I like working with the system
SI	SI1	People who influence my behaviour think that I should use the system
	SI2	People who are important to me think that I should use the system
	SI3	The senior Management of this business has been helpful in the use of the system
	SI4	In general the organization has supported the use of the system
FC	FC1	I have the resources necessary to use the system
	FC2	I have the knowledge necessary to use the system
	FC3	The system is not compatible with other systems I use
	FC4	A specific person (or group) is available for assistance with system difficulties
SE I could complete	SE1	If there was no one around to tell me what to do as I go
a job or task using the system …	SE2	If I could call someone for help if I got stuck
	SE3	If I had a lot of time to complete the job for which the software was provided
	SE4	If I had just the built-in help facility for assistance
ANX	ANX1	I feel apprehensive about using the system
	ANX2	It scares me to think that I could lose a lot of information using the system by hitting the wrong key
	ANX3	I hesitate to use the system for fear of making mistakes I cannot correct
	ANX4	The system is somewhat intimidating to me
BI	BI1	I intend to use the system in the next <n> months
	BI2	I predict I would use the system in the next <n> months
	BI3	I plan to use the system in the next <n> months
	BI4	I won't use the apps for my learning
REL/REC	REL1	I think that a quality certification of Apps is necessary
	REL2	I would recommend the use of Apps for learning to my colleagues

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