Computers & Education 59 (2012) 1054–1064

Contents lists available at SciVerse ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

An investigation of mobile learning readiness in higher education based on the theory of planned behavior

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A R T I C L E I N F O

Article history:
Received 19 January 2012
Received in revised form
5 April 2012
Accepted 25 April 2012

Keywords:
Mobile learning
m-learning
Higher education
m-learning adoption

A B S T R A C T

This study investigated the current state of college students' perceptions toward mobile learning in higher education. Mobile learning is a new form of learning utilizing the unique capabilities of mobile devices. Although mobile devices are ubiquitous on college campuses, student readiness for mobile learning has yet to be fully explored in the United States. The paper describes a conceptual model, based on the theory of planned behavior (TPB), which explains how college students' beliefs influence their intention to adopt mobile devices in their coursework. Structural equation modeling was used to analyze self-report data from 177 college students. The findings showed that the TPB explained college students' acceptance of m-learning reasonably well. More specifically, attitude, subjective norm, and behavioral control positively influenced their intention to adopt mobile learning. The results provide valuable implications for ways to increase college students' acceptance of mobile learning.

1. Introduction

Advancements in mobile technology are rapidly widening the scope of learning in areas outside of formal education (i.e., informal learning) by allowing flexible and instance access to rich digital resources. Mobile learning (m-learning) can also play a significant supplemental role within formal education. The potential benefits of m-learning have been widely touted from a range of purposes, including cost savings, ubiquitous communications, study aids, and location-based services. For example, the U.S. government is seeking to reduce costs by encouraging schools to transition from paper-based to digital textbooks within next five years (Hefling, 2012). Students can communicate with other students and their instructors through text messages. Mobile device applications (i.e., Apps) can be used as study aids (e.g., anatomical models of human organs for medical students) that students can access from virtually anywhere (Young, 2011). In addition, students are able to have relevant place-based information about nearby buildings or landmarks with geolocation capability. However, to realize these benefits, students must first adopt m-learning. The availability of mobile devices does not guarantee their use in education; we must first assess students' readiness for mobile learning (Corbeil & Valdes-Corbeil, 2007; Keller, 2011). Despite the importance of the adoption of m-learning, very little research has been conducted concerning the factors affecting the acceptance of m-learning by students in higher education.

Higher education students may be ready to adopt m-learning sooner than K-12 students because more college students have their own mobile devices (Traxler, 2007). However, m-learning in higher education is still in the early stages of development (Park, 2011). For instance, while many universities provide free Apps, their contents are primarily non-instructional (e.g., news, event calendars, and maps). In order for m-learning to succeed in higher education, it is necessary to understand the factors college students' consider important in the adoption of m-learning. To this end, the current study addressed two research questions:

1. What factors do college students consider important in the adoption of m-learning?
2. What is the relationship among those factors in higher education?

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0360-1315/$ – see front matter
doi:10.1016/j.compedu.2012.04.015

The theory of planned theory (Ajzen, 1991) is used as a framework for exploring the factors affecting college students' adoption of m-learning and the relationships among those factors.

This study contributes to the literature in education in three ways. First, the adoption of m-learning is explored from a multi-faceted perspective including attitude to m-learning, subjective norm, and perceived behavioral control. This implies that university practitioners should consider these three factors before employing m-learning. Second, the current study shows the relative importance of perceived behavior control (i.e., perceptions of internal and external constraints on behavior) (Taylor & Todd, 1995) in the decision to adopt m-learning. That is, students who are confident with mobile devices are likely to adopt m-learning. Therefore, universities need to provide students with training opportunities about the basic functions and applications of m-learning technologies. Lastly, the current findings reveal that usefulness and ease of use affect students' attitude for adopting m-learning. Thus, to facilitate the acceptance of m-learning, the learning environment should be perceived as useful and easy to use. A better understanding of the process of m-learning adoption will help researchers and decision makers work together to implement proper strategies for m-learning.

This paper is organized in the following manner. First, the m-learning literature is reviewed followed by a discussion of the research framework for the current study. Next, the research methodology is described, including a discussion of the sample and the variables and their measurement. Finally, the results are presented, followed by a discussion of the findings, important implications, and directions for future research.

2. Literature review

2.1. Mobile learning

Mobile learning is a specific type of learning model using mobile technology (Naismith, Lonsdale, Vavoula, & Sharples, 2004; Yuen & Yuen, 2008), while e-learning is learning experiences to support individual learning with various types of computer technologies (Clark & Mayer, 2008; Horton, 2006). Thus, m-learning embraces many features of e-learning such as multimedia contents and communications with other students (Horton, 2006), but it is unique in terms of flexibility of time and location (Peters, 2007). The characteristics of mobile devices are three fold: (a) portability: mobile devices can be taken to different locations, (b) instant connectivity: mobile devices can be used to access a variety of information anytime and anywhere, and (c) context sensitivity: mobile devices can be used to find and gather real or simulated data (BenMoussa, 2003; Churchill & Churchill, 2008; Klopfer, Squire, & Jenkins, 2002; Sharples, 2000). These three idiosyncratic features of m-learning can constitute a unique learning experience (Traxler, 2007, 2008, 2010; Wang & Higgins, 2006). In addition, advanced hardware of mobile devices (e.g., camera, accelerometer) and various software (e.g., Apps) availabilities provide more capabilities to organize, manipulate and generate information for teaching and learning (Chen, Tan, Looi, Zhang, & Seow, 2008; Keskin & Metcalf, 2011).

Based on the features of m-learning, four types of learning approaches can be supported by mobile devices, including individualized learning, situated learning, collaborative learning, and informal learning. First, m-learning supports individualized learning by allowing students to pace learning at their own speed. Second, the situated learning is realized as students use mobile devices to learn within a real context. For example, students can learn about social responsibility through Starbucks Shard Planet, a program that minimizes environmental impact with the use of recycled and reusable cups. Third, m-learning enables collaborative learning when students use mobile devices to easily interact and communicate with other students. Finally, informal learning is realized when students learn out of class at their convenience.

On the other hand, some studies show that students are not likely to use mobile devices for learning because of the limitations of m-learning. First, some technical limitations of mobile devices have been voiced (Haag, 2011; Huan, Kuo, Lin, & Cheng, 2008; Lowenthal, 2010; Park, 2011; Wang & Higgins, 2006; Wang, Wu, & Wang, 2009), such as the small screens with low resolution display, inadequate memory, slow network speeds, and lack of standardization and comparability. Second, users' psychological limitations have been addressed (Park, 2011; Wang et al., 2009). For example, students are more likely to use mobile devices for hedonic uses such as texting with friends, listening to music, and checking social network services, rather than for instructional purposes (Park, 2011; Wang et al., 2009). Last, there are pedagogical limitations (Corbeil & Valdes-Corbeil, 2007; Park, 2011; Wang et al., 2009). For example, using mobile devices in class may hinder student concentration and interrupt class progress. Previous research has proposed design guidelines for m-learning (e.g., Gu, Gu, & Laffey, 2011; Hwang & Chang, 2011; Sharples, 2000; Shih & Mills, 2007) to overcome the technical limitations. For example, instructional content for m-learning should be adapted to the small screen size (Lowenthal, 2010). In addition, the instruction should be provided in a granular fashion because the amount of time to access the content is limited with a mobile device in general. Shieh (2009) and Gu et al. (2011) introduced a micro lecture format that contained fewer concepts in one-to-five minutes. In addition, the audio format of the contents should be suitable for a mobile situation. Instructional models that consider both advantages and limitations of mobile devices are still in the early stages of development.

2.2. Mobile learning in higher education

While m-learning has the potential to support all forms of education, higher education is a particularly appropriate venue for the integration of student-centered m-learning because mobile devices have become ubiquitous on college campuses. Various m-learning attempts have been applied in higher education. For example, college students can receive formative evaluation and feedback from their instructors via a mobile device (Crawford, 2007). A face-to-face course can be supported by Quick Response (QR) codes that offer an Internet link to supplemental resources (Grant & Gikas, 2011). Administrative tasks, such as checking attendance and learning progress, can also be done with a mobile device. Some universities such as Stanford, Abilene Christian, and the University of Washington, have been pioneering m-learning (Keller, 2011); but implementing m-learning in higher education is still challenging because of social, cultural, and organizational factors (Corbeil & Valdes-Corbeil, 2007; Traxler, 2007, 2010). Therefore, understanding perceptions toward m-learning should be the first step to implementing m-learning on college campuses.

Few researchers have studied how and why college students adopt m-learning (Liu, Li, & Carlsson, 2010; Lowenthal, 2010; Wang et al., 2009). Those researchers mainly focus on students' acceptance of m-learning by using intension or use as dependent variable. Liu et al. (2010) find that perceived usefulness and personal innovation have influenced the adoption of m-learning when they investigated the factors of m-learning adoption with Chinese college students using the Technology Acceptance Model (TAM) which explains how people accept a new system (Davis, 1989). Using the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh & Davis, 2000), Wang et al. (2009) found that five factors including performance expectancy, effort expectancy, social influence, perceived playfulness, and self-management of learning were significant factors in adopting m-learning with Taiwanese college students. Unlike the study of Lowenthal (2010), Wang et al. (2009) employed only three factors including performance expectancy, effort expectancy, and self-management of learning and find that three factors have influenced the adoption of m-learning of U.S. college students. To the best of our knowledge, however, no studies have considered students' perception concerning the ease or difficulty of m-learning. The technology acceptance models used in previous studies focused on users' perception toward a specific technology's functionality and characteristics (Benbasat & Barki, 2007), but m-learning is a whole new approach to learning. Thus, we conjecture that students will adopt or abandon m-learning based on their judgments about their capability to perform in an m-learning environment. Thus, we are particularly interested in the theory of planned behavior (Ajzen, 1991) that considers such factors as behavioral control.

3. Research model and hypothesis development

3.1. Theory of planned behavior

As a theory for explaining general individual behavior, the Theory of Planned Behavior (TPB) posits that individual behavior is driven by behavior intentions, where behavior intentions are a function of three determinants; an individual's attitude toward behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). Attitude toward behavior is about the individual's positive or negative feelings about performing behavior. Subjective norm is about the individual's perception that people important to the individual should perform the behavior in question. Perceived behavior control is defined as an individual's perception of the difficulty or ease of performing a behavior. TPB has been applied in various contexts such as technology, health care, and politics, and has explained the individual behavior of adoption quite well (Barnard-Bark, Burley, & Crooks, 2010; Conner & Armitage, 1998; Davis, 1989; Taylor & Todd, 1995).

When formulating our research model using the TPB, we take care of the following three points. First, we differentiate perceived behavioral control from attitude conceptually. As Ajzen have already point out (Ajzen, 2002), personal behavioral control does not denote the likelihood that performing a behavior will produce a given outcome, but refers to a subjective degree of control over performance of a behavior. Thus, perceived behavioral control is the students' perceived ease or difficulty when involving m-learning. Second, we use intention instead of actual behavior as a final dependent variable. Ajzen (1991) argue that "intentions are assumed to capture the motivational factors that influence a behavior (p. 181)." Thus, the stronger the intention to perform a behavior, the more likely the individual is to perform the actual behavior. The positive relationship between intention and actual behavior is confirmed by Venkatesh and Davis (2000) and Venkatesh, Morris, and Ackerman (2000). Given that few students have experience using m-learning, their actual behavior might lead incorrect inferences. Thus, we use behavioral intention as a final dependent variable, because it is assumed to be the immediate antecedent of actual behavior (Ajzen, 2002). Third, we draw external beliefs to three categories of constructs including attitudinal, normative, and control from the context of m-learning. Because salient beliefs are conditional to context, Ajzen and Fishbein (1980) suggest that researchers identify beliefs for behavior from a specific population and context. Fig. 1 depicts our proposed adoption model. Our research model proposes that external beliefs influence attitude, subjective norm, and perceived behavior control, and then three constructs affect intention to adopt m-learning. We will describe external beliefs and hypotheses in the following section.

3.2. Attitudinal constructs and behavioral intention

The first attitudinal construct, attitude, refers to the degree to which a person has a favorable or unfavorable feeling about performing a particular behavior. Previous studies have found that attitude was a strong predictor of intention (Ajzen, 1991; Taylor & Todd, 1995). The second construct, subjective norm, pertains to a person's perception of the social environment surrounding the behavior. In other words, important others' opinions are significant in shaping an individual's intention to use new technologies (Venkatesh & Davis, 2000), because individuals are dependent on context (Shah, 1998). In this way, subjective norm is related to behavioral intention. Last, behavioral control refers to a person's perception of control over a particular behavior. An individual's perception of behavioral control is directly related to their intention to perform the behavior. Behavioral control is increased when individuals perceive that they have more resources and confidence than expected obstacles (Ajzen, 1985; Hartwick & Barki, 1994; Lee & Kozar, 2005). Therefore, we developed the following hypotheses:

- H1: College students' attitude toward m-learning positively influences their intention to adopt m-learning.
- H2: College students' subjective norm toward m-learning positively influences their intention to adopt m-learning.
- H3: College students' perceived behavioral control toward m-learning positively influences their intention to adopt m-learning.

3.3. Attitudinal beliefs toward attitude

The antecedents of the first attitudinal construct (i.e., attitude) are attitudinal beliefs. In our research model, variables for attitudinal beliefs are derived from TAM. TAM argues that there are causal relationships between perceived ease of use, perceived usefulness, attitude toward a new system, and behavioral intention to use the system (Davis, 1989; Teo, 2009). Accordingly, we included the two perceptions (i.e., ease of use and usefulness) as attitudinal beliefs and developed the following hypotheses:

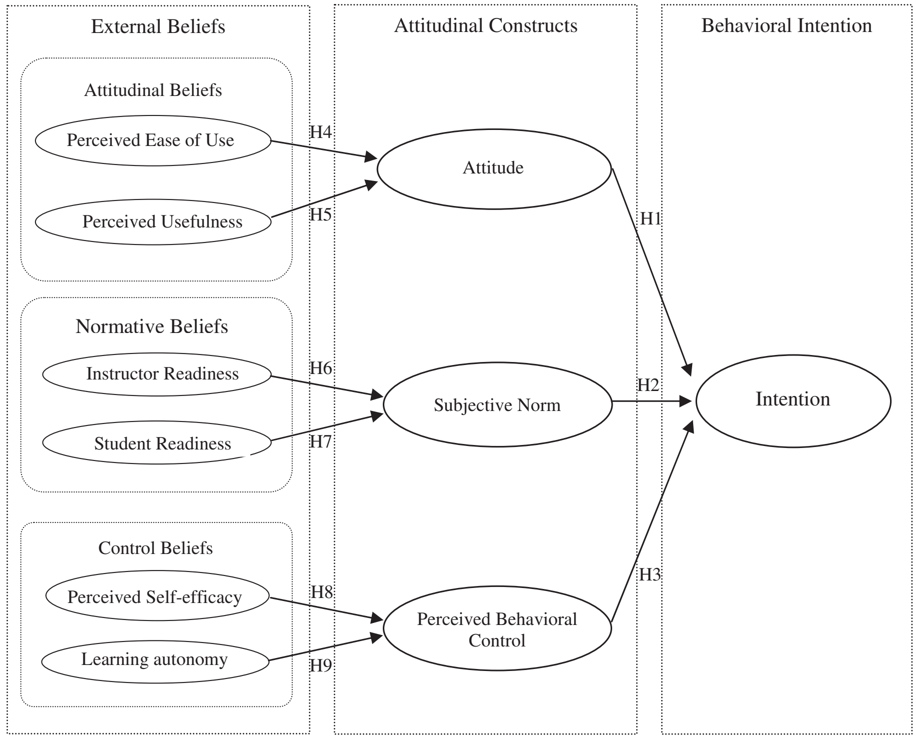

Fig. 1. Research model.

- H4: College students' perceived ease of use of m-learning positively influences their attitude toward m-learning.
- H5: College students' perceived usefulness of m-learning positively influences their attitude toward m-learning.

3.4. *Normative beliefs toward subjective norm*

Subjective norm is determined by the accessible normative beliefs that account for the expectations of other people as an important determinant in behavioral intention (Ajzen, 1991). The normative beliefs can be decomposed into multiple referent groups because each group may have different views (Taylor & Todd, 1995). For example, peers may have a positive opinion toward a particular system whereas managers may be opposed to the system. Normative beliefs are usually measured when a new system is introduced or tested. This study measures normative beliefs as participants' perceptions toward the extent to which other people are in favor of using mobile devices in their courses. As previous studies suggested, two relevant referent groups in higher education are peer students and instructors (Liu, 2008; Taylor & Todd, 1995). Thus, we propose normative beliefs of other students and instructors as antecedents of subjective norm. We developed the following hypotheses:

- H6: Perceived instructor readiness for m-learning positively influences subjective norm for m-learning.
- H7: Perceived peer student readiness for m-learning positively influences subjective norm for m-learning.

3.5. *Control beliefs toward perceived behavioral control*

Perceived behavioral control refers to individuals' perceptions of their ability to perform a particular behavior, and it is compatible with the concept of self-efficacy (Ajzen, 2002). In other words, an individual's confidence in performing a specific task significantly influences behavior (Ajzen, 1991). Self-efficacy refers to individuals' beliefs about their ability and motivation to perform specific tasks (Bandura, 1986, 1997). More specifically, individuals who believe that they can master a certain skill or an activity tend to have higher intention to perform the skill or perform the activity. Previous studies have found that higher levels of self-efficacy with respect to computers lead to higher levels of behavioral intention and the usage of information technology (Compeau & Higgins, 1995; Gist, Schwoerer, & Rosen, 1989).

In addition, this study employed learning autonomy as the second antecedent. While self-efficacy represents judgment of general ability to perform a behavior (Agarwal & Karahanna, 2000), learner autonomy is the extent to which students are responsible and have control over the process of learning with mobile devices. Autonomy has proved to be a major contributor to system acceptance (Liaw, Huang, & Chen, 2007). Although m-learning could provide more mobility and flexibility, it requires learners to be self-motivated and self-disciplined (Liu, 2008). Thus, autonomy is an important antecedent of behavioral control for m-learning. Our hypotheses are as follows:

- H8: College students' perceived self-efficacy toward m-learning positively influences their behavioral control with m-learning.
- H9: College students' perceived learning autonomy toward m-learning positively influences their behavioral control with m-learning.

In summary, we hypothesized that the TPB can explain college students' acceptance of m-learning. If the hypothesis is true, we can examine significant determinants of their intention to adopt m-learning in their coursework, and how these factors are related.

4. Methodology

4.1. Participants

This study used a nonrandom sampling technique (i.e., convenience sampling) to collect data (Creswell, 2012). The participants in this study were 189 undergraduate students at a large, public research-intensive university located in the Southwest, United States. They were enrolled in a course "Computing and Information Technology" that was one of the core curriculum courses required for all undergraduate students. The participants voluntarily signed up for a module involving technology-related research participation. The module was optional and was offered three times throughout the semester. The students could receive extra points by either taking the module or submitting a research report. We report data from 177 participants, because 12 participants were removed due to missing responses. There were 84 males and 93 females, and their majors varied. Among the participants, 133 students had a smartphone (iPhone: 82, 46.3%; other types of smartphones: 51, 28.8%) and 49 students had a web enabled mobile device other than a smartphone (25.9%), making a total 152 of students (86%) with a mobile device. Twenty-five students did not have a mobile device.

4.2. Data collection

The survey instrument contained 30 items (three items for each of the 10 constructs) adapted from previous studies (see Appendix A). The survey measured participants' perceptions with a 7-point Likert scales, ranging from totally disagree to totally agree. Higher scores on this instrument indicated more positive perceptions toward m-learning. All data were collected by online survey. This study consisted of three parts. First, the participants were asked to provide general information (e.g., gender and phone type). Second, they watched three video clips describing m-learning (i.e., what mobile learning is: http://www.youtube.com/watch?v=Pnlmp0EXoU8, mobile learning institute: http://vimeo.com/10364680, mobile devices for academic uses: http://www.youtube.com/watch?v=TLCTpX3tJEQ), and one presentation about m-learning. Last, they completed the survey about their perception toward m-learning.

4.3. Data analysis

This study used structural equation modeling (SEM) to test the model. The advantage of SEM is that it considers both the evaluation of the measurement model and the estimation of the structural coefficient at the same time. Mplus 6.11 was used to evaluate the measurement model and estimate the structural coefficients. If the chosen indicators for a construct do not measure that construct, the testing of the structural model will be meaningless (Jöreskong & Sörbom, 1998, p. 113). Thus, a two-step modeling approach, recommended by Anderson and Gerbing (1988) and McDonald and Ho (2002), was followed such that the confirmatory factor analysis (CFA) was carried out first to provide an assessment of convergent and discriminant validity, and then SEM was carried out to provide the path coefficients.

4.4. Measurement model

The measurement model was assessed using Mplus 6.11 with the maximum likelihood estimation (MLE) in terms of individual item loadings, reliability of measures, convergent validity and discriminant validity. MLE allows computation of assorted indices of goodness-of-fit and the testing of the significance of loadings and correlations between factors, but requires the assumption of multivariate normality. Table 1 presents a summary of the Cronbach's α, standardized factor loadings, composite reliability, and variance extracted estimate. Cronbach's α reflects the internal consistency reliability among indicators of a construct. As shown in Table 1, all values of the Cronbach's α exceed 0.7, showing satisfactory reliability for all the ten constructs. Fornell and Larcker (1981) proposed three measures for assessing convergent validity of the measurement items; a) item reliability of each measure, b) composite reliability of each construct, and c) the average variance extracted. On the reliability of the items, the standardized loading values exceeded 0.7 that are ranging from 0.754 to 0.942, the recommended threshold by Gefen, Straub, and Boudreau (2000), thus demonstrating convergent validity at the item level. For composite reliability, all values exceeded 0.7 that are ranging from 0.78 to 0.90, the recommended threshold by Nunnally and Bernstein (1994). Lastly, on the average variance extracted, all values exceeded 0.5 that are ranging from 0.71 to 0.87. Given the satisfaction of three criteria, the convergent validity for the proposed constructs of the measurement appears to be adequate.

For the discriminant validity, the square root of the average variance extracted (AVE) for a given construct was compared with the correlations between the construct and other constructs (Fornell & Larcker, 1981). If the square root of the AVE of a construct is greater than the off-diagonal elements in the corresponding rows and columns, this indicates that a construct is more closely related with its indicators than with the other constructs. In the Table 2, the diagonal elements in the matrix are the square roots of the AVE. Because the square roots of the AVE are higher than the values of its corresponding rows and columns, discriminant validity appears satisfactory for all constructs.

5. Results

5.1. Structural model

The proposed structural model was estimated using Mplus 6.11 with the maximum likelihood method. Model fit determines the degree to which the sample variance-covariance data fit the structural equation model. Kline (2005) and Schumacker and Lomax (2010) recommended a variety of model fit criteria when determining model fit of a structural model. Table 3 presents several model fits as well as the recommended thresholds. Except for χ^2, for all model fits, the model fits exceeded the recommended level of acceptable fit. Because χ^2 is too sensitive to a large sample, the ratio of χ^2 to its degree of freedom was computed, and the value should be below three for a good model fit.

Table 1
Results for the measurement model.

alpha值 < 組成信度(composite reliability, CR)

Construct	Mean	Std dev	Standardized factor loadings (>0.70)[a]	Cronbach's alpha (>0.70)	Composite reliability (>0.70)	Variance extracted estimate (>0.50)
Perceived Ease of Use				0.902	0.940	0.870
PEOU1	5.17	1.46	0.934			
PEOU2	5.16	1.40	0.921			
PEOU3	5.31	1.46	0.934			
Perceived Usefulness				0.795	0.887	0.725
PU1	4.64	1.44	0.867			
PU2	4.91	1.50	0.871			
PU3	5.08	1.38	0.816			
Attitude				0.901	0.948	0.878
ATT1	4.58	1.55	0.930			
ATT2	4.95	1.42	0.942			
ATT3	4.84	1.44	0.939			
Instructor Readiness				0.780	0.890	0.734
IR1	4.27	1.60	0.861			
IR2	4.59	1.45	0.903			
IR3	4.49	1.53	0.804			
Student Readiness				0.853	0.879	0.716
SR1	5.44	1.16	0.850			
SR2	5.45	1.10	0.916			
SR3	5.51	1.15	0.765			
Subjective Norm				0.860	0.899	0.761
SN1	4.82	1.30	0.891			
SN2	5.50	1.19	0.784			
SN3	4.92	1.33	0.935			
Perceived Self-efficacy				0.836	0.917	0.759
SE1	5.18	1.29	0.924			
SE2	5.12	1.28	0.754			
SE3	5.29	1.29	0.925			
Learning Autonomy				0.804	0.900	0.714
LA1	5.50	1.24	0.787			
LA2	5.13	1.37	0.884			
LA3	5.31	1.34	0.861			
Behavioral Control				0.852	0.913	0.797
BC1	4.82	1.47	0.844			
BC2	5.15	1.33	0.923			
BC3	5.25	1.36	0.910			
Intention				0.803	0.921	0.786
INT1	5.15	1.60	0.917			
INT2	5.11	1.62	0.909			
INT3	4.75	1.64	0.833			

[a] Indicates an acceptable level of reliability and validity.

Hu and Bentler (1999) suggested that instead of evaluating each index independently, a strict combination rule needs to be applied to model fit indices to control types I and II errors simultaneously; (1) Standardized RMR < 0.08 and (2) either CFI > 0.95 or RMSEA < 0.06. A set of model fits in Table 3 satisfies the combination rule as well as the independent level of recommended fits. Thus, the result of the model fit indicates that the proposed model has a good fit.

The results support the first research question concerning the validity of the TPB, and its three constructs, as a model for m-learning acceptance among higher education students. In other words, 87.2% of intention to adopt m-learning can be explained by all attitudinal constructs (i.e., attitude, subjective norm and perceived behavioral control).

5.2. Hypothesis testing

Fig. 2 shows the graphical description of the results of path coefficients. Consistent with hypothesis 1, 2, and 3, attitude ($\beta = 0.431$), subjective norm ($\beta = 0.158$), and perceived behavioral control ($\beta = 0.501$), significantly impact intention to use m-learning. However,

Table 2
Discriminant validity for the measurement model.

Construct	PEOU	PU	ATT	IR	SR	SN	SE	LA	BC	INT
PEOU	0.933									
PU	0.771	0.852								
ATT	0.863	0.837	0.937							
IR	0.579	0.688	0.687	0.857						
SR	0.520	0.570	0.652	0.736	0.846					
SN	0.568	0.724	0.712	0.669	0.589	0.872				
SE	0.721	0.752	0.732	0.581	0.563	0.553	0.871			
LA	0.761	0.842	0.813	0.685	0.673	0.676	0.753	0.845		
BC	0.620	0.618	0.652	0.475	0.459	0.456	0.815	0.723	0.893	
INT	0.774	0.845	0.843	0.687	0.618	0.675	0.841	0.830	0.823	0.886

The items on the diagonal represent the square roots of the AVE; off-diagonal elements are the correlation estimates.

Table 3
Model fit indices.

Fit indices	Values	Recommended guidelines	References
χ^2	627.18	Non-significant	Klem, 2000; Kline, 2005
χ^2/df	1.646	<3	Kline, 2005; Tabachnick & Fidell, 2007
CFI	0.955	≥0.90	Hu & Bentler, 1999
TLI	0.949	≥0.90	Hu & Bentler, 1999; Kline, 2005
RMSEA	0.060 (0.052, 0.069)	<0.05 (good fit) <0.08 (fair fit)	Kline, 2005; McDonald & Ho, 2002
Standardized RMR	0.066	<0.05 (good fit) <0.08 (fair fit)	Byrne, 1998; Hu & Bentler, 1999; Kline, 2005

perceived behavioral control has the highest impact followed by attitude and subjective norm. Perceived ease of use and perceived usefulness were found to significantly relate to attitude with 0.486 and 0.491, respectively. The results support hypothesis 4 and 5. Concerning normative beliefs, instructor readiness significantly influenced subjective norm ($\beta = 0.579$), but student readiness did not influence subjective norm. Therefore, hypothesis 6 was supported but hypothesis 7 was not. Finally, for control beliefs, both perceived self-efficacy and learning autonomy were significantly related to perceived behavior control with 0.639 and 0.243, respectively. Therefore, the results support hypotheses 8 and 9 about the relationship between control beliefs and perceived behavioral control.

Regarding the second research question, perceived behavioral control was the most significant contributor to acceptance of m-learning ($\beta = 0.501$) followed by attitude ($\beta = 0.431$) and subjective norm ($\beta = 0.158$).

6. Discussion

The purpose of this study was to identify factors that affect the adoption of m-learning and to investigate the relationships among those factors. Drawing upon the theory of planned behavior, we found that college students' attitudes toward m-learning, subjective norm, and behavioral control influenced their intention to adopt m-learning. This implies that the adoption of m-learning should be viewed from multiple perspectives. The well-established TPB was extended to predict those three factors with their respective beliefs. The significant impact of perceived ease of use ($\beta = 0.486$) and usefulness ($\beta = 0.491$) shows that college students who feel that m-learning is easy to use and useful are more likely to use mobile devices for their coursework. We assume that they were already familiar with mobile devices because 85% of the participants already had mobile devices. However, a new m-learning system should be easy to use considering the technical limitations of mobile devices mentioned earlier. For example, when designing a user interface and content structure, the smaller screen size and slower network speed should be considered. Since there are various platforms and screen sizes, more technical efforts are needed to provide intuitive and comparable interfaces for different types of mobile devices.

On the other hand, because the usefulness of using mobile devices in courses highly influenced attitudes toward m-learning, the meaningful use of mobile devices for their courses would be a key means of persuading college students to utilize m-learning (Liu et al.,

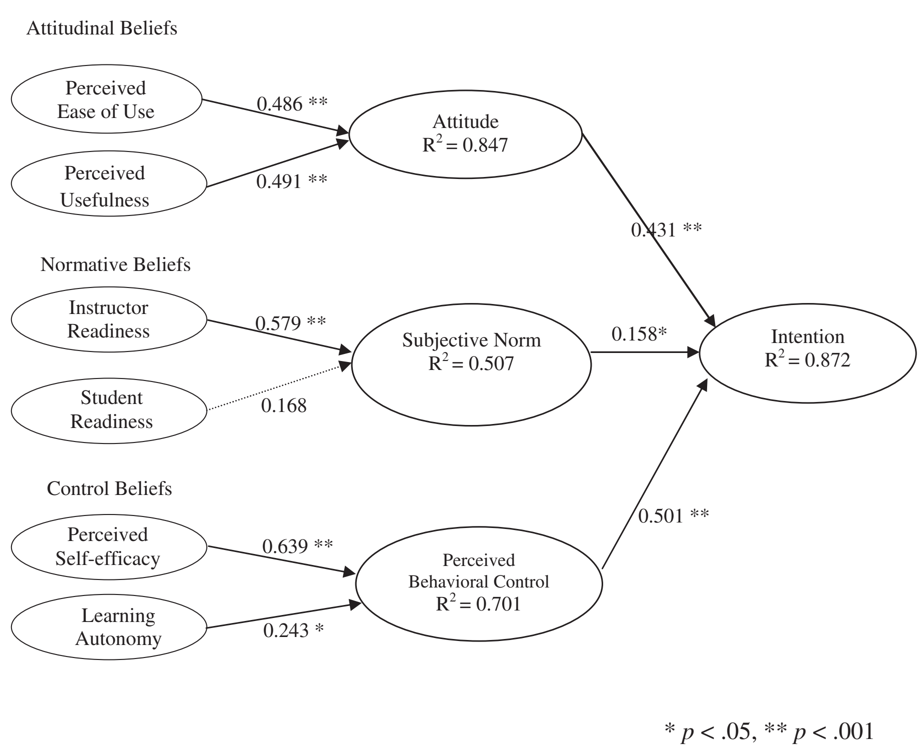

Fig. 2. Path coefficients of the research model.

2010). Valuable learning experiences should decrease college students' psychological resistance toward m-learning. Although a number of new pedagogical approaches have been introduced, we found that the expectation of college students were rather unsophisticated. For example, the data in Fig. 3 provide a means of designing m-learning for college courses. At the end of the survey, the participants were asked to indicate the extent to which course activities they prefer for their courses, and accessing course information was the highest preference of using mobile devices as shown in Fig. 3. The results are similar to Al-Mushasha's finding (2010) that accessing online educational content was ranked the highest. It can be said that providing mobile friendly course information would be the first step to implement m-learning, but more instructional models employing unique capacities of mobile devices should be investigated in college courses.

We find that college students' behavioral control was a key determinant in their intention to adopt m-learning. Although both antecedents positively affect behavioral control, self-efficacy ($\beta = 0.639$) had a higher effect on perceived behavioral control than learning autonomy ($\beta = 0.243$). This implies that empowering students with confidence in using m-learning would lead to a greater likelihood of m-learning adoption. As Shih and Mills (2007) suggested, mobile activities that are familiar to students, such as texting, voice recording, taking pictures, or shooting videos, can be used to accomplish an educational goal. However, the level of self-efficacy of using mobile devices for a course was measured in general. College students' self-efficacy would be different depending on the functions of mobile devices or learning activities. For example, students' confidence in augmented reality games would be lower than their confidence in online chatting. Thus, m-learning designers should implement m-learning components that students feel comfortable with, and more complicated activities can be used later. Further studies should investigate the difference of the level of self-efficacy on m-learning types.

Finally, we found that a significant relationship exists between subjective norm and intention. Nonetheless, the effect was somewhat lower ($\beta = 0.158$) than other two constructs. This finding is consistent with what Shiue (2007) found in which the subjective environment weakly influenced the actual use of technology. In the context of this study, only instructor readiness significantly influence subjective norm, whereas student readiness did not affect subjective norm. In other words, instructors may significantly influence college students' intention to adopt m-learning. In addition, the students perceived that their instructors ($M = 4.45$) were not ready for m-learning comparing to other students ($M = 5.47$, $t = -12.552$, $p < .001$). This implies that higher education institutions should be aware of the importance of faculty members' role when initiating m-learning. A related study found that college students were more likely to use Facebook or similar technologies, while faculty members were more likely to use more traditional methods, such as email (Roblyer, McDaniel, Webb, Herman, & Witty, 2010). These findings suggest that institutional support and provision of m-learning for faculty members are needed, such as technical support and professional development (Becta, 2004; Crow, Santos, LeBaron, McFadden, & Osborne, 2010; Traxler, 2007).

6.1. *Theoretical implications*

Most m-learning studies are based upon the theory of reasoned action (e.g., TAM, UTAUT) (Fishbein & Ajzen, 1975), but this study found that an additional factor, perceived behavioral control, was a key factor affecting the adoption of m-learning. Because perceived behavioral control is unique to the TPB, we argue that studies on m-learning should include perceived behavioral control. Indeed, omitting perceived behavioral control as a factor and relying on simple adoption models may not completely explain students' behavior for the adoption of m-learning. In addition, the six external beliefs identified in this study can be referred when researchers apply the TPB for the adoption of m-learning.

6.2. *Managerial implications*

The proposed adoption model of m-learning describes a set of factors affecting college students' use of m-learning. Thus, decision-makers in colleges or universities manipulate those factors to facilitate students' involvement and use of m-learning. In particular, our findings about the importance of perceived behavioral control suggest that managers of colleges enhance perceived behavioral control and improve students' attitude toward m-learning by providing opportunities to learn various functions of mobile devices for learning. In addition, an m-learning platform should be developed so that faculty can easily post course information or supplemental information first. As they become more familiar with mobile environments, more advanced m-learning strategies (e.g., producing, sharing, collaborating and capturing) can be adapted in their courses. Further research on m-learning from instructors' perspectives should reveal meaningful suggestions.

6.3. *Limitations*

This study has a number of limitations that circumscribe our interpretation and create opportunities for future research. First, since the participants watched three video clips that showed some examples of m-learning, their responses may have been biased toward the version

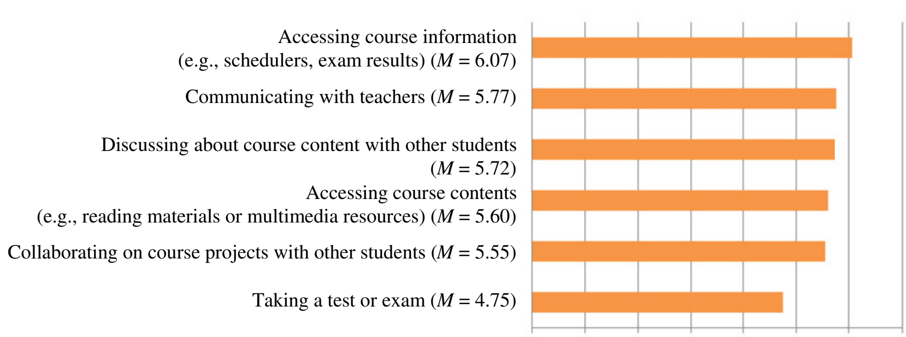

Fig. 3. Favorite m-learning activities for course works.

of m-learning depicted in the videos. This study was not able to include students' actual use of m-learning because they had not utilized m-learning in their coursework, except exchanging email with their mobile device. Future researcher should examine the perceptions of students' who have been exposed to m-learning in their coursework. Because individuals' perceptions change over time as they gain experience (Venkatesh & Davis, 2000), a series of studies on students' perceptions toward m-learning could assess the success of m-learning implementation. Second, the sampling method (i.e., convenience sample) introduced a potential bias in this study, although participants in this study were from various majors. Hence, the results may not be generalizable to a broader student population. Future studies should take a random sample from across a university or multiple campuses. Third, this study is limited to college students' perceptions. Further research should examine college faculty and compare their perceptions to students' perceptions to determine differences. Future research of this type should provide more detailed implementation guidelines to higher education institutions.

7. Conclusion

This study investigated the factors affecting college students' intention to use m-learning based on the TPB. The results showed that 87.2% of intention to adopt m-learning in an American higher education context was explained by components of the TPB. The significant factors were attitude, subjective norm and behavioral control. It is important for practitioners and researchers to understand what makes end-users accept or resist m-learning and how to improve user acceptance of m-learning. The findings indicated that higher education institutions should implement strategic efforts to build m-learning implementation plans, such as design guidelines, development phases and articulating norms, and considering the current level of students' readiness. For example, m-learning initiatives can be assessed by the three points of view proposed in this study. In order to increase students' positive attitude, meaningful information should be easily accessed by mobile devices. Also, a new system should be within students' comfort level of using mobile devices in order to ensure their confidence. Since faculty members significantly influence students' use of m-learning, faculty needs to be more familiar with m-learning. In addition to students, other stakeholders such as faculty should be involved in implementation plans.

Mobile learning implementation is a complex technical and cultural challenge for higher education institutions. Emerging technologies could resolve the technical limitations of mobile devices, such as lower resolution, network speed, and platform comparability. However, it would be hard to shift a pedagogical culture to a mobile format. Since learning involves the orchestration of students, instructors, content, and institutions, all participants should play their role in creating a new pathway to learning with mobile devices. The findings of this study should help in the design of more user-accepted m-learning systems.

Acknowledgments

This study was partially supported by a grant from Sogang Business School's World Class University Project (R31-20002) funded by the Korea Research Foundation. This study was also partially supported by the Sogang University Research Grant of 2011.

Appendix A. Survey items used in the study

Perceived Ease of Use
PEOU1: I believe that mobile devices would be easy to use.
PEOU2: I believe it would be easy to access course material with my mobile device.
PEOU3: I believe that mobile devices would be easy to operate.

Perceived Usefulness
PU1: I believe that using mobile devices would improve my ability to learn.
PU2: I believe that mobile devices would allow me to get my work done more quickly.
PU3: I believe that mobile devices would be useful for my learning.

Attitude
ATT1: I would like my coursework more if I used m-learning.
ATT2: Using m-learning in my coursework would be a pleasant experience.
ATT3: Using m-learning in my coursework is a wise idea.

Instructor Readiness
IR1: I think instructors would be in favor of utilizing m-learning for their courses.
IR2: I think instructors would believe that a mobile device could be a useful educational tool in their courses.
IR3: I think instructors would possess adequate technical skills to use a mobile device in their teaching.

Student Readiness
SR1: I think other students would be in favor of utilizing m-learning in their coursework.
SR2: I think other students would believe that a mobile device could be a useful educational tool in their coursework.
SR3: I think other students would possess adequate technical skills to use a mobile device in their coursework.

Subjective Norm
SN1: Most people who are important to me think that it would be fine to use a mobile device for university courses.
SN2: I think other students in my classes would be willing to adapt a mobile device for learning.
SN3: Most people who are important to me would be in favor of using a mobile device for university courses.

Perceived Self-efficacy

SE1: I am confident about using a mobile device for my courses.
SE2: Using a mobile device for my courses would not challenge me.
SE3: I would be comfortable to use a mobile device in my courses.

Learning Autonomy

LA1: I would be able to actively access coursework material with a mobile device.
LA2: I would have more opportunities to create knowledge in my coursework with a mobile device.
LA3: I would be able to control the pace of learning in my classes with a mobile device.

Behavioral Control

BC1: I have a sufficient extent of knowledge to use m-learning.
BC2: I have a sufficient extent of control to make a decision to adopt m-learning.
BC3: I have a sufficient extent of self-confidence to make a decision to adopt m-learning.

Intention

INT1: I predict I would use a mobile device for my courses.
INT2: I plan to use a mobile device if a course has mobile learning functions.
INT3: I intend to adopt a mobile device for university courses.

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