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Understanding Pre-Service Teachers' Mobile Learning Readiness Using Theory of Planned Behavior

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ABSTRACT: The study aimed to understand pre-service teachers' mobile learning readiness with Theory of Planned Behavior using external salient beliefs. There were nine hypotheses tested with a total of 533 pre-service teachers in two cities in Turkey. Several scales adapted from Cheon et al. (2012) included 10 psychological variables. The results indicated that the TPB model explained 58% of the variance in intention to adopt mobile learning. The results of structural equation modeling (SEM) showed that the proposed model of the current study has acceptable fit data. The results of the SEM revealed that attitude, subjective norm and perceived behavioral control have significant impact on intention to adopt mobile learning. In addition, salient beliefs had an influence on the constructs of TPB. Therefore, all the hypotheses within the model were statistically supported in understanding determinants of mobile learning readiness. All in all, the study approved the effectiveness of well-structured cognitive psychological model in understanding pre-service teachers' intention towards adoption of mobile learning in the Turkish context. The study has important implications for researchers, educators, education stakeholders, policy makers and mobile learning application designers.

Keywords: Mobile learning readiness, Pre-service teachers, Theory of planned behavior

1. Introduction

The popularity of mobile devices is increasing and is being used in many areas of the education process (Zydney & Warner, 2016). Therefore, due to the increased affordability and functionality, mobile learning has been involved in a new study trend that attracts many researchers to discover this technology, examine its impact on students and academicians, and develop the necessary infrastructure (Al-Emran, Elsherif & Shaalan, 2016; Kinash, Brand, & Mathew, 2012). Mobile learning can be defined as "*the process of development, delivery, and consumption of learning material via a learning system subscriber using mobile devices*" (Yousafzai, Chang, Gani, & Noor, 2016, p. 785). Mobile learning is accomplished with the use of a wide range of mobile devices such as data-travelers, mp3 and mp4 players, digital cameras, tablets, laptops, netbooks, personal digital assistants, pads, pods, and smartphones (Pargman, Nouri & Milrad, 2018; Şad & Göktaş, 2014).

Considering the education process, a great potential positive effect of mobile technology on learning was accepted by researchers (e.g., Nikolopoulou, Gialamas, Lavidas, & Komis, 2020; Wang, Hwang, Yin, & Ma, 2020) and mobile learning has numerous benefits to achieve education goals. It promotes established and context-aware learning, facilitates personalized learning, forges a link between formal and informal learning, improves continuous learning, and develop collaboration and communication between learning societies as it was involved in UNESCO Policy Guidelines (West & Vosloo, 2013). Furió, Juan, Seguí, and Vivo (2015) stated that because of mobile technology, children have the chance to find out what they have learned from a diverse range of different points of view. In addition, mobile devices offer a number of different ways to promote authentic learning environments in the courses (Cotič, Plazar, Starčič, & Zuljan, 2020) and enable students to connect with courses (Sullivan, Slater, Phan, Tan, & Davis, 2019).

Although mobile technologies have a very important place about informing teachers (Kim & Kim, 2017), mobile learning is not adequately theorized, especially in teacher education (Sánchez-Prieto, Hernández-García, García-Peñalvo, Chaparro-Peláez, & Olmos-Migueláñez, 2019). There is a limited number of teacher development or training activity related to mobile learning (Carpenter, Krutka, & Trust, 2016). Therefore, teacher education programs are in need of providing theoretically and pedagogically effective mobile learning technologies due to several reasons such as the fast growth of mobile devices as an effective teaching tool in the teaching process and the pressure of providing teachers with effective technology integration skills (Newhouse, Williams, & Pearson, 2006). Especially, including mobile learning in teaching process of pre-service teachers (PST) has great importance on increasing quality in future generations' education (Baydas & Yilmaz, 2018; Sánchez-Prieto et al., 2019). Moreover, PST have an important role on mobile technology adoption, because their capabilities and views have the longtime effect and potential to affect change (Tondeur, van Braak, Ertmer, & Ottenbreit-Leftwich, 2017)

Accordingly, a better comprehension of the mobile technology adoption process in the education of PST will help scholars and stakeholders collaborate to implement proper methods and strategies for mobile learning. In this vein, understanding PST' mobile learning intention to adopt mobile learning provides important clues about how to include mobile learning in the classroom environment throughout their professional life. To determine the factors predicting mobile learning intentions, some valid and well-established models were preferred by researchers (e.g., Sidik & Syafar, 2020). Among them, Theory of Planned Behavior (TPB) developed by Ajzen (1991) has been mostly used as a theoretical framework. Therefore, the current study aims to predict PST' intentions towards mobile learning readiness (MLR) with the framework of TPB which is derived from self-interest motive and includes rational considerations. There are some empirical supports confirming the importance of psychological factors on MLR of PST implying that PST have the possibility of using technologies (e.g., Sánchez-Prieto et al., 2019; Teo, Zhou, & Noyes, 2016). However, no studies have been conducted to examine the role of pro-social roles in forming PST' behavioral intentions within the rational-choice model. Therefore, it is unclear whether the rational antecedents proposed by the TPB are also predictive of PST' MLR. In addition, it is yet unclear the extents to which PST have positive attitudes, subjective norms and, perceived behavioral control (PBC) and whether such psychological variables are related to their MLR. Moreover, it is not clear to what extent salient beliefs including behavioral beliefs, normative beliefs and control beliefs have an effect on the rational considerations. Therefore, to increase understanding of PST' mobile learning readiness, the study attempted to test a model that investigated the importance of salient beliefs on attitudes, subjective norms and, PBC which in turn influence intention to adopt mobile learning. Accordingly, it is expected that the study will make significant contributions to the literature in order to establish a solid foundation of the importance of mobile technologies in teacher education since it is recommended that teachers give more place mobile devices in their classrooms and professional development (Baran, 2014).

2. Literature review and hypothesis development

2.1. Mobile learning in pre-service teacher education

Mobile learning provides a number of benefits to teachers such as reflection of professional learning as a critical component of action (Kearney & Maher, 2019), younger generations such as PST who are more comfortable using technology are inclined to use mobile technology in their classrooms in future (Thomas & Bannon, 2013). However, although it could be emphasized that PST are in need of teaching models on how to integrate technology into the education process and should understand the pedagogical role of technology in education (Baydas & Yilmaz 2018), previous studies indicated that using a mobile learning environment can provide successful results in PST' education (Baran, 2014; Olpak & Ateş, 2018). Mobile technology has the makings of promoting PST to grasp and improve new consciousness (Husbye & Elsener, 2013), conduct a scientific study (Gado, Ferguson, & van't Hooft, 2006) and improve professional training (Kearney & Maher, 2019) and ease mentoring through collaboration (Husbye & Elsener, 2013).

2.2. Theory of planned behavior

TPB was developed from the earlier study of Theory of Reasoned Action (Ajzen & Fishbein, 1980). The theory explains systematically investigating the factors affecting behavioral choices (Ajzen, 1991). According to the TPB, the closest prediction of behavior is the intention which is individuals' readiness to implement a specific behavior and determined by attitude, subjective norm, and PBC (Ajzen & Madden, 1986). This section includes definitions of each factor and purposed hypotheses in compliance with the proposed model outlined in Figure 1.

2.2.1. Attitude

Attitude (ATT) can be defined as a "*learned predisposition to respond in a consistently favourable or unfavourable manner with respect to a given object*" (Fishbein & Ajzen, 1975, p. 6). The theory claims that in case people have more positive attitude towards a particular behavior, they are more chances to act that behavior (Ajzen, 1991). Mobile learning can increase collaboration between students and promote interaction among them and educators (Al-Emran et al., 2016). Therefore, attitudes towards educational technology can be used to gauge whether this technology has a positive or negative influence on the classroom environment (Ardies et al., 2015). However, the number of the studies investigating pre-service or in-service teachers' attitudes toward mobile learning adoption is limited (e.g., Kim & Kim 2017; Thomas & Bannon, 2013), within our knowledge, there is no empirical study examining the relationship between PST' attitudes toward mobile learning and their intention to adopt mobile learning. Based on earlier studies (e.g., Al-Emran et al., 2016), the study assumed that there is a positive relationship between PST' attitudes and their MLR. On the basis of this discussion, the following hypothesis can be proposed:

H1: Attitude toward mobile learning is positively related to intention (INT) to adopt mobile learning.

2.2.2. Subjective norm

Subjective norm (SN) reflects assessment and support of persons who are important to him/her such as family members, friends, co-workers for a behavior (Werner, 2004). In the educational technology context, although teachers are the most important decision-maker in the class, social pressure has an important effect on the decision (Teo, 2015). For this reason, teachers are conscious that some people such as colleagues and school principal have some expectations regarding the use of mobile devices for teaching in lessons (Sánchez-Prieto et al., 2019). Before teaching career, PST tend to receive feedback and value it more positively since they have some deficiencies in terms of professional development and experience (Lamote & Engels, 2010). Therefore, the study assumed that the perception that PST are pressured to use mobile technologies may influence their intention to adopt mobile learning. Accordingly, in a limited number of similar studies conducted with PST (e.g., Sánchez-Prieto et al., 2019), past empirical studies emphasized that the subjective norm is related to intention to adopt mobile learning. The discussion leads to the following hypothesis:

H2: Subjective norm is positively related to intention to adopt mobile learning.

2.2.3. Perceived behavioral control

PBC is referred to as an individual perceived ease or difficulty of performing a particular behavior and predicts behavioral intention (Ajzen, 1991). In the study context, PBC is defined as PST' perception of the ease or difficulty of adopting mobile learning. Therefore, we assumed that PST' intentions toward mobile learning depend on their confidence in mastering the new learning approach and their perceptions about acting a behavior as ease or difficulty have an influence on their readiness toward mobile learning. In a study conducted by Teo et al. (2016), a positive relationship was found between teachers' PBC and technology usage intentions. Therefore, the hypothesis is proposed as follows:
H3: PBC is positively related to intention to adopt mobile learning.

2.2.4. Salient beliefs

Behavior is a function of salient beliefs which are thought to be important predictors of people's intentions in the TPB, three salient beliefs were postulated (behavioral beliefs, normative beliefs, and control beliefs (Ajzen, 1991). Among them, behavioral beliefs are related to attitudes; normative beliefs are assumed to be the main predictors of subjective norms and control beliefs underlies perceptions toward behavioral control (Fishbein & Ajzen, 1975). Considering the mobile learning studies, salient beliefs were also involved in the framework of behavioral models or theories such as TAM (e.g., Huang, Teo, & Scherer, 2020) and TPB (e.g., Gómez-Ramirez et al., 2019). Looking at behavioral beliefs, perceived ease of use (PEOU) can be defined as "*the degree to which a person believes that using a particular system would be free of effort*" and perceived usefulness (PU) as "*the degree to which a person believes that using a particular system would enhance his or her job performance*" (Davis, 1989, p. 320). PU and PEOU were approved as an essential determinant of the technology acceptance and applicability of mobile technology systems (Al-Emran, Mezhuyev, & Kamaludin, 2020; Teo et al., 2016). Further, the concepts of PEOU and PU were also involved in many studies because of a significant impact on attitude to use mobile technology and mobile learning acceptance referring that people who see mobile technology as useful or easy to use are more likely to adopt it (e.g., Briz-Ponce Pereira et al., 2017). Earlier studies conducted with pre-service and in-service teachers proved that attitude toward the use of mobile technologies was influenced by PEOU and PU (e.g., Bower, DeWitt, & Lai, 2020; Teo et al., 2016). Therefore, the study proposes the following hypotheses:

H4: PEOU is positively related to attitude toward mobile learning.
H5: PU is positively related to attitude toward mobile learning.

Considering normative beliefs which are the second salient belief type, the subjective norm is influenced by existing normative beliefs that explain the anticipations of other people as an essential factor in intention (Ajzen, 1991). The scope of the study is interested in normative beliefs as perceptions towards to what extent other people are in favor of using mobile technology in their classroom. Earlier studies indicated that instructors and peer students are considered as prominent referent sets in higher education (Taylor & Todd, 1995), so they are thought to be the antecedents of subjective norm. Based on this discussion, the hypotheses are developed as follows:

H6: Instructor readiness (IR) is positively related to subjective norm for mobile learning.
H7: Student readiness (SR) is positively related to subjective norm for mobile learning.

Control beliefs, the last salient variable in the model, can be affected by the experience of friends, acquaintance, and other factors that enhance or reduce the perceived difficulty related to exhibiting the behaviors (Ajzen & Driver, 1991). Among the beliefs, perceived self-efficacy can be defined as "*people's beliefs about their capabilities to exercise control over their own level of functioning and over events that affect their lives*" (Bandura, 1991, p. 257). Individuals who believe they have an ability to act a certain skill or activity are inclined to intend to do the skill or perform the activity (Cheon et al., 2012). In line with the theoretical framework, if an individual has self-efficacy toward computers at high level, he/she is also inclined to higher levels toward the usage of information technology (Compeau & Higgins, 1995). In addition, the concept of learner autonomy involved in the scope of control beliefs is related to participation, control and evaluation and autonomous learners are responsible for all decisions regarding all directions of learning including specifying aims, describing the scope and the advancement, determining method, monitoring procedure related to acquiring the proper speech and evaluating acquired (Holec, 1981). Since mobile learning is regarded to be self-disciplined and self-motivated as necessary (Liu, 2008), learning autonomy could be a significant factor of behavioral control for mobile learning (Cheon et al., 2012). Hence, the hypotheses are formulated as:

H8: Perceived self-efficacy (SE) toward mobile learning is positively related to PBC.
H9: Learning autonomy (LA) toward mobile learning is positively related to PBC.

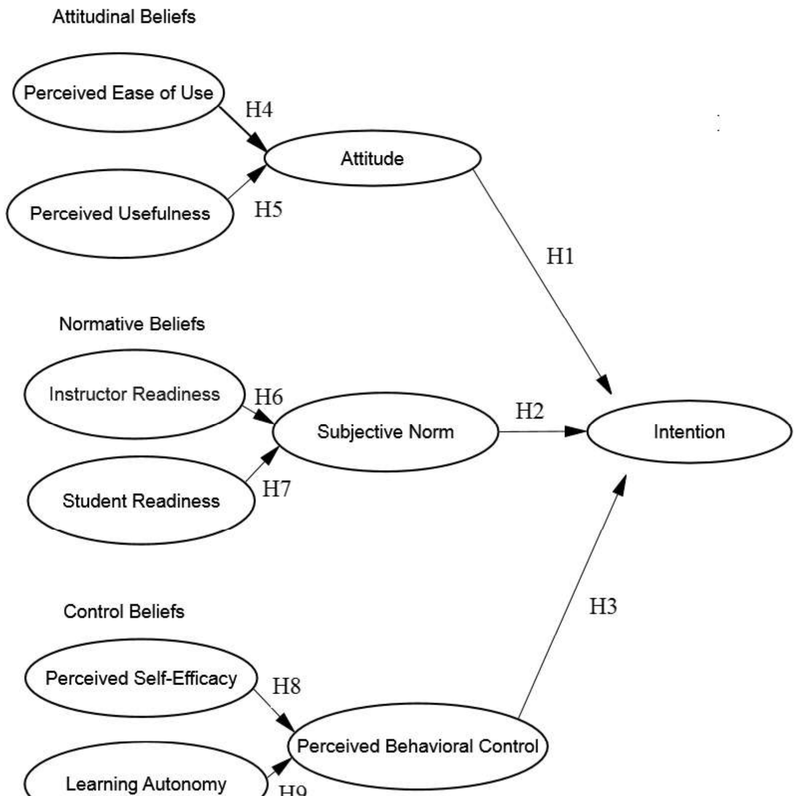


Figure 1. Research model of the study adapted from Cheon et al. (2012)

3. Methodology

3.1. The instrument

The Mobile Learning Readiness Scale (MLRS) was used as a data collection instrument. The original version of the MLRS was obtained from Cheon et al. (2012). In addition, the MLRS was adapted to the Turkish language by Sungur Gül and Ateş (2021). MLRS based on TPB consists of 30 items (three items for each of the 10 factors); 3 items for PEOU, 3 items for PU, 3 items for ATT, 3 items for IR, 3 items for SR, 3 items for SN, 3 items for SE, 3 items for LA, 3 items for BC and finally 3 items for INT to adopt mobile learning. All of the items on the scale are positively coded. The respondents of the scale are required to indicate on a Likert scale of totally disagree (1) to totally agree (7).

3.2. Sample and data collection

The participants of the study are 533 PST (62 males, 471 females) who were determined by using the convenience sampling method and participated voluntarily educating at two different faculties of education in the fall semester of 2019-2020 in Turkey. The reason for choosing these universities is that PST have been introduced to mobile applications in their content, content education and pedagogy courses and the universities' accessibility to mobile learning environments is similar. In addition, the students actively participated in the lessons by sharing files and voice using mobile applications via moodle in distance education. Hair, Babin, Anderson, and Black (2018) noted that the sample size was 10-15 sample/item for applying structural equation modeling (SEM). The current sample size of 533 with ten constructs of 30 items was also considered to be fit and above (533 > 30*15 = 450) the desired level. Therefore, the sample size was considered to be appropriate. The descriptive statistics are expressed in Table 1.

Table 1. Demographic characteristics

Characteristic	Demographic	Frequency	%
Gender	Male	62	11.63
	Female	471	88.37
Department	Preschool education	104	19.43
	Primary education	86	16.14
	Science education	343	64.43
Grade level	1st grade	157	29.45
	2nd grade	123	23.07
	3rd grade	148	27.78
	4th grade	105	19.70
Using mobile devices in education	Yes	448	84.05
	No	85	15.95
Using mobile devices in daily life	Yes	504	94.56
	No	29	5.44
The duration of mobile devices in daily use	Less than 1 hour	39	7.32
	1–4 hours	213	39.96
	5–8 hours	195	36.59
	More than 9 hours	86	16.14

The departments of the participants were science education, preschool education, and primary education in two mid-sized universities. In Turkey, students in the 3-6 years are educated by PST who graduated from the department of preschool education, students in the 7-10 years are educated by PST who graduated from the department of primary education, and students in the 11-14 years are educated by PST who graduated from the department of science. For preschool and primary school students, mobile applications such as sky map, anatomy 4D, Geogebra classic, geometry pad make learning concrete and provide fast access to information.

3.3. Data analysis

The proposed research model was analyzed using SPSS V.20 & AMOS V.24 software, respectively. Two staged SEM procedure suggested by Anderson and Gerbing (1988) was used. At the first stage, Confirmatory Factor Analysis (CFA) was performed and checked reliability and validity among items and constructs by using measurement model. In the second stage, the structural model was evaluated by testing the model fit, research hypothesis, and moderator effects.

4. Results

4.1. Measurement model: Reliability and validity

Prior to CFA, we performed Keiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity to evaluate multivariate normality and sampling adequacy. Since Bartlett's test of sphericity showed a significant value ($p < 0.01$) and KMO value (0.92) was higher than 0.60 (Tabachnick & Fidell, 2019), the data was suitable for factor analysis. We also examined univariate statistics for all the study items to assess multivariate normality. (see Table 2). Tabachnick and Fidell (2019) suggested that univariate skewness values should be < |2| and univariate kurtosis values should be < |4| to provide a normal distribution. And then index of multivariate kurtosis and its critical ratio (c.r) were evaluated. Mardia's multivariate kurtosis estimate (Mardia, 1970) in the study was 408.30 lower than 960 calculated according to the formula, p (p + 2) (Raykov & Marcoulides 2008). (p: the number of observed variables in the model). Thus, the assumptions of multivariate normality were provided in this study.

Table 2. Descriptive statistics and measurement model: Reliability and validity

Construct	Items	Mean	SD	FL	CA	CR	AVE	Skewness	Kurtosis
PEOU	PEOU1	5.58	1.14	0.75	0.79	0.80	0.57	-1.26	1.75
	PEOU2	5.73	1.06	0.80				-1.52	3.46
	PEOU3	5.49	1.01	0.72				-0.71	0.53
PU	PU1	5.55	1.10	0.68	0.70	0.70	0.43	-0.95	1.23
	PU2	5.74	1.07	0.58				-1.18	1.88
	PU3	5.68	1.11	0.71				-1.29	2.41
ATT	ATT1	4.77	1.43	0.55	0.78	0.70	0.44	-0.47	-0.09
	ATT2	5.26	1.28	0.70				-1.00	1.25
	ATT3	5.43	1.20	0.72				-0.93	1.02
IR	IR1	5.28	1.24	0.73	0.61	0.63	0.38	-0.86	0.70
	IR2	5.21	1.28	0.67				-0.91	0.69
	IR3	4.85	1.40	0.39				-0.67	-0.06
SR	SR1	5.20	1.29	0.72	0.67	0.69	0.44	-0.80	0.37
	SR2	5.19	1.26	0.75				-0.78	0.48
	SR3	4.79	1.37	0.48				-0.41	-0.29
SN	SN1	5.21	1.26	0.72	0.79	0.76	0.51	-0.80	0.63
	SN2	5.32	1.21	0.70				-0.96	1.15
	SN3	5.42	1.18	0.73				-0.87	0.88
SE	SE1	5.35	1.26	0.76	0.77	0.77	0.52	-1.03	1.24
	SE2	5.40	1.27	0.69				-0.90	0.66
	SE3	5.30	1.23	0.72				-0.86	0.76
LA	LA1	5.66	1.06	0.75	0.79	0.79	0.56	-1.05	1.71
	LA2	5.65	1.07	0.80				-1.11	1.74
	LA3	5.49	1.15	0.70				-1.07	1.62
BC	BC1	5.18	1.38	0.57	0.82	0.66	0.39	-0.89	0.54
	BC2	5.26	1.31	0.64				-0.84	0.64
	BC3	5.54	1.25	0.66				-1.08	1.17
INT	INT1	5.44	1.21	0.78	0.78	0.76	0.52	-1.03	1.23
	INT2	5.54	1.11	0.74				-1.01	1.23
	INT3	5.26	1.37	0.64				-0.92	0.64

According to the two stage SEM procedures suggested by Anderson and Gerbing (1988), in the first stage, the information about convergent and divergent validity was accessed via CFA on the measurement model. Cronbach's Alpha (CA) and composite reliability (CR) test was performed to assess reliability. CA was applied to measure the internal consistency among items, while CR was utilized to describe the extent to which a train of items can represent potential constructs. In the current study, the factor loadings (FL) were higher than 0.30, Cronbach α values were ranged from 0.61 to 0.82, CR values were ranged from 0.63 to 0.80 and finally, the values of Average Validity Extracted (AVE) of variables were ranged from 0.38 to 0.57 as seen in Table 2. Fornell and Larcker (1981) suggested that if AVE is less than 0.50, but CR is higher than 0.60, the convergent validity of the construct is still satisfactory. In the literature, the minimum acceptable value for CA was suggested as 0.60 (Hair et al., 2018).

Lastly, since the values of the square root of AVE were all greater than the correlation between a pair of research constructs, sufficiency of discriminant validity seen in Table 3 was provided (Fornell & Lacker, 1981). Goodness of fit indices was examined with the following assessment criteria: χ^2 /df value should be between 2 and 5 (Hair et al., 2018), CFI and GFI values should be higher than 0.90 (Kline, 2005), IFI should be above 0.90 (Schumacher & Lomax, 2004), RMSEA and RMR should be less than 0.08 (Hu & Bentler, 1999). Therefore, it was determined that value of CFA fit indices represented a good model fit (Goodness-of-Fit Statistics: χ^2 = 772.97, df = 359, $p < 0.001$, χ^2 /df = 2.150, RMSEA = 0.047, CFI = 0.99, GFI = 0.91, IFI = 0.99, SRMR = 0.039).

Table 3. Correlation between the constructs, construct mean and standard deviation

	PEOU	PU	ATT	IR	SR	SN	SE	LA	BC	INT
PEOU	**0.757**									
PU	0.594	**0.659**								
ATT	0.458	0.563	**0.727**							
IR	0.412	0.438	0.402	**0.613**						
SR	0.452	0.397	0.417	0.492	**0.663**					
SN	0.455	0.481	0.421	0.465	0.583	**0.743**				
SE	0.477	0.525	0.546	0.441	0.492	0.544	**0.721**			
LA	0.551	0.567	0.487	0.430	0.464	0.509	0.640	**0.748**		
BC	0.444	0.360	0.347	0.337	0.517	0.422	0.563	0.530	**0.772**	
INT	0.478	0.508	0.516	0.396	0.492	0.578	0.653	0.632	0.653	**0.736**
M	5.60	5.65	5.15	5.11	5.06	5.32	5.35	5.60	5.33	5.41
SD	0.89	0.86	1.08	0.98	1.01	1.02	1.03	0.92	1.13	1.04

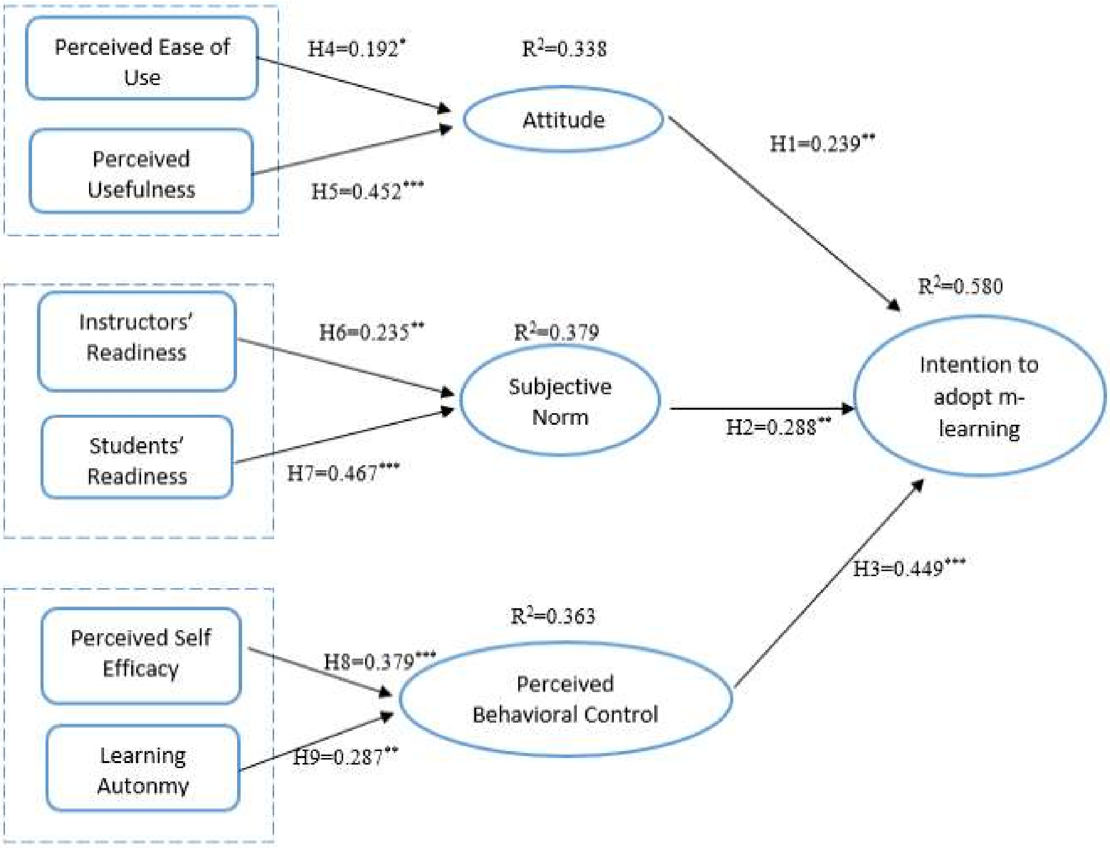
Note. Diagonal values show the square of AVE.

4.2. Structural model: Goodness of fit statistics, hypotheses testing, and modeling comparisons

SEM analysis revealed that goodness of fit statistics of theoretical framework represented a good fit (χ^2 = 877.04, df = 380, $p < 0.001$, χ^2 /df = 2.308, RMSEA = 0.050, CFI = 0.98, GFI = 0.90, IFI = 0.98, SRMR = 0.045). Assessment of the direct effects between the research constructs was performed, and the results were as follows: Attitude ($\beta = 0.239$, $t = 6.145$, $p < 0.01$), SN ($\beta = 0.288$, $t = 6.896$, $p < 0.01$) and PBC ($\beta = 0.449$, $t = 8.478$, $p < 0.001$) were significant in determining the INT to adopt mobile learning. PEOU ($\beta = 0.192$, $t = 4.368$, $p < 0.05$) and PU ($\beta = 0.452$, $t = 8.634$, $p < 0.001$) had a significant positive influence on attitude. IR ($\beta = 0.235$, $t = 5.995$, $p < 0.01$) and SR ($\beta = 0.467$, $t = 9.889$, $p < 0.001$) showed significant effects on SN. Lastly, SE ($\beta = 0.379$, $t = 7.421$, $p < 0.001$) and LA ($\beta = 0.287$, $t = 6.867$, $p < 0.01$) had a significant positive effect on PBC. In addition, the proposed model had superior ability for predicting ATT ($R^2 = 0.338$), SN ($R^2 = 0.379$), PBC ($R^2 = 0.363$) and INT ($R^2 = 0.580$). Thus, all hypothesis were supported and shown in Table 4 and Figure 2.

Table 4. Structural Equation Modeling results of the proposed model

Hypotheses	Standardized estimate	*t*-value	Hypothesis
H1: ATT → INT	0.239	6.145	Supported
H2: SN → INT	0.288	6.896	Supported
H3: PBC → INT	0.449	8.478	Supported
H4: PEOU → ATT	0.192	4.368	Supported
H5: PU → ATT	0.452	8.634	Supported
H6: IR → SN	0.235	5.995	Supported
H7: SR → SN	0.467	9.889	Supported
H8: SE → PBC	0.379	7.421	Supported
H9: LA → PBC	0.287	6.867	Supported



Note. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Figure 2. Result of Structural Equation Modelling

4.3. Moderating effects of personal characteristics

Invariance test for measurement and structural models program was conducted to explore the effect of PST' department and grade level as moderators in their mobile learning readiness. In the process, non-restricted model and full-metric invariance were produced. As seen in Table 5, the values of goodness of fit indices for models were favorable and according to the Chi-square difference test, two models were no significantly different. Thus, full metric invariance supported. Chi-square difference was compared between the baseline and the nested models according to the difference in the degrees of freedom (Byrne, 2016). The baseline model's goodness of fit indices was acceptable for department and grade level.

Table 5. Results for the moderating role of department

Measurement invariance model for grade levels

Models	χ^2	df	$\Delta\chi^2$	Full metric invariance
Non-restricted model	331.430	62	$\Delta\chi^2(19)$= 34.30 p > 0.01 (insignificant)	Supported
Full-metric invariance model	297.127	43		

Other goodness of fit indices of non-restricted model: RMSEA=0.057; CFI=0.92; IFI=0.92
Other goodness of fit indices of full-metric invariance model: RMSEA=0.058; CFI=0.91; IFI=0.91

Paths	Science		Primary		Preschool		Baseline model	Nested model
	β	t-values	β	t-values	β	t-values		
H1: ATT → INT	0.255	7.057***	0.193	3.035**	0.173	2.833**	χ^2 (63) = 357.127	χ^2 (65) = 359.186[a]
H2: SN → INT	0.294	7.745***	0.192	3.025**	0.346	5.442***		χ^2 (65) = 359.320[b]
H3: PBC → INT	0.361	10.131***	0.676	10.537***	0.511	9.084***		χ^2 (65) = 365.122[c]
H4: PEOU →ATT	0.281	4.296***	0.110	1.173	0.136	1.147		χ^2 (65) = 358.536[d]
H5: PU → ATT	0.584	8.478***	0.625	6.691***	0.371	2.890**		χ^2 (65) = 363.297[e]
H6: IR → SN	0.218	4.013***	0.246	2.772**	0.324	4.066***		χ^2 (65) = 358.355[f]
H7: SR → SN	0.433	8.333***	0.546	6.150***	0.557	7.053***		χ^2 (65) = 358.946[g]
H8: SE → PBC	0.387	6.409***	0.466	4.682***	0.408	3.117**		χ^2 (65) = 358.321[h]
H9: LA → PBC	0.325	4.701***	0.304	3.054**	0.416	3.152**		χ^2 (65) = 357.607[i]

Goodness of fit indices of the baseline model for three groups: RMSEA = 0.052, CFI = 0.91, GFI = 0.91, IFI = 0.90.	[a] $\Delta\chi^2(2) = 2.059$ [b] $\Delta\chi^2(2) = 2.193$ [c] $\Delta\chi^2(2) = 7.995^*$ [d] $\Delta\chi^2(2) = 1.409$ [e] $\Delta\chi^2(2) = 6.170^*$ [f] $\Delta\chi^2(2) = 1.228$ [g] $\Delta\chi^2(2) = 1.819$ [h] $\Delta\chi^2(2) = 1.194$ [i] $\Delta\chi^2(2) = 0.480$

Note. $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

The findings of multiple group analysis revealed that there were significant differences in the PBC-INT link and PU-ATT link. On the other hand, ATT-INT path, SN-INT path, PEOU-ATT path, IR-SN path, SR-SN path, SE-PBC path, LA-PBC path were not statistically significant differences between departments.

Table 6. Results for the moderating role of grade level

Measurement invariance model for grade levels				
Models	χ^2	df	$\Delta\chi^2$	Full metric invariance
Non-restricted model	215.375	82	$\Delta\chi^2(17)= 26.73$ $p > 0.01$ (insignificant)	Supported
Full-metric invariance model	188.642	65		
Other goodness of fit indices of non-restricted model: RMSEA=0.051; CFI=0.91; IFI=0.91				
Other goodness of fit indices of full-metric invariance model: RMSEA=0.052; CFI=0.90; IFI=0.90				

Paths	1st grade		2nd grade		3rd grade		4th grade		Baseline model	Nested model
	β	*t*-values	*β*	*t*-values	*β*	*t*-values	*β*	*t*-values		
H1: ATT → INT	0.272	2.994^{**}	0.110	1.447	0.184	2.276^*	0.103	1.414	$\chi^2(84)$ =	$\chi^2(87)$ = [a]218.549
H2: SN → INT	0.052	0.484	0.240	2.567^*	0.345	4.625^{***}	0.545	7.661^{***}	216.642	$\chi^2(87)$ = [b]225.783
H3: PBC → INT	0.555	7.274^{***}	0.601	6.747^{***}	0.421	6.839^{***}	0.583	8.738^{***}		$\chi^2(87)$ = [c]220.159
H4: PEOU → ATT	0.192	0.859	0.165	0.764	0.140	1.208	0.302	1.321		$\chi^2(87)$ = [d]217.048
H5: PU → ATT	0.633	4.089^{***}	0.449	1.843	0.445	3.759^{***}	0.458	2.009^*		$\chi^2(87)$ = [e]219.293
H6: IR → SN	0.379	3.311^{***}	0.091	0.681	0.350	3.677^{***}	0.276	2.165^*		$\chi^2(87)$ = [f]219.802
H7: SR → SN	0.621	5.564^{***}	0.580	5.084^{***}	0.533	5.188^{***}	0.538	4.445^{***}		$\chi^2(87)$ = [g]217.059
H8: SE → PBC	0.600	3.173^{**}	0.274	2.141^*	0.425	2.655^{**}	0.875	4.965^{***}		$\chi^2(87)$ = [h]224.262
H9: LA → PBC	0.279	1.283	0.542	3.632^{***}	0.467	2.430^*	0.152	0.357		$\chi^2(87)$ = [i]224.003
Goodness of fit indices of the baseline model for three groups: RMSEA = 0.048, CFI = 0.90, GFI = 0.91, IFI = 0.92.										[a] $\Delta\chi^2(3) = 1.907$ [b] $\Delta\chi^2(3) = 9.141^*$ [c] $\Delta\chi^2(3) = 3.517$ [d] $\Delta\chi^2(3) = 0.406$ [e] $\Delta\chi^2(3) = 2.651$ [f] $\Delta\chi^2(3) = 3.160$ [g] $\Delta\chi^2(3) = 0.418$ [h] $\Delta\chi^2(3) = 7.620$ [i] $\Delta\chi^2(3) = 7.361$

Note. $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Similarly, non-restricted model and full-metric invariance were produced for grade levels. As seen in Table 6, the values of goodness of fit indices for models were favorable and according to the Chi-square difference test, two models were no significantly different. Thus full metric invariance supported. Based on the findings from the moderator analysis, there were significant grade level differences on the SN-INT linkage. However, ATT-INT path, PBC-INT path, PEOU-ATT path, PU-ATT path, IR-SN path, SR-SN path, SE-PBC path, LA-PBC path were found not to be significantly different between grade levels.

5. Discussion and implications

Given today's world in which teaching-learning in the classroom environment is transforming into mobile learning tools very rapidly and the importance of mobile learning in the education of PST was stressed in past studies (e.g., Kearney & Maher, 2019). There is a need to investigate which factors predict PST' intentions towards mobile learning. Therefore, the current study aimed to examine this gap and investigate to reveal a deeper understanding of PST' intention to adopt mobile learning incorporating three critical salient beliefs — Attitudinal Beliefs, Normative Beliefs, and Control Beliefs –into the TPB model.

There was strong support for the proposed model and thus, results indicated that the model had a satisfactory fit to the data. The explanatory power of the study showed that the TPB model explained 58% of the variance in intention to adopt mobile learning. SEM results revealed that PBC was the most predictive antecedent for the intention to adopt mobile learning. Revealing this finding has an important role in the research area of MLR since PBC has been considered an effective determinant of people's intentions in higher education (Cheon et al., 2012). Considering the sample of the study, the finding implies that PST believe that they have controls and self-confidence over use of mobile learning and making decisions to adopt mobile learning. This is consistent with the idea of Ajzen (1985) who stated that PBC is increased in case people believe that they have the self-confidence that they can handle obstacles. These results supported most of the previous studies (e.g., Cheon et al., 2012; Raza et al., 2018). However, some researchers stated that the most effective variable on mobile adoption intention was subjective norm (e.g., Yeap et al., 2016), while others reported that the attitude was the most predictor variable on intention (e.g., Azizi & Khatony, 2019; Gómez-Ramirez et al., 2019). The most important reasons for this difference between the studies may be due to the fact the departments of the individuals studying at the university are different and they have various cultural characteristics.

Results of the study also suggested that attitude and subjective norm increase the individuals' intention toward the adoption of technology. Accordingly, it can be implied that PST think that they show higher concern for mobile learning in their coursework and the significant others' willingness to adopt mobile devices for learning is an important determinant for MLR. These findings were supported most of the past studies, while some studies found that subjective norm (e.g., Azizi & Khatony, 2019; Buabeng-Andoh, 2020) and PBC (e.g., Buabeng-Andoh, 2020) have no significant effect on intention to adopt mobile learning. Accordingly, considering the results of the current study, the first three hypotheses were supported.

Results of salient beliefs showed that PEOU and PU had a positive influence on attitude toward the use of mobile learning, explaining the variance by 34%. This finding implies that PST who believe that mobile learning is easy to use and had high feelings about its PU will have stronger attitude toward mobile learning. This result shows that H4 and H5 are supported. The findings are in line with earlier study results (e.g., Buabeng-Andoh, 2020) which revealed that university students who believe that mobile learning is easy and useful are more likely to take advantage of mobile learning tools for their classes.

The current study also revealed that IR and SR are positively associated with subjective norm, accounting for the variance by 38%. In other words, subjective norm is predicted by PST' accessible normative beliefs that explain other PST' expectations as a significant antecedent of intention to adopt mobile learning, therefore, H6 and H7 were supported. This finding is consistent with the earlier studies (e.g., Gómez-Ramirez et al., 2019). However, there were a few researches that revealed no significant effects of normative beliefs on subjective norm. For example, in a study conducted by Azizi and Khatony (2019), while IR had a significant influence, there was no significant influence of student readiness on the subjective norm. The different results obtained between the studies may be due to the different samples and the countries in which the study was conducted.

Further, the study revealed that SE and LA had positive influences on PBC. The control beliefs explained 36% of the variance in PBC. This finding which was consistent with earlier studies (e.g., Raza et al., 2018; Yeap et al., 2016) implies that PST have positive beliefs and self-confidence about their capabilities to use a mobile device for their course. It can be also implied that PST take high responsibility and gain control over the learning process in educational environments driven by mobile technology (Cheon et al., 2012). Accordingly, H8 and H9 were supported. Finally, results of the multi-group analysis indicated that the moderation effect of department and grade level on mobile learning readiness was significant. However, within our knowledge, none of the earlier studies examined the moderator influence of department and grade level on mobile learning readiness.

The study offers some theoretical and practical implications. The proposed model well explained PST' MLR. The present study confirmed that attitude, subjective norm, and PBC significantly establish a linkage with intention towards the adoption of mobile learning. The results suggest that PST' PEOU and PU significantly influence their attitude toward mobile learning. The result supports the idea of Davis (1993) who developed TAM, stating that both PEOU and PU play an essential role in explaining the attitude towards mobile learning. The results also suggest that PST' beliefs related to the readiness of instructors and readiness of students considerably influence subjective norm. The result expands the previous literature which pointed out that the readiness of individuals on mobile learning is important (Azizi & Khatony, 2019). Another theoretical implication relates to stating the important role of SE and LA on the PBC which in turn affected intention towards the adoption of mobile learning. This finding confirms the idea that people who think that they can be gifted in a particular skill or behavior and can control their behaviors are in the tendency to have stronger intentions to act the skill or act the behavior (Cheon et al., 2012).

The results present important practical implications to the researchers, educators, education stakeholders, policymakers, and mobile learning application designers. The study can help researchers to further examine the other constructs which can influence PST' intention towards the adoption of mobile learning. The study has also increased the education stakeholders and policy makers' understanding and knowledge about the determinants of MLR in the Turkish context. It has shown that Turkish PST cope relatively well with the inhibiting factor when using mobile devices in the classroom environment since PBC was found as the most significant antecedent of intention towards the adoption of mobile learning among constructs of the TPB. This emphasizes the importance of creating useful conditions with regards to availability that can facilitate and ease the individuals' use of mobile devices in lessons. For example, educators and education stakeholders can use different methods including providing adequate education and technical and managerial support to enhance PST' intentions toward mobile adoption of mobile learning (Hsia, 2016). In addition, the policymakers and mobile learning application designers should focus on the PST' attitudes towards mobile learning and subjective norm since they have important roles in influencing intention towards the adoption of mobile learning. Individuals' attitudes and subjective norm can be increased by making mobile devices easier to use in the classroom, which may shape a positive image of mobile learning among educators. This is an important implication for PST who will become teachers in the future. In order for mobile integration to be successful in PST, teacher educators must integrate the efficient use of mobile technology into their courses and establish connections with classroom practice (Husbye & Elsener, 2013).

6. Limitations and future studies

The present study has several limitations which should be considered for future studies. First of all, the demographic characteristics of the study are a group of PST within a university. As different results can be revealed using different sample groups, teacher-based study groups can't reflect the perspectives of different students in higher education. Therefore, it may be useful for future studies to be able to examine and compare different sample groups. There is a very serious disproportion in the distribution of some variables including using mobile devices in education and daily life and gender. This situation constitutes one of the most important limitations of this study. Therefore, it is not possible to perform statistical analysis and compare research results in terms of these variables. In addition, the data for this study were collected in Turkey and thus the fact that the findings obtained from this study cannot be generalized to other countries constitutes one of the limitations of this study. Cross-country comparison studies may be conducted for future studies to fully reflect the MLR. Further, the study only focused on PST. Therefore, it may not be concluded as a general representation of MLR in Turkey. The study can be repeated in students in other education levels such as elementary, secondary and high school or in-service teachers to reveal whether the findings are similar. Moreover, the present study is limited to determining intention rather than behavior. Thus, future researchers may use the actual behaviors regarding mobile learning implementation that can help to establish a connection between intentions towards the adoption of mobile learning and using mobile devices in education.

7. Conclusion

The TPB presents a very useful theoretical framework in understanding wide-ranging behavioral intentions across different research areas including the adoption of mobile learning. However, the present study is the first attempt in the Turkish context that has used TPB for predicting factors affecting PST' MLR. Results of the study confirmed the effectiveness of a well-structured cognitive psychological model in understanding PST' intention towards the adoption of mobile learning in the Turkish context. Moreover, the findings approved the feasibility of the TPB model and the inclusion of the salient beliefs enhanced the robustness and predictive power of the proposed model in measuring the MLR. Overall, it can be concluded that the salient beliefs are obtained to be having a significant positive impact on Turkish PST' attitudes, subjective norms, and PBC as well as on their intentions towards the adoption of mobile learning.

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