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Students' Adoption of m-Learning in Higher Education: An Empirical Study

Yüksek Öğretimde Öğrencilerin m-Öğrenmeyi Benimsemesi: Ampirik Bir Çalışma

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ABSTRACT

Universities have an important role in integrating technology into education; therefore, it is crucial to increase technology use in higher education. Technological improvement, especially in mobile technology, has a great impact on education, leading to the shift in educational activities from the web environment to mobile platforms. Since mobile technology is important for education, it is necessary to evaluate how students benefit from the adoption of the mobile learning concept and its systems. Considering the importance of mobile technology in education, this study aimed to reveal the factors affecting students' intentions toward m-learning. An adoption model was examined by taking the technology acceptance model as a base. A questionnaire was employed on 417 undergraduate or postgraduate students to collect data. Model validation was performed by structural equation modeling. The model revealed the factors that affect students' acceptance of m-learning as perceived usefulness, technical efficacy, social norm, system features, perceived trust, and innovativeness. Examination of these factors will be useful for the design of m-learning applications, understanding the main reasons behind the users' attitude toward m-learning and promoting the use of m-learning in education.

Keywords: Mobile learning, mobile learning acceptance, technology acceptance

ÖZ

Teknolojinin eğitime entegre edilmesinde üniversiteler önemli bir role sahiptir; bu nedenle yükseköğretimde teknoloji kullanımının artırılması büyük önem taşımaktadır. Teknolojik gelişmeler, özellikle mobil teknolojide, eğitim üzerinde büyük bir etkiye sahip olup, eğitim faaliyetlerinin web ortamından mobil platformlara kaymasına neden olmaktadır. Mobil teknoloji eğitim için önemli olduğundan, öğrencilerin mobil öğrenme kavramı ve sistemlerinin benimsenmesinden nasıl yararlandığını değerlendirmek gerekir. Mobil teknolojinin eğitimdeki önemi göz önünde bulundurularak, bu çalışma ile öğrencilerin m-öğrenmeye yönelik niyetlerini etkileyen faktörlerin ortaya çıkarılması amaçlamıştır. Teknoloji kabul modeli temel alınarak bir benimseme modeli incelenmiştir. Veri toplamak için 417 lisans ve lisansüstü öğrenciye anket uygulanmıştır. Model doğrulaması, yapısal eşitlik modellemesi ile gerçekleştirilmiştir. Model, algılanan fayda, teknik yeterlik, sosyal norm, sistem özellikleri, algılanan güven ve yenilikçilik faktörlerinin öğrencilerin m-öğrenmeyi kabul etmelerini etkileyen faktörler olduğunu ortaya çıkarmıştır. Bu faktörlerin incelenmesi, m-öğrenme uygulamalarının tasarlanması, kullanıcıların m-öğrenmeye yönelik tutumlarının ardındaki temel nedenlerin anlaşılması ve m-öğrenmenin eğitimde kullanımının teşvik edilmesi için faydalı olacaktır.

Anahtar Kelimeler: Mobil öğrenme, Mobil öğrenmenin kabulü, Teknoloji kabulü

Introduction

Technology, especially mobile technology, has changed substantially over the last three decades. The irrepressible growth in mobile technology has influenced the countries and their policies to encourage the efficient diffusion of this technology in the field of education. With recent developments, the delivery of educational activities has switched from online web applications to mobile applications (Bustos Andreu, Delgado Almonte, & Pedraja Rejas, 2011). Earlier educational technologies (referred to as e-learning), such as learning management systems (LMS), Blackboard, and WebCT have started to be applied using mobile technologies. The combination of mobile technology and e-learning has created m-learning (Abernathy, 2001). m-Learning refers to the realization of educational activities and learning through mobile technologies which include wireless networks, Internet, mobile devices, and e-learning applications (Motiwalla, 2007). Activities such as establishing an Internet connection, making phone calls, and using audio and video recordings via mobile devices could be used to support educational activities in m-learning. m-Learning has various advantages and benefits such as mobility (M), collaborative learning, and self-learning for end-users (Alrasheedi & Capretz, 2015; Iqbal & Qureshi, 2012). Mobility refers to being free from time and location constraints. Users can reach the educational resources via their mobile devices without being in a classroom or having a computer. Furthermore, it provides collaborative learning and creates communication between students and educators from different locations (Alrasheedi & Capretz, 2015). Another advantage of m-learning is self-learning, which provides students or learners to manage their learning time, place, and pace (Alrasheedi & Capretz, 2015; Vate-U-Lan, 2008). Although m-learning allows for free learning environments, technological infrastructure issues, e.g., bandwidth and wireless network capacity, can limit this (Kılınç, 2015). In order to take advantage of m-learning, applications should be supported by educational institutions and appropriate technological infrastructure should be established (Al-Emran, Elsherif, & Shaalan, 2016). In addition to all these, the success of m-learning depends on the acceptance and adoption of end-users (Al-Emran *et al.*, 2016). Therefore, the investigation of the implementation of m-learning and understanding of the attitudes of users toward m-learning will increase the motivation (Mot) necessary to remove the barriers to m-learning and contribute to prioritizing m-learning in the field of education.

The attitude of students and educators toward m-learning is crucial for the successful integration of related technologies. The importance of determining the effective factors in students' adoption of m-learning becomes apparent when considering the widespread use of the student-centered education approach and the shift of focus in education to the student and the learning process, In literature, there are various researches concerning m-learning and the attitudes of higher education students and have concentrated on different dimensions of m-learning acceptance, such as M (Iqbal & Bhatti, 2017; Mohammadi, 2015), mobile self-efficacy (Nikou & Economides, 2017a, 2017b), system functions (Liaw, Hatala, & Huang, 2010), system characteristics (Wang, 2013), perceived trust (PT) (Nikou & Economides, 2017b), cost and price value (Bere & Rambe, 2016), and innovativeness (Inn) (Karimi, 2016). Furthermore, the majority of the research in the literature concentrated on a specific m-learning application or system, e.g., a vocabulary app (Shroff & Keyes, 2017), instant messaging (Bere & Rambe, 2016), and a book reader (Hsia, 2016).

The current study focuses on the m-learning concept as a general medium of delivering educational activities and contributes to the literature by combining different dimensions of m-learning adoption in a single model without focusing on a specified m-learning system. In this context, this research proposes one research question, "what are the influencing factors of higher education students' acceptance of m-learning?" In this study, the technology acceptance model (TAM), which is the prominent theory to explain the acceptance of information technologies since it was proposed in the 1980s (Davis, 1989), is used as the theoretical framework. Based on this theoretical framework, this research aims to determine the factors that affect students' behavioral intentions (BIs) toward m-learning and elucidate the effects of these factors on each other with the presented structural model. The factors in the proposed model were identified using a deep systematic review conducted by the researchers of the current study (Alkis, Findik-Coskuncay, 2018). The validated constructs offered by the final model were perceived usefulness, technical efficacy (TE), social norm, system features, PT, Inn, and BI.

It is hoped that this research will be valuable in helping policy developers to understand students' attitude toward m-learning and the related factors and thus to understand the value of promoting the use of m-learning in the higher education context. This is also an important study for the literature to validate a generalized m-learning acceptance model including factors with significant effects on the attitude of students.

Theoretical Background

Technology Acceptance Model

Despite the significant increase in the use of information technologies, there remains some resistance in adopting them. Technology acceptance model has become the prominent theory to explain the intention of end-users toward a specific technology (Alkis, Coskunçay, & Yildirim, 2014; Ding & Er, 2018; Lee, Kozar, & Larsen, 2003; Rahimi, Nadri, Afshar, & Timpka, 2018), thus, it was taken as a theoretical framework to propose the m-learning acceptance model in this research. Technology acceptance model was introduced by adapting the Theory of Reasoned Action to the information technology domain and it explains why an end-user adopts or rejects a specific technology (Davis, 1985; Davis, Bagozzi, & Warshaw, 1989). According to this theory, BI determines technology use, perceived usefulness, perceived ease of use, and attitude are the determinants of BI (Davis *et al.*, 1989). Behavioral intention refers to "the measure of the strength of the intention toward performing a behavior." It is the major determinant of the actual behavior (Davis *et al.*, 1989; Fishbein & Ajzen, 1975). Therefore, BI has been considered as the determinant of m-learning use in the scope of this research.

Research Model

Initially, a systematic review was performed on the studies concentrating on m-learning and the adoption of students to identify the determinative factors (Alkis, Findik-Coskuncay, 2018). Fifty-one research articles obtained using a systematic procedure were examined based on the samples, theories behind the research, factors affecting m-learning, and the relationships between them.

From the systematic review, a total number of 13 factors, which have many statistically significant results on acceptance of m-learning literature, were selected for the research model proposed in the current study (referred to as the m-learning acceptance model). It is aimed to create a new and comprehensive m-learning acceptance model. Behavioral intention refers to the degree of the intention to perform the target behavior (Davis, 1989). In the scope of this study, it refers to the level of intention to use m-learning.

Perceived Usefulness

Perceived usefulness is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989). Perceived usefulness is the main determinant of BI according to TAM. In line with TAM, the following hypothesis was created.

H1: PU has a positive and direct effect on BI.

Technical Efficacy

In the scope of this study, TE is defined as “Users’ ease of use and ability perceptions toward m-learning use” by taking TAM’s perceived ease of use factor as a base (Davis, 1989). Perceived ease of use affects both perceived usefulness and BI in TAM so the following two hypotheses were proposed.

H2: TE has a positive and direct effect on PU.

H3: TE has a positive and direct effect on BI.

Social Norm

Social norm (SN) is defined as “social pressure to perform or not to perform the behavior” (Ajzen, 1991) and one of the major factors of Theory of Planned Behavior (TPB). In this context, SN refers to the effects of students’ social environment, including friends, colleagues, teachers, and institutions, on their m-learning use. According to TPB, SN affects BI directly and positively (Ajzen, 1991). Also, it was found that SN affects perceived usefulness positively in m-learning acceptance literature (Hao *et al.*, 2017; Park *et al.*, 2012). To be consistent with TPB and the previous studies, two hypotheses were created.

H4: SN has a positive and direct effect on PU.

H5: SN has a positive and direct effect on BI.

System Features

System features (SF) factor is used to refer to the characteristics, navigation, and functions of m-learning systems. In the previous studies, system features including navigation affected perceived ease of use and perceived usefulness positively (Cheng, 2015). Also, the study conducted by Liaw et al (2010) found a positive and significant relation between system functions with m-learning acceptance. In line with these findings, two hypotheses were proposed.

H6: SF affects PU significantly and positively.

H7: SF affects TE significantly and positively.

Perceived Trust

Perceived trust is defined as “students’ perceptions about the reliability and trustworthiness of the system” (Arpaci, 2016; Nikou & Economides, 2017b). Nikou and Economides (2017b) found a significant relationship between PT and PU in the m-learning acceptance context. Arpaci (2016) examined the effect of PT on attitude toward the acceptance of mobile cloud services. The researcher found a significant relationship between these factors. Based on these, the below hypothesis was generated.

H8: PT has a positive and direct effect on PU.

Mobility

Mobility as a general term refers to access to information over mobile devices and wireless networks anywhere and anytime. In the scope of this study, M refers to the extent of students’ access to learning materials anytime and anywhere without boundaries (Iqbal & Bhatti, 2017; Merhi, 2015). When the literature was examined, it was found that M affects usefulness (Iqbal & Bhatti, 2017; Merhi, 2015) and intention (Mohammadi, 2015). To be parallel with the literature, the following two hypotheses were generated.

H9: M has a positive and direct effect on PU.

H10: M has a positive and direct effect on BI.

Motivation

Motivation has different dimensions in definitions. In m-learning acceptance studies, Mot has been referred to as users’ perception of curiosity, enjoyment, and perceived interest in m-learning use (Chang, Tseng, Liang, & Yan, 2013; Cheng, 2015; Shroff & Keyes, 2017). It is emphasized that motivational dimensions such as curiosity, enjoyment, and perceived interest are effective in continuous intention toward mobile learning (Chang, Tseng, Liang, & Yan, 2013; Poong, Yamaguchi, & Takada, 2017; Shroff & Keyes, 2017). Accordingly, the following hypothesis was proposed.

H11: Mot has a positive and direct effect on BI.

Perceived Behavioral Control

Perceived behavioral control (PBC) is one of the major factors that determine intention toward a specific behavior according to TPB. Perceived behavioral control is defined as “people’s perception of ease or difficulty in performing the behavior of interest” (Ajzen, 1991). To be parallel with TPB, the following hypothesis was proposed.

H12: PBC has a positive and direct effect on BI.

Content

Content (Cnt) refers to course content and assessment questions of the specified course provided with m-learning applications (Nikou & Economides, 2017a, 2017b). Nikou and Economides (2017b) have found a significant relationship between Cnt and perceived usefulness. One hypothesis was proposed to examine the effect of Cnt over perceived usefulness parallel with the literature.

H13: Cnt has a positive and direct effect on PU.

Cost

The study conducted by Bere and Rambe (2016) investigated the effect of the cost of devices, communication, and the Internet on m-learning acceptance. By taking their study as the base, the following hypothesis was generated to test the effect of the cost of the m-learning device over BI toward m-learning acceptance.

H14: C has a positive and direct effect on BI.

Anxiety

Anxiety (Anx) is defined as "a state of mind of being fearful or apprehensive when using or considering the use of a system" (Mac Callum *et al.*, 2014; Moran, Hawkes, & El Gayar, 2010). Anxiety is used to measure the negative effects of emotions while using m-learning tools. Mac Callum *et al.* (2014) found a negative relationship between Anx and the perceived usefulness of m-learning. Similarly, Moran et al (2010) identified a negative relation between Anx and BI toward tablet use in higher education. In this context, the following hypotheses were written.

H15: Anx has a direct and negative effect on PU.

H16: Anx has a direct and negative effect on TE.

H17: Anx has a direct and negative effect on BI.

Innovativeness

Innovativeness refers to the "level of intention to accept new technology quicker than other constituents of the social structure" (Joo *et al.*, 2014; Rogers, 1995). Innovative individuals are volunteer to use new technologies more than others (Agarwal & Prasad, 1998). In the previous studies, it is stated that Inn affects perceived ease of use (Joo *et al.*, 2014; Liu *et al.*, 2010; Tan *et al.*, 2014), BI (Abu-Al-Aish & Love, 2013; Milošević, Živković, Manasijević, & Nikolić, 2015; Mohammadi, 2015; Poong *et al.*, 2017), and perceived usefulness (Liu *et al.*, 2010) significantly in the scope of m-learning acceptance. In line with these findings, three hypotheses were proposed as below:

H18: Inn has a positive and direct effect on PU.

H19: Inn has a positive and direct effect on TE.

H20: Inn has a positive and direct effect on BI.

The final proposed research model with the hypothesis is given in Figure 1.

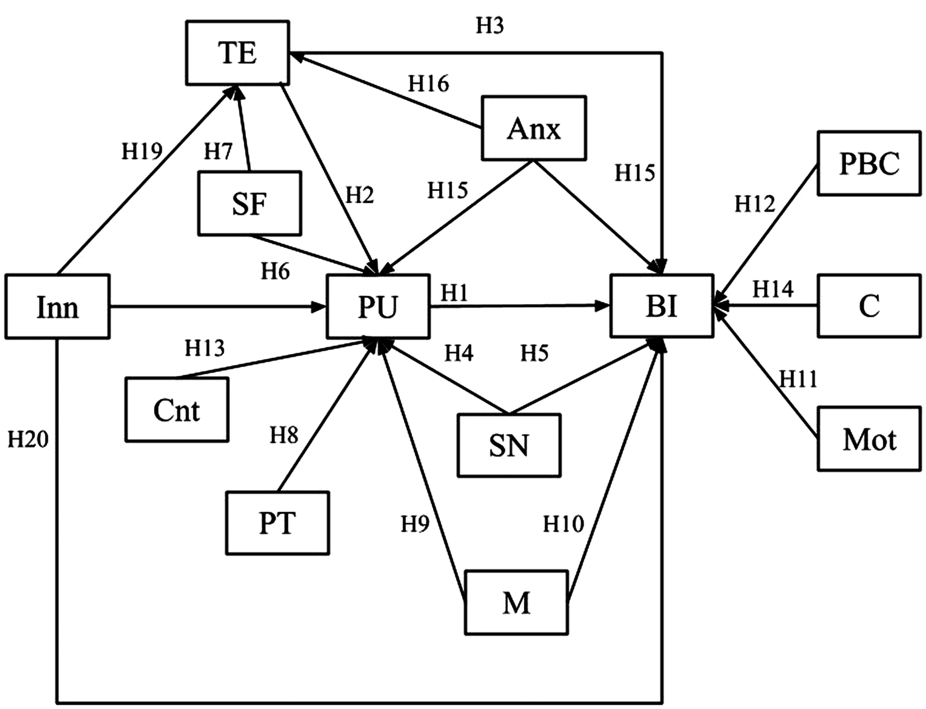

Figure 1.
Proposed Research Model (m-Learning Acceptance Model).

Methodology

Instrument Development

A two-part questionnaire was conducted to collect data. The first part contained 11 items designed to collect demographic data related to gender, age, education level, education area, computer proficiency, experience and competency in mobile device use, and familiarity with m-learning. There were 63 items in the second part to evaluate the 13 factors in the proposed model. These items were presented with a five-point Likert scale (1 'strongly disagree' to 5 'strongly agree'). The measurement items were adapted from the validated scales in the existing studies. A group of three academicians with a Ph.D. degree in the information systems field evaluated the content validity of the developed scale.

The reliability of the instrument was tested with a pilot study which was conducted in a public university in Turkey. The data were collected from the students in an associate degree program. The survey instrument was distributed online over a period of 1 month using a website (www.docs.google.com), and the link to the survey was sent via e-mail. Of 125 responses, 115 were usable for further analyses due to the uncompleted survey items.

The sample of the pilot study was selected by applying the convenience sampling method. Of the 115 respondents, 50% were female and 50% were male. The age of the participants ranged from 17 to 40 and had a mean age of 21. Inter-item consistency was performed to evaluate the reliability of the survey instrument, which means that Cronbach's alpha value needs to be greater than 0.7. The Cronbach's alpha value of the total scale was found as .985. After the reliability analysis, four problematic survey items were reworded, and the number of items was reduced to ensure that the completion time of the survey instrument would not exceed 15 minutes for the main survey.

Ethics Committee Approval

Necessary permissions were obtained from the ethics committee of Başkent University to collect data from the participants (Document no. 62310886-604.01.01/31934 dated 13.09.2018).

Study Setting

The main study was carried out in two universities (one public and one private) in Turkey, and the student participants were from different educational levels of these universities. The survey instrument was prepared in the native language of the participants (Turkish) and distributed online to students' school e-mail addresses and a short mobile message (SMS) to their mobile phones. Data collection was completed over a period of 2 months.

Sample

After receiving the results of the questionnaire sent to 821 students, null, incomplete, and repetitive scores were removed from the data set. Further analysis was performed on 417 complete responses. Based on the '10 times' rule for the minimum sample size requirement (Peng & Lai, 2012), the response rate (50.8%) was sufficient. Of the participants, 58% were from the public university, and 42% were from the private university. The sample consisted of 54% male and 46% female students. The age of the participants ranged from 17 to 61 years, and the mean age was 22.74 years. The education level of the participants ranged from associate degree to Ph.D., and the students were grouped under four different educational disciplines. The percentages of the students according to the area were as follows: 27.1% for social sciences, 22.5% for engineering sciences, 44.4% for interdisciplinary sciences, and 5.8% for educational science. The students evaluated their computer skills as very good, good, acceptable, poor, and very poor at a rate of 24.7%, 40.3%, 31.2%, 3.1%, and 0.7%, respectively. Of the participants, 99.8% used mobile devices, and 52.5%, 41.7%, and 5.8% of the participants evaluated their ability to use mobile devices as very good, good, and acceptable, respectively. Forty-one percent of the students reported that their mobile device use was between 3 and 6 hours, 29% used their mobile device more than 6 hours in a day, and 83.9% had not previously used the m-learning platform. Lastly, when the participants were asked which m-learning platforms they were familiar with, Moodle and Udemy were found to be the most known platforms.

Data Analysis and Results

Initially, preliminary examinations were carried out, including missing value analysis, outlier detection, and normality analysis to prepare the data set for further analyses. This began with a missing value examination; however, no missing value was detected in the data set; therefore, no action was required. Then, the outliers in the data set were examined and their effects on the data set were investigated through the comparison of the mean and trimmed mean values (Walfish, 2006). The differences between the mean and trimmed mean values were not high; thus, it was decided that the outliers did not cause any problem in the data set. Lastly, the normality of the data was evaluated with the skewness and kurtosis values (>-1.96 or $<+1.96$) and the Kolmogorov–Smirnov test (Field, 2009). According to the skewness and the kurtosis values, the data set was normally distributed. However, since the Kolmogorov-Smirnov test was found to be significant ($p < .05$), further analyses were carried out with the assumption of non-normality.

Exploratory Factor Analysis and Reliability Results

Exploratory Factor Analysis was performed to reveal the factor structure in the data set (Stevens, 2012) with the maximum likelihood method and direct oblimin rotation because of the correlation between the scale items (Field, 2009). According to the Kaiser–Meyer–Olkin measure value (0.959), which is greater than 0.5, the sample size is sufficient to perform factor analysis (Field, 2009), and the data set had a meaningful factor structure according to the Bartlett's test of sphericity values, $\chi^2(1953) = 16{,}930.434$ ($p < .001$).

Exploratory factor analysis revealed a ten factors structure explaining 63.29% of the total variance. Factor loadings (FL) of scale items and Cronbach's alpha score of factor structures are given in Table 1. The measurement items of Mot (Mot1 to Mot5), PBC (PBC1 to PBC5), and Cnt (Cnt1 to Cnt5) factors, as well as PU3, Inn3, BI1, and BI2 items had low FLs (<0.4) or they were not clustered properly under a factor. The FL values of PU3 and Inn5 were slightly lower than 0.4, but they were clustered properly under the PU and Inn factors,

Table 1.
Factor Loadings and Reliability Results

Item ID	New Item ID	Factor Loading										Cronbach Alpha
		1	2	3	4	5	6	7	8	9	10	
PU1	PU1	.626										.884
PU2	PU2	.468										
PU3	PU3	.339										
PU4	PU4	.553										
PU5	PU5	.526										
TE1	TE1		.543									.902
TE2	TE2		.752									
TE3	TE3		.650									
TE4	TE4		.529									
TE5	TE5		.605									
SN1	SN1			−.583								.869
SN2	SN2			−.872								
SN3	SN3			−.763								
SN4	SN4			−.728								
SN5	SN5			−.572								
SF1	SF1				.497							.875
SF2	SF2				.641							
SF3	SF3				.749							
SF4	SF4				.648							
PT1	PT1					.642						.860
PT2	PT2					.616						
PT3	PT3					.724						
PT4	PT4					.779						
PT5	PT5					.533						
M1	M1						.405					.836
M2	M2						.608					
M3	M3						.556					
M4	M4						.409					
M5	M5						.477					
C1	C1							.509				.869
C2	C2							.695				
C3	C3							.621				
C4	C4							.778				
Anx1	Anx1								.648			.827
Anx2	Anx2								.676			
Anx3	Anx3								.672			
Anx4	Anx4								.689			
Anx5	Anx5								.754			
Inn1	Inn1									.549		.765
Inn2	Inn2									.640		
Inn4	Inn3									.468		
Inn5	Inn4									.379		
BI3	BI1										.602	.751
BI4	BI2										.516	
BI5	BI3										.432	

Note: Anx=Anxiety; BI=Behavioral intentions; C=Cost; Inn=innovativeness; M=Mobility; PU=Perceived usefulness; PT=Perceived trust; SF=System features; SN=Social norm; TE=Technical efficacy.

respectively. Therefore, the items were kept in the data set. As a result, further analyses were performed by excluding the Mot, PBC, and Cnt factors and the given problematic items based on FL. Ten factors with alpha values greater than 0.7 were found reliable (Hair, Black, Babin, & Anderson, 2014); therefore, with an alpha value of 0.939, the overall questionnaire was considered to be significantly reliable.

Model Assessment

Measurement and structural assessments were performed to evaluate the proposed research model. The research model was assessed with structural equation modeling. SmartPLS was used to assess the structural model due to the non-normal data distribution.

Measurement Model

Confirmatory factor analysis (CFA) was conducted to evaluate the measurement model from the convergent and discriminatory perspectives. Factor loadings, average variance extracted (AVE), and composite reliability (CR) values were used to validate the model in terms of convergence (Table 2). For adequate convergent validity, each observed variable should load its latent variable with at least 0.7 (Hair *et al.*, 2014). The observed variables Anx1, Anx5, Inn1, Inn3, M2, M3, PT1, SN2, SN5, C3, and BF1 did not load the related latent variables adequately; therefore, they were excluded from the dataset. After the items which had lower FLs were removed, the CR and AVE

Table 2.
Convergent Validity Findings

Item ID	FL	CR	AVE
PU1	.712	.883	60%
PU2	.721		
PU3	.837		
PU4	.794		
PU5	.812		
TE1	.807	.903	65%
TE2	.817		
TE3	.736		
TE4	.822		
TE5	.847		
SN1	.920	.808	59%
SN2	.630		
SN3	.727		
SN4	.818		
SN5	.599		
SF1	.798	.875	64%
SF2	.794		
SF3	.747		
SF4	.847		
PT1	.599	.842	57%
PT2	.839		
PT3	.716		
PT4	.846		
PT5	.702		
M1	.716	.753	51%
M2	.619		
M3	.608		
M4	.767		
M5	.814		
C1	.761	.848	65%
C2	.893		
C3	.665		
C4	.840		
Anx1	.269	.731	48%
Anx2	.770		
Anx3	.786		
Anx4	.852		
Anx5	.140		
Inn1	.531	.675	51%
Inn2	.720		
Inn3	.639		
Inn4	.779		
BI1	.623	.709	55%
BI2	.707		
BI3	.795		

Note: Anx=Anxiety; BI=Behavioral intentions; C=Cost; M=Mobility; PU=Perceived usefulness; PT=Perceived trust; SF=System features; SN=Social norm; TE=Technical efficacy.

values were evaluated to ensure internal consistency. The CR value should be 0.7 or higher and the AVE value should be 0.5 or greater for each latent variable (Hair *et al.*, 2014). It was observed that all the factors had an adequate CR value, except Inn, which was only slightly lower than 0.7; therefore, this construct was kept in the data set. The AVE value of Anx (48%) was lower than the adequate value of 0.5; therefore, this construct was removed from the data set. As a result, it was assumed that the dataset had adequate convergent validity based on the CR and AVE values.

For adequate discriminant validity presented in Table 3, "the square root of AVE values for each factor on the diagonal must be higher than the correlations with the related factor structure and all other correlations to ensure the discriminant validity of the factors" (Peter, 1981). As a result, the factors of the dataset adequately differed from each other.

Structural Model

In order to evaluate the structural model and the proposed hypothesis, path coefficients were calculated. A bootstrapping procedure was followed in SmartPLS to analyze the dataset having 417 samples. Figure 2 presents the estimated path coefficients. The results of the structural model are presented in Table 4. Some of the hypotheses could not be evaluated due to the lack of adequate results gained during the analysis process. Motivation, PBC, and Cnt factors are excluded in the structural model since any measurement items were

Table 3.
Discriminant Validity Findings

	BI	C	INN	M	PT	PU	SF	SN	TE
BI	0.742								
C	0.747	0.807							
INN	0.811	0.714	0.714						
M	0.762	0.754	0.772	0.711					
PT	0.523	0.529	0.457	0.613	0.757				
PU	0.763	0.718	0.710	0.717	0.696	0.777			
SF	0.713	0.694	0.714	0.741	0.644	0.765	0.797		
SN	0.620	0.526	0.503	0.514	0.656	0.620	0.622	0.766	
TE	0.665	0.647	0.671	0.723	0.642	0.775	0.746	0.630	0.807

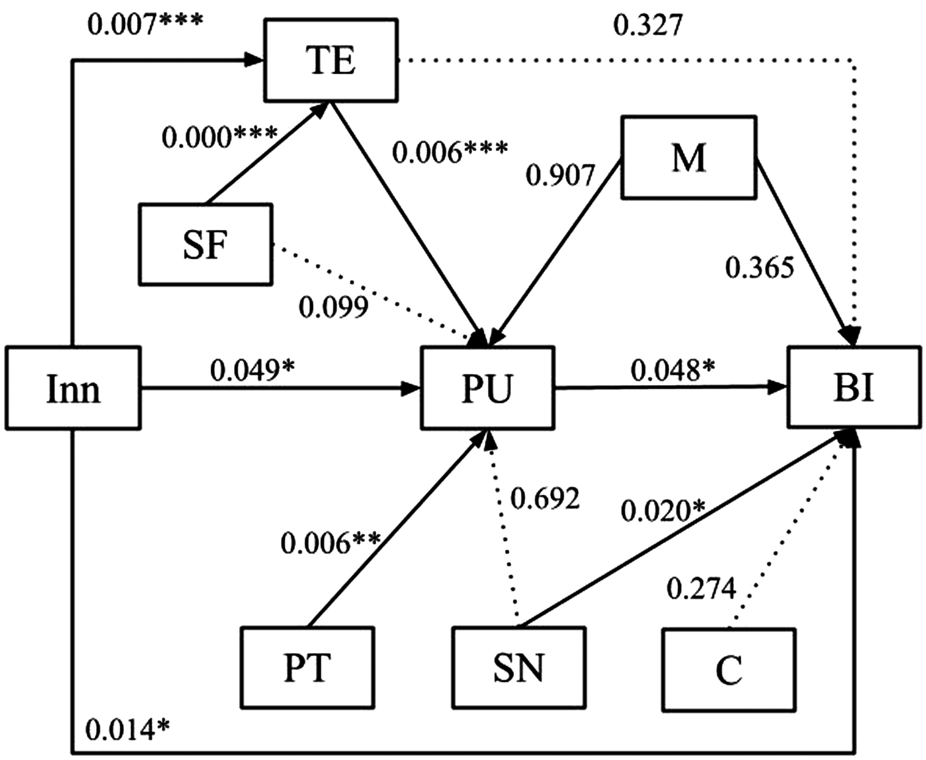

Figure 2.
Structural Model.

Table 4.
Summary of Hypotheses Tests

Hi	Relationships	*T*-values	*β*	Decision
H1	PU -> BI	1.981	0.048*	**Accepted**
H2	TE -> PU	2.741	0.006***	**Accepted**
H3	TE -> BI	0.980	0.327	Rejected
H4	SN ->PU	0.396	0.692	Rejected
H5	SN ->BI	2.331	0.020*	**Accepted**
H6	SF -> PU	1.650	0.099	Rejected
H7	SF -> TE	5.375	0.000***	**Accepted**
H8	PT -> PU	2.767	0.006**	**Accepted**
H9	M -> PU	0.117	0.907	Rejected
H10	M -> BI	0.907	0.365	Rejected
H11	Mot -> BI			Cannot be determined
H12	PBC -> BI			Cannot be determined
H13	Cnt -> PU			Cannot be determined
H14	C -> BI	1.095	0.274	Rejected
H15	Anx -> PU			Cannot be determined
H16	Anx -> TE			Cannot be determined
H17	Anx ->BI			Cannot be determined
H18	Inn -> PU	1.969	0.049*	**Accepted**
H19	Inn -> TE	2.713	0.007**	**Accepted**
H20	Inn -> BI	2.459	0.014*	**Accepted**

Note: Anx=Anxiety; BI=Behavioral intentions; C=Cost; Cnt=Content; Inn=Innovativeness; M=Mobility; Mot=Motivation; PBC=Perceived behavioral control; PU=Perceived usefulness; SF=System features; SN=Social norm; TE=Technical efficacy. *p<.05, **p<.01, ***p<.001

not loaded under these factors in the exploratory factor analysis. So that, H11, H12, and H13 could not be examined. The Anx construct did not ensure convergent validity; therefore, it was extracted from the research model, and H15, H16, and H17 could not be assessed. H3, H4, H6, H9, H10, and H14 were rejected because the relations between the variables were not significant. A positive relationship was identified between the constructs of H2 and H7 at the level of $p < .001$. The relationships between the constructs of H1, H5, H,18, and H20 were also significant at the $p < .01$ level. Also, H1, H5, H,18, and H20 were supported and found to be significant at the $p < .05$ level.

Discussion

This study was performed to identify and validate the factors that affected the m-learning acceptance of students and present a structural model. In the validated model, perceived usefulness and BI were taken from the original TAM. The model was extended with external factors that consisted of TE, social norm, system features, PT, M, Mot, PBC, content, cost, Anx, and Inn. The proposed hypotheses related to Mot, PBC, content, and Anx factors could not be investigated because of the inefficient results in the preliminary analysis conducted before the hypotheses tests. The remaining hypotheses were analyzed with structural equation modeling.

According to the results of the study, perceived usefulness was found as a significant predictor of BI toward m-learning use. The relation between perceived usefulness and BI was direct and positive. This result is consistent with the original TAM (Davis *et al.*, 1989). This relation implies that when students perceive m-learning to be useful, their BI toward m-learning will be affected positively and increase. This outcome is also similar to the previous findings in the literature (Hao, Dennen, & Mei, 2017; Hsia, 2016; Iqbal & Bhatti, 2017; Poong *et al.*, 2017; Tan, Ooi, Leong, & Lin, 2014). If m-learning applications are designed to increase students' usefulness perception and students benefit from m-learning activities in their training, their intention toward such applications will increase. As Lee and his friends (2009) stated, e-learning systems should add value to students learning and be designed and developed in this direction. The same result was observed in the m-learning context, and the value of the m-learning application should be improved by supplying enhanced m-learning services.

The TE factor covers perceived ease of use, effort expectancy, and students' mobile skills in the scope of this research. Two relations were proposed between TE, perceived usefulness, and BI. Only the relation between TE and perceived usefulness, which was direct and positive, was found to be significant. This relation implies that when students find the system easy to use which means using the system does not require too much effort, and their mobile skills are sufficient to use m-learning system, their usefulness perception of m-learning application will increase. This finding is parallel with the findings in the literature (Joo, Lee, & Ham, 2014; Lu, Chang, Kinshuk, Huang, & Chen, 2014; Mac Callum, Jeffrey, & Kinshuk, 2014). This result is important to understand the consequence of designing low complex m-learning systems to increase the easiness perception of students and promote their ability toward system use. In addition, there was no significant relation between TE and BI. This could be the result of many students' lacking previous experience with any m-learning system. A similar result was observed in a study conducted in Iran by Mohammadi (2015). Although the relation between TE and BI was not significant in the current work, many studies in the literature support that easiness perception of the students and their ability perception toward system use enhanced their BI toward m-learning systems (Merhi, 2015; Nikou & Economides, 2017b; Tan, Ooi, Sim, & Phusavat, 2012).

Two relations were proposed between social norm and BI, and perceived usefulness, but only one was found significant. The results of the study revealed that social norm significantly and positively affected students' BI toward m-learning use. This finding is parallel to previous findings (Cheon, Lee, Crooks, & Song, 2012; Mohammadi, 2015; Park, Nam, & Cha, 2012; Tan *et al.*, 2012; Yeap, Ramayah, & Soto-Acosta, 2016) and implies that students are encouraged by their instructors, their educational institution, and people around them to use m-learning systems and applications. The relation between social norm and perceived usefulness was not significant, which indicates that students' usefulness perception was not affected by their peers. Since students do not use any m-learning application to support their courses officially, there is a very low possibility of an interaction between instructors and students or only between students in which they would discuss the provided values of the m-learning system. The absence of such a system use may have resulted in a non-significant relation between social norm and perceived usefulness. Our results differ from the findings of some studies in the literature (Hao *et al.*, 2017; Park *et al.*, 2012).

In the scope of this study, system features include navigation, tracking information, and accessing online resources. Two relations were proposed between system features and TE and perceived usefulness. A positive relation was found between system features and TE in the structural model. This finding is parallel to the findings of Cheng (2015), who found a significant, positive relation between navigation and perceived ease of use. Wang (2013) also found a significant relation between system characteristics and perceived ease of use, which supports our finding. Most of the participant students evaluated their computer skills and ability to use mobile devices as fairly good. The self-ability and confidence of the students toward such technological devices may have created this significant relation between system feature and TE. The relation between system features and perceived usefulness was not significant. Most of the participants of the study had not used any m-learning system/application before. Therefore, the participants were not aware of what kinds of values could be obtained from m-learning systems, which may have affected the result concerning the relation between system features and usefulness perception.

Perceived trust is related to students' perceptions concerning the reliability of a system. It is seen that PT had a positive and significant effect on perceived usefulness in m-learning. This finding validates the results of Nikou and Economides (2017b). If the students believe that a system supporting m-learning is trustworthy, their usefulness perception of the system will be positive and their use of m-learning will increase. It is necessary to design m-learning systems that promote security policies to protect the personal data, privacy, information security, and data ethics of students.

Innovativeness emphasized that individuals are volunteer to use new information technologies (Agarwal & Prasad, 1998). It is found that Inn had a significant effect on perceived usefulness, TE, and BI. Liu *et al.* (2010) stated that personal Inn was important to understand new information systems, technology diffusion, and users' intentions. Parallel to this indication, innovative students tend to think that m-learning is useful and they are more willing to use such systems and applications. In addition, the positive relation between Inn and TE implies that innovative students will have more self-confidence in using new technologies and will easily learn to use them. A similar finding between Inn and perceived ease of use was also validated in the previous researches (Hao *et al.*, 2017; Joo *et al.*, 2014; Liu *et al.*, 2010; Tan *et al.*, 2014). Lastly, the current study revealed a significant relationship between Inn and BI. This finding validates the results of previous studies (Abu-Al-Aish & Love, 2013; Liu *et al.*, 2010; Milošević *et al.*, 2015; Mohammadi, 2015) and implies that innovative students tend to use m-learning systems. As Liu and his friends (2010) emphasized, personal traits have an important impact on the students' intentions to enhance their adoption of m-learning.

The cost factor was evaluated within the scope of the proposed m-learning acceptance model to investigate the effect of the cost of the device, communication, and Internet on the BI of students. It was observed that cost was not a determinant of m-learning intention. This could be related to the fact that most of the students already had mobile phones and an Internet connection and did not need to pay an additional fee for this service. Therefore, they might not be concerned about the cost of Internet access, bandwidth, or device use. In contrast to this finding, previous work conducted by Bere and Rambe (2016) found a direct and positive relationship between low-cost communication and attitude in the context of m-learning. Similarly, Bere and Rambe (2016) stated that providing learning at lower costs enhanced the adoption of m-learning in developing countries.

Two relations between M, perceived usefulness, and BI were proposed, but none were found significant, unlike the findings reported by Merhi (2015) and Mohammadi (2015). The non-significant relations between these factors in the current study could result from most of the participants being inexperienced in m-learning and not being aware of the value of M during the learning process.

The findings of the study reveal several issues for the policymakers and education administrators when developing m-learning applications and integrating them into courses. First of all, m-learning systems stand out in the education-teaching process since they allow students to enroll in courses, access course content wherever and whenever they want, and follow the course content at their own pace. Students should benefit from these advantages of m-learning; therefore, it is important to design and implement m-learning systems in a way that will enhance students' interaction with the course and their classmates. Second, in order to support educational activities with m-learning, it is necessary to introduce students to the interfaces of the m-learning system by training to improve students' m-learning efficacy. Lastly, user-friendly designs and user-experience tests should be conducted to increase the usability of m-learning systems. When developing systems, it is important to take into account current and emerging technologies and innovations, protect student data, and develop security strategies against external threats.

Limitations and Future Implications

This study aimed to elucidate the factors that play a leading role in higher education students' acceptance of m-learning in a developing country. Six influencing factors affecting their BI toward m-learning use were validated based on quantitative research. Technology acceptance model was extended with the social norm, TE, system features, PT, and Inn factors. This study also contributes to the literature by validating a new m-learning acceptance model, which has potential to guide the implementation of m-learning. However, it has some limitations. First, the data was collected from only two universities in Turkey, which restricts the generalization of the results to the whole population. The number of universities could be extended to improve the results. Besides, four factors, namely Mot, PBC, content, and Anx, were excluded from the data set because their measurement items did not load properly or did not ensure convergent validity. Thus, the relations related to these four factors could not be tested. Also, the validated model explains 55% of BI toward m-learning acceptance. The model should be improved to increase its predictive power with different factors.

Ethics Approval: This study was approved by the Başkent University Human Research Ethics Committee and all procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee.

Consent to Participate: The following statement was included in the cover page of the questionnaire: "Responding to the questionnaire will not affect the respondents. So please give as accurate answer as possible. In this regard, the researcher will present the overall information only. If you are not comfortable with answering any questions, you may skip or cancel the participation at any time."

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Katılım Onayı: Anketin giriş sayfasında aşağıdaki ifade yer almaktadır: "Anketi yanıtlamak katılımcıları hiçbir şekilde etkilemeyecektir. Bu yüzden lütfen mümkün olduğunca doğru cevap veriniz. Bu bağlamda, araştırmacı sadece genel bilgileri sunacaktır. Herhangi bir soruyu yanıtlamaktan çekinirseniz, soruyu dilediğiniz şekilde atlayabilir veya ankete katılımı sonlandırabilirsiniz."

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